Summer 8-15-2021

Patterns and Trends Among Intimate Partner Homicide Cases: An Analysis by Victim’s Sex and Race/ethnicity

Shih-Ying Cheng
Washington University in St. Louis

WASHINGTON UNIVERSITY IN ST. LOUIS

The Brown School

Dissertation Examination Committee:
Melissa Jonson-Reid, Chair
Jami Ake
Tonya Edmond
Shenyang Guo
Lindsay Stark

Patterns and Trends Among Intimate Partner Homicide Cases:
An Analysis by Victim's Sex and Race/ethnicity

by

Shih-Ying Cheng

A dissertation presented to
The Graduate School
of Washington University in
partial fulfillment of the
requirements for the degree
of Doctor of Philosophy

August 2021
St. Louis, Missouri

Table of Contents

List of Tables

List of Figures

Acknowledgments

This dissertation cannot be completed without the generous support and guidance from my dissertation committee chair, Dr. Melissa Jonson-Reid, and the dissertation committee members, Dr. Tonya Edmond, Dr. Shenyang Guo, Dr. Jami Ake, and Dr. Lindsay Stark. They diligently reviewed the dissertation (for many times) and offered extremely helpful feedback and guidance. Dr. Melissa Jonson-Reid and Dr. Tonya Edmond are my rock in this PhD journey. In addition to offering me research and teaching opportunities which helped me grow, they were always there for me whenever I needed them. I can never thank Melissa and Tonya enough. The dissertation analyses relied on guidance from Dr. Shenyang Guo, Dr. Derek Brown, and Dr. Brett Drake. They patiently walked me through data puzzles and tirelessly responded to my questions. I am very grateful to Prof. Katie Ciorba VonDeLinde for all her support in my research on gender-based violence. I wish I can teach gender-based violence like how she taught me. As a social worker, I knew that the most difficult work is in the field with survivors. My sincere gratitude to the social workers and activists who work with survivors of gender-based violence. I also wanted to acknowledge Taiwan Ministry of Education, National Association of Social Workers, and Influencing Social Policy for the fellowship support to my PhD education and dissertation writing. Many thanks to my partner, mother, and sister for their love and support. I am beyond lucky to have them in my life.

Shih-Ying Cheng

Washington University in St. Louis

August 2021

ABSTRACT OF THE DISSERTATION

Patterns and Trends Among Intimate Partner Homicide Cases:

An Analysis by Victim's Sex and Race/ethnicity

by

Shih-Ying Cheng

Doctor of Philosophy in Social Work

Washington University in St. Louis, 2021

Professor Melissa Jonson-Reid, Chair

Professor Tonya Edmond

Professor Shenyang Guo

Professor Jami Ake

Professor Lindsay Stark

Data suggest sex and race/ethnicity disparities in intimate partner homicide (IPH) and different trends in the IPH rates over time by sex and racial/ethnic groups. It is, however, less clear how to explain the disparities using the existing literature. This dissertation investigates the patterns and trends among IPH cases with a focus on differences within and between victims' sex and race/ethnicity subgroups using the National Violent Death Reporting System, Restricted Access Database (NVDRS-RAD). Data were linked to Census and policy data using the geographic indicator in the NVDRS-RAD. Latent class analysis (LCA) and mixed-effects modeling were performed to identify patterns of case characteristics of IPHs and to investigate the differential impacts of policies on subgroups over time. In total, 5,771 IPHs (n = 4,530 female IPHs; n =

1,241 male IPHs) across 16 states from 2005 to 2017 (13 years) were analyzed. The results of LCA suggested a 2-class model for male IPHs and a 3-class model for female IPHs. With male IPHs, the classes identified were (a) Physical Fight and Substance Use and (b) Justice-Involved. For female IPHs, the classes identified were (a) Multiple Homicides Followed by Suicides, (b) History of IPV and Substance Use, and (c) Justice-Involved. Significant differences in victim's race/ethnicity and other demographics (e.g., age) by class were found with both samples. For example, White women were more likely to be in the Multiple Homicides Followed by Suicides class, whereas Black/AA women were more likely to be in the Justice-Involved class. The percentage of victims reported as other race/ethnicity (e.g., AI/AN) and multiracial were highest in the History of IPV and Substance Use class. Furthermore, analysis results on the trend of IPH suggested that minority groups—particularly multiracial, Black/AA, and AI/AN—had a higher IPH rate, compared to Whites. The results of mixed-effects modeling suggested distinct factors of the IPH rate by victim's sex and race/ethnicity. For example, the mandatory arrest policies were never significantly associated with a decrease in IPH for victims who belong to a minority group although they were a significant factor for all victims and White victims in bivariate analysis. The findings suggest heterogeneity in IPHs and distinct factors of the IPH rate by victim's identity markers, underscoring the utility of intersectionality frame in analyzing social policies. The findings also indicate the complexity of IPV issues and their connectedness with multiple systems including health systems, legal systems, welfare resources, and social service.

Definition and Acronym

A useful conceptualization of intimate partner violence (IPV) is action(s) among those who were previously or are currently romantically involved, which intend to control the will, existence, well-being, or actions of another person (Cheng et al., 2019). Such behavior may or may not cause physical harm and can occur single or multiple instances as part of a pattern. However, many of the variables explored in this dissertation are bound to acts of criminality that in the U.S. system are referred to as domestic violence (DV). Therefore, throughout this dissertation, I use IPV in a broader sense and DV when referring to specific, criminalized forms of IPV associated with court adjudication.

In this dissertation, intimate partner homicide (IPH) is defined as deaths classified as homicides committed by the victim's current or former intimate partner (e.g., spouse, ex-spouse, boyfriend, girlfriend, ex-boyfriend or ex-girlfriend). This study is limited to analyzing IPHs in which the suspects and victims were opposite-sex intimate partners. Female IPHs refer to IPHs in which the victim was identified as female, and the suspect was identified as male. In contrast, male IPHs refer to IPHs in which the victim was identified as male, and the suspect was identified as female.

Furthermore, I use the term legal systems refer to legal services and the police in the criminal justice systems in recognition that some IPV survivors may not experience justice from criminal justice systems (Cheng et al., 2020).

Initialisms used in this dissertation study are listed in below.

IPH	Intimate partner homicide
IPV	Intimate partner violence
DV	Domestic violence
FBI	Federal Bureau of Investigation
SHR	Supplementary Homicide Reports

CDC	Centers for Disease Control and Prevention
NVDRS-RAD	National Violent Death Reporting System, Restricted Access Database
USDA	United States Department of Agriculture
ACS	American Community Survey
AA	African American
AI/AN	American Indian/Alaska Native
PI	Pacific Islander
AFDC	Aid to Families with Dependent Children
TANF	Temporary Assistance for Needy Families
RUCC	Rural-Urban Continuum Codes
GCA	Gun Control Act
LCA	Latent Class Analysis
FIML	Full information maximum likelihood
ICC	Intraclass correlation statistics
INT	Inverse normal transformation

Chapter 1: Introduction

Homicide is one of the most severe forms of violence among intimate partners. Although rare in comparison to intimate partner violence (IPV), intimate partner homicide (IPH) accounts for a significant number of deaths among women across a wide range of countries, including the U.S. (Stöckl et al., 2013). Data suggest sex and racial/ethnic disparities in IPH. About eighty percent of IPH victims are female (Fridel & Fox, 2019), with Black/African American (AA) and American Indian/Alaska Native (AI/AN) women linked to higher overall homicide rates than White women (Petrosky et al., 2017). Data also indicate different trends in the IPH rates over time by sex and racial/ethnic groups. According to the latest disaggregated analyses (Fox & Zawitz, 2007), between 1976 and 2005, the number of Black/AA men killed by intimate partners dropped by 83%, White men by 61%, Black/AA women by 52%, and white women by 6% (see Figure 1.1).

It is, however, less clear how to explain the disparities using the existing literature. A set of studies (e.g., Campbell et al., 2003; Glass et al., 2008; Miner et al., 2012) have explored risk factors associated with IPH and found an array of predictors of IPH among women with histories of IPV victimization. This literature does not explain the differential risk of IPH by racial/ethnic group, as these studies tend to conceptualize the racial category as a controlling factor rather than exploring variations between and within racial/ethnic groups.

Other researchers have proposed possible theories and typologies to describe different types of IPHs. Some research (e.g., Banks et al., 2008; Salari & Sillito, 2016) compared homicide–suicide IPH cases and homicide-only cases and indicated significant differences in the victim's and suspect's demographic factors, substance use, use of firearms, and "red flags" prior to the incident. Although these studies shed light on typologies of IPH cases, it is unclear how these proposed typologies can explain the observed disparities in IPHs by sex and race/ethnicity.

Other studies on IPH trends (e.g., Dugan et al., 1999; Zeoli & Webster, 2010) have identified social policies associated with the recent decrease in the IPH rate, including (a) mandatory and warrantless arrest policies that helped keep IPV offenders away from victims at critically dangerous moments, (b) firearm restriction laws that decreased the use of lethal means in IPV, and (c) welfare benefits that decreased financial stress families experience. Although some evidence suggests differential impacts of social policies in preventing IPH for certain subgroups in the population (e.g., Dugan et al., 2003; Raissian, 2016), the existing studies are either based on older data or do not account for differences by both sex and racial/ethnic subgroups.

To address this empirical phenomenon—the sex and race/ethnicity disparities in IPH—this dissertation investigated the patterns and trends among IPH cases with a focus on differences within and between victims' sex and race/ethnicity subgroups. Guided by the intersectionality frame (Crenshaw, 1991, 2017) and an ecological conceptual perspective (Heise, 1998), this study has two specific questions: (a) What are the patterns among IPH cases and their associations with victim's sex and race/ethnicity? (b) How are state policies associated with the IPH rate, particularly the sex- and race-specific IPH rate?

Consistent with prior studies (Dugan et al., 2003; Zeoli & Webster, 2010), IPH is defined as deaths classified as homicides committed by the victim's current or former intimate partner. This study analyzed IPHs in which the victim was identified as female and the suspect was identified as male (i.e., female IPHs), and the reverse (i.e., male IPHs), separately, because the literature has suggested qualitative differences in female IPHs and male IPHs (Daly & Wilson, 1988a, 1988b; Eriksson & Mazerolle, 2013; Serran & Firestone, 2004; Websdale, 2010; Wilson & Daly, 1996, 1998; Wilson et al., 1995).

The analyses were conducted using the National Violent Death Reporting System, Restricted Access Database (NVDRS-RAD). The data were linked to Census and policy data using the geographic indicator in the NVDRS-RAD. Latent class analysis (LCA) was performed to identify patterns of case characteristics among female IPHs and male IPHs and to investigate the associations between the identified patterns and victim's race/ethnicity. Mixed-effects modeling was used to investigate the differential impacts of policies on subgroups over time since the state data of multiple years are nested within states, and the clustering effects needed to be controlled for. The policies examined in the current studies include domestic violence (DV) arrest policies, gun control policies, and Temporary Assistance for Needy Families (TANF) benefit level. Implications for policy, practice, and future research are discussed herein.

Chapter 2: Literature Review

It is, obviously, imperative to address the issues of IPH in the U.S. It has been estimated that the economic toll of IPH in the U.S. is $1.2 billion based on the loss of productivity of adult victims (Max et al., 2004). Furthermore, individuals outside the intimate relationship may also be involved in IPH incidents and become corollary homicide victims (Smith et al., 2014). Research indicates that the corollary homicide victims can include the victim's new intimate partners, the suspect's or victim's family members and friends/acquaintances, police officers, and strangers (Smith et al., 2014). IPH also creates tremendously negative downstream impacts on surviving family members, particularly to children who lost their parent(s) due to IPH. Concerns about bereaved children include placement with a new family, mental health care, and contact with the perpetrating parent (Alisic et al., 2015).

Although the costs of IPH are unrecoverable, IPHs—or, at least some IPHs—are likely preventable. Petrosky et al. (2017) found that over 11% of IPH victims were known to have experienced some form of violence in the month preceding their deaths. Koppa and Messing (2019) found that 91% of female IPH victims and 73% of male IPH victims had a prior contact with the police for a DV complaint in the 3 years prior to the IPH incident. Studies that examined risk factors of IPHs also found a specific set of IPV history that was associated with an increase in lethality (Bailey & Kellermann, 1997; Campbell et al., 2007; Campbell et al., 2003; Glass et al., 2008; McFarlane et al., 2002; Sheehan et al., 2015).

2.1 Theory of IPV

Theories and typologies specifically to explain IPH haven been proposed. The major theories and typologies include (a) sexual proprietariness (IPH is in response to sexual infidelity, primarily explaining female IPH), (b) modern transgression (IPH is in response to perceived failures of modern masculinities, primarily explaining female IPH), and (c) self-defense/help (IPH is a way to get out from long-term IPV, primarily explaining male IPH), and (d) primarily homicidal versus suicidal (these two types of cases have distinct case characteristics).

2.1.1 Male Sexual Proprietariness Theory

Grounded in evolutionary psychology, the male sexual proprietartiness theory links men's mindset toward gender relationships with human evolutionary history to explain men's perpetration of IPH (Wilson & Daly, 1996). This theory proposes that men's and women's proprietary feelings toward their intimate partners have evolved to be different. Men are more concerned with sexual infidelity whereas women are more concerned with the allocation of their partners' resources and attention (Daly & Wilson, 1988b). Male sexual proprietariness presumes men's entitlement to their female partners' sexual and reproductive capacities and leads to inclinations to exercise control. This theory explains the role jealousy—often caused by known or suspected adultery—plays in female IPHs (Serran & Firestone, 2004).

2.1.2 A Modern Transgression

The framework of modern transgression explains how and why men commit familicides—deliberate killing of a current or former intimate partner plus one or more of their children (Websdale, 2010). Rather than an isolated, discrete event, this theory conceptualizes familicide as an intensely emotional process with two primary emotional styles: livid coercive and civil reputable (Websdale, 2010). The livid coercive style describes obsessive attempts to control and regulate one's intimate partner and children. Familicides committed by perpetrators of this type respond to "a threat to their very identity as men in a world policed by the imperatives of modern masculinities" (Websdale, 2010, p. 243). An intensity of shame and powerlessness that typically coincides with a lower social standing has been observed among this type of perpetrator. In contrast, the civil reputable type describes a taciturn emotional style among a group of IPH perpetrators who are typically upwardly mobile or economically aspiring. When perpetrators of this type feel their lives spinning painfully out of control (e.g., being laid off, bankruptcy), they see themselves obligated to “save” their family members from negative consequences (e.g., destitution, illness). Despite differences in the two emotional styles, both types of perpetrators share similar exhaustion of pride, an eclipse of self-respect, and a triumph of shame and humiliation—these qualities are associated with the failure to meet masculine norms in a modern society.

2.1.3 Self-Help/Defense Theories

Self-help/defense theories were developed to explain IPH in the context of long-term abuse, mainly applied to explain women’s perpetration of IPH. Research suggests that IPHs committed by women are qualitatively different from those committed by men. For example, female-perpetrated IPHs often involve no advanced planning and frequently occur in the contexts of long-term abuse (Peterson, 1999; Serran & Firestone, 2004). This perspective suggests that low social status and failure of external support systems leads to decreased access to effective remedies that address IPV, which in turn leads women to resort to lethal violence against their intimate partners to resolve the abuse. In short, women kill their abusive intimate partner to protect themselves from continued abuse or death at the hands of their partner.

2.1.4 Primarily Homicidal versus Suicidal

Researchers have attempted to develop typologies to differentiate IPH cases. One approach is to classify IPHs by the perpetrator’s motive. Belknap et al. (2012) categorized male IPH cases into self-defense and sexual proprietariness in light of the existing theories (Peterson, 1999; Wilson & Daly, 1996). Another approach is to compare homicide–suicide IPH cases to homicide-only IPH cases by identifying the presence of suicidal ideation and by indicating differences between these two types of cases in their characteristics. Banks et al. (2008) analyzed female IPHs (46 homicide–suicides, 78 homicides-only) and found that compared to homicide-only cases, homicide–suicide cases were more likely to involve the use of a firearm. Victims and perpetrators in homicide–suicide cases were older and more likely to be in a current or former marital relationship. Furthermore, victims in this type of cases had lower blood alcohol levels compared to victims in homicide-only cases.

Salari and Sillito (2016) applied a similar approach to a sample of murder–suicide news stories. They analyzed the news stories and categorized the murder–suicide events into primarily homicidal and primarily suicidal by examining the existence of the offender's suicidal intention prior to the incident. They suggested that offenders with primarily suicidal intentions were older; more likely to be described as quiet, nice, tired, worn out, or in poor health; and likely to be noticed with a depressed mood or financial trouble prior to the incident. In contrast, cases with primarily homicidal intentions were likely to be noticed with a history of IPV (e.g., power and control, stalking, kidnapping, isolation) and involve a protection order. This type of case (primarily homicidal) was also more likely to be involved with killings of the victim's new intimate partner. Relatedly, victims and offenders in the primarily homicidal cases were more likely in an estranged relationship.

2.2 Risk Factors Associated with IPH

In addition to theories and typologies explaining IPH, existing research has explored risk factors associated with IPH at the individual-, relationship-, and community- level.

2.2.1 The Individual and Relationship Level

Studies comparing IPH cases and IPV cases have been conducted to identify risk factors at the individual and relationship levels. They have found that female victims with a history of IPV are at a higher lethal risk if the victim has experienced a specific set of violent acts—forced sex, threats to kill, nonfatal strangulation, previous threat with a weapon, stalking, abuse during pregnancy, if the victim has a child not sired by the abusive partner, if the relationship has been estranged, and if the abuser has access to a gun, or has substance abuse issues (Campbell et al., 2003; Campbell et al., 2009; Glass et al., 2008; McFarlane et al., 2002; Miner et al., 2012; Sharps et al., 2001; Sheehan et al., 2015). This set of studies employed a case-control design that matches IPH cases and IPV-controls and analyzed data collected from multiple sources, including interviewing family members or friends of IPH victims. Findings from this scholarship has informed the development of assessment tools used in risk assessment and safety planning (Campbell et al., 2009; Messing & Thaller, 2013).

Another approach to identify risk factors of IPH is to compare IPH cases and non-IPH cases (i.e., homicide committed by a nonintimate partner, such as a stranger). Frye et al. (2008) analyzed data of female homicide victims and compared female IPHs to stranger homicides. They identified variables that distinguish female IPHs from stranger homicides. Specifically, female victims of IPH cases were younger and more likely to be foreign-born than female victims of stranger homicides.

2.2.2 The Community and Social Level

Studies also have identified risk factors of IPH at the community and social level. The index of socioeconomic status (e.g., percentage employed, percentage 12 years of school and above, percentage families not receiving public assistance) was associated with a decrease in female IPH (Frye & Wilt, 2001), whereas economic depreivation (e.g., percentage unemployed, median family income) and residentail instability (e.g., percentage living in a different house 5 years ago) were associated with an increase in IPH (Beyer et al., 2015; Diem & Pizarro, 2010).

Additionally, contray to the criminology theory that proposes an assoication between the crime rate and community characteristics respresnting social disorganization, the social disorganization theory does not seem to be viable to explain IPH. Research indicates that the index of social disorganization (e.g., percentage of housing units vacant, percentage of female-headed households with children, percentage divorced, percentage foreign-born) appered to be either nonsingificantly associated with female IPH (Frye et al., 2008; Frye & Wilt, 2001) or assocaited with a decrease in IPH (Diem & Pizarro, 2010). The negative association between social disorganization and the IPH rate is puzzling. Diem and Pizarro (2010) explained this unexpected relationship with the inclusion of percentage of foreign-born in the social disorganization index. They suggested that immigrant communities, particularly those dominated by Hispanics, might have strong family values and stronger social support, and in turn, resulting in a decrease in the IPH rate. To sum up, existing research suggests a positive relation between economic deprivation and IPH (Diem & Pizarro, 2010; Frye & Wilt, 2001), whereas the association between social disorganization and IPH is inconclusive (Beyer et al., 2015; Frye et al., 2008).

2.2.3 Women's Economic and Social Status

Feminist research has found associations between patriarchal norms, gender inequality, and prevalence of violence against women (Dobash & Dobash, 1979, 2015; Rothenberg, 2003; Stark, 2007; Taylor & Jasinski, 2011). From this perspective, violence is used by men as a means to control female partners; in contrast, when women engage in acts of violence, it is primarily due to self-defense (Dobash & Dobash, 1979; Kurz, 1989; Saunders, 1988; Walker, 1979; Yllö, 2004). Empirical studies, despite being few, suggest that increases in measures of women's status are associated with a decrease in IPHs—with evideince from both female and male IPHs. Vieraitis et al. (2008) identified a significant association between women's status (e.g., women's median annual income, percentage of women with a college degree, percentage of employed women) and a decrease in female IPHs. Dewees and Parker (2003) found an association between the percentage of women in part-time work and a decrease in female-perpetrated male IPHs.

2.3 Factors Associated with the Recent Decline in IPH

The above studies reviewed are mostly cross-sectional or do not examine data across a wide time frame. Other studies analyze aggregate data and look into the trend of IPH.

2.3.1 Reduction of Exposure to Abuse

Dugan et al. (1999) attributed the recent decline in IPH to: (a) declining domesticity (e.g., decreased marriage rate, increased divorce rate), (b) improved economic status of women (e.g., female-male education/earnings ratio), and (c) an increase in the availability of DV services (e.g., hotline, legal advocacy services). Because their results indicated that the associations were mainly significant for male IPHs and nonsignificant for female IPHs, Dugan et al. (1999) concluded that these factors contributed to the recent decline in IPH by allowing women to exit violent relationships prior to responding to ongoing violence with lethal force against their male intimate partner. In other words, increased women's agency in escaping from a violent relationship reduced women's exposure to violent intimate relationships, and in turn contributed to the decline in male IPHs committed by female IPV survivors, who resort to lethal violence. These findings echo Browne and Williams' (1989) finding of an association between legal and extralegal resources (e.g., civil relief for DV victims, number of DV shelters) and a decrease in male IPH only. Both studies viewed killings of men by female partners as victim-perpetrated crimes and considered legal interventions or DV resources as an alternative to killing for those who intend to exit an abusive relationship.

2.3.2 Focusing on DV Policies and Resources

Focusing on associations among DV policies, resources, and the trend of IPH, researchers have found that the presence of DV resources (e.g., shelters, rape crisis centers), welfare resources (AFDC benefit levels), and legislative responses to address DV (e.g., DV arrest policies) were associated with a decrease in IPH (Dugan et al., 2003; Stout, 1989; Zeoli & Webster, 2010). However, another study had a contradictory finding regarding DV arrest policies. Iyengar (2009) found an unexpected association between the mandatory arrest laws and the IPH rate in which the adoption of the mandatory arrest laws was associated with an increase in the IPH rate. Iyengar explained the results using the theory of decreased reporting—victims are less willing to report an incident if their abuser will be arrested, and therefore put themselves in a greater danger.

Relatively fewer studies examined the effects of DV policies and resources while taking the victim's characteristics other than sex into consideration. An exception was Dugan et al. (2003) who examined the associations between DV arrest policies, welfare resources, and the rate of IPH disaggregated by victim's marital status, sex, and race (Black, White, and other). By analyzing the FBI-Supplementary Homicide Reports (SHR) data, Dugan et al. found that although AFDC benefit level and DV arrest policy were linked to a decrease in IPH for all groups of victims, the significance level varied by victim demographics. For instance, AFDC benefit level was more likely to be significant for male IPHs than female IPHs. The mandatory arrest policy was only significant for married female victims. In addition, some of Dugan et al.'s findings suggested an undesired, retaliation effect (i.e., leading to an increase in IPH) of DV policies and resources, whereas others suggested a desired effect (i.e., larding to a decrease in IPH). The willingness of prosecutors' offices to take cases of protection order violation, for example, appeared to be associated with an increase in IPH among White married female victims, White unmarried female victims, and Black unmarried male victims. Similarly, Wells et al. (2010) also found distinct predictors of female IPH by race/ethnicity. Rurality appeared to be associated with an increase in IPH for Hispanic women only, whereas the male arrest rate was associated with an increase in IPH for Black women only.

2.3.3 Restriction of Firearm Access

Individual access to firearms was found to be a risk factor for IPH in several cross-sectional studies (e.g., Campbell et al., 2009). Zeoli et al. (2016) and Zeoli and Webster (2010) found that state laws that restrict access to firearms among individuals with DV histories were associated with a decrease in IPH. For example, Zeoli and Webster found significant associations between decreases in both total IPH and firearm IPH and the presence of state statutes restricting those under DV restraining orders (DVRO) from accessing firearms. Raissian (2016) found that the 1996 expansion of the federal Gun Control Act (GCA) led to fewer gun-related homicides among female IPHs and a reduction in gun-related homicides among other family members (e.g., parents, siblings). However, Raissian did not find a significant relationship between the GCA expansion and changes in gun-related homicides among male victims. Lastly, a systematic review of 12 studies also concluded that state statutes prohibiting persons under DVROs from accessing firearms were associated with a decrease in IPH (Zeoli et al., 2016).

2.3.4 A Different Story in Rural Counties

Rurality appears to be an important but often neglected factor of IPH as the majority of the existing IPH studies analyzed data from large U.S cities (e.g., Dugan et al., 1999; Zeoli &

Webster, 2010). In contrast to the overall decline in IPH in the U.S., research suggests that IPHs in rural counties were either nondeclining (Jennings & Piquero, 2008) or increasing (Gallup-Black, 2005). It is not clear exactly what characteristics related to rurality contributed to a different IPH trajectory. Gallup-Black (2005) suggested that the lack of access to health and DV services, poverty, unemployment, and lower educational attainment in rural counties are associated with increased IPHs. Focusing on IPH in rural counties, AbiNader (2020) examined individual- and community-level characteristics associated with IPH in rural counties and found that only individual-level factors (e.g., sex, race) were significantly associated with IPH, and that community-level factors (e.g., percentage unemployment, percentage educational attainment, percentage household below the poverty line) were nonsignificantly associated with IPH. Fewer studies have compared IPH occurring in different contexts (rural vs. urban counties).

2.4 Gaps in Existing Literature

The current literature provides theoretical explanations for IPH, examines typologies of IPH, and identifies individual-level and policy-level factors associated with IPH but is less clear in explaining the observed sex and racial disparities in IPH (Fox & Zawitz, 2007; Fridel & Fox, 2019; Petrosky et al., 2017). Some studies (Campbell et al., 2003; Glass et al., 2008; Miner et al., 2012) explored risk factors associated with IPH and found an array of predictors of IPH among women with a history of IPV. They do not explain the differential risk by racial and ethnic groups, as these studies tended to conceptualize the racial category as a controlling factor rather than exploring variations between and within racial/ethnic groups.

Other researchers proposed theories and typologies to describe different types of IPHs. Some research (Banks et al., 2008; Salari & Sillito, 2016) compared homicide–suicide IPH cases and homicide-only cases and indicates significant differences in the case characteristics.

Although these studies shed light on typologies of IPH cases, it is unclear how these proposed typologies can explain the observed disparities in IPHs by sex and race/ethnicity.

Studies on the trends of the IPH (e.g., Dugan et al., 1999; Zeoli & Webster, 2010) have identified social policies that are associated with the decrease in the IPH rate. Although some evidence suggests differential impacts of social policies in preventing IPH for certain subgroups in the population (Dugan et al., 2003; Raissian, 2016), most studies are either based on older data or do not account for differences by both sex and racial/ethnic subgroups.

It is also difficult to explain the disparities in IPH with studies that examine racial/ethnic differences in experiences related to IPV. Some studies present the unique challenges Black women encounter when addressing IPV—including being marginalized by institutions (e.g., social service agencies), feeling reluctant to request police intervention in order to be "loyal" to their ethnic groups, and feeling left to "fight on their own" by using physical violence (Potter, 2008; Richie, 1996, 2012). Researchers have also found that Black women are more likely to avoid legal systems in their service use when addressing IPV (Cheng et al., 2020; Durfee & Messing, 2012). However, it is unclear how these findings from IPV studies can be generalized to IPH given that most IPV does not result in lethality.

Researchers have also not fully examined IPH among other marginalized racial/ethnic groups. More recent evidence suggests a disproportionately higher risk in the overall homicide rate among the AI/AN population (Petrosky et al., 2017), earlier IPH research has mainly focused on the White and Black populations (Fox & Zawitz, 2007; Stark, 2007). Furthermore, some research has suggested a different trend of IPH in the rural communities (Gallup-Black, 2005; Jennings & Piquero, 2008) and the importance of examining corollary homicide victims (e.g., family members, new intimate partners) involved in IPH incidents (Smith et al., 2014).

However, relatively few IPH studies have examined how rurality and urbanity intersect with IPH or examined corollary homicides in addition to IPHs.

This dissertation investigated the patterns and trends of IPH cases in the contexts of acknowledging these research gaps. Guided by intersectionality (Crenshaw, 1991, 2017) and an ecological conceptual perspective (Heise, 1998), this study paid special attention to differences within and between victims' sex and race/ethnicity subgroups and included factors at the individual, community, and policy levels. This study addressed two research questions: (a) What are the patterns among IPH cases and their associations with victim's sex and race/ethnicity? (b) How are state policies associated with the IPH rate—particularly the sex- and race-specific IPH rate?

Chapter 3: Methods

3.1 Conceptual Model

This study combines both intersectionality and an ecological conceptual frame. Intersectionality posits that socially constructed categories of oppression and privilege, such as race, class, gender, and age, simultaneously interact to create unique life experiences, and that oppression and privilege magnify across targeted and privileged identities (Crenshaw, 1991, 2017; Murphy et al., 2009). This theoretical perspective is rooted in reflections on distinct everyday experiences and diverse perceptions of the feminist movements *within* groups of women (hooks, 1984). This study employs the intersectionality frame in the recognition that the risks for IPH are sex- and race/ethnicity-specific in the U.S. This frame guides the conceptualization regarding distinct effects of social policies on women in different social groups.

This study also relies on the ecological model, in which gender-based violence is conceptualized as influenced by different levels of factors (Fulu & Miedema, 2015; Heise, 1998), including the individual level (e.g., experiences of childhood violence), the interpersonal level (e.g., high relationship conflict), the community level (e.g., isolation of family), and the social level (e.g., gender norms, policy). Available empirical work on IPH has identified the significant factors at the interpersonal, community, and social levels (see Figure 3.1). This study accounts for factors at different levels when investigating the patterns and trends among IPH cases.

3.2 Research Question

This study attempts to build knowledge about the typologies and trends of IPH for specific subpopulations by addressing some of the research gaps stated previously. The study addressed two research questions: (a) What are the patterns among IPH cases and their associations with victim's sex and race/ethnicity? (b) How are state policies associated with the IPH rate—particularly the sex- and race-specific IPH rate?

In light of the existing literature, I hypothesized that patterns of IPH emerge from the data analysis although I did not have an estimate on the number of patterns that would be identified. Furthermore, I hypothesized that the DV arrest policies, firearm restriction laws, and welfare benefit levels are associated with decreases in the overall IPH rate. However, existing studies are not sufficient to guide hypotheses on how these policies affect the IPH rate by victim's sex and race/ethnicity. It is possible that, for example, DV arrest policy is associated with changes in IPH for male victims but not female victims.

3.3 Data

3.3.1 NVDRS-RAD

This study analyzed data from the NVDRS-RAD. Data sources of the NVDRS-RAD include death certificate, medical examiner reports, and law enforcement reports. The geographic indicator (i.e., victim's residence county and state) in the NVDRS-RAD was requested and was used to link data of the American Community Survey (ACS), Rural-Urban Continuum Codes (RUCC), and state policies.

The NVDRS is a multi-state surveillance system initiated by the Centers for Disease Control and Prevention (2019) since 2002. NVDRS covers all types of violent deaths—including homicides and suicides. By compiling data from police, hospital, and death records, NVDRS includes data elements that provide contexts about violent deaths such as mental health issues, life stressors, toxicology results, and information about the incidents. The use of the NVDRS-RAD allowed me to access more details of IPH cases (e.g., history of IPV between the suspect and victim, whether the suspect attempted suicide) that are not contained in the FBI-SHR data, another dataset often used by IPH researchers (Dobash & Dobash, 2015; Regoeczi & Banks, 2014). Furthermore, the NVDRS-RAD contains more information regarding the victim's race/ethnicity. Specifically, the victim's race variable in the FBI-SHR dataset has only the following categories: White, Black, other and the FBI-SHR dataset does not contain the variable victim's ethnicity (Fox & Swatt, 2009)

3.3.2 United State Department of Agriculture

The RUCC is a classification scheme that distinguishes metropolitan counties and nonmetropolitan counties by the population size and by degree of urbanization (United States Department of Agriculture, 2020). The codes range from 1 to 9, with higher numbers indicating a higher level of rurality. Furthermore, counties coded as 1 (counties in metro areas of 1 million population or more) to 3 (counties in metro areas of fewer than 250,000 population) are categorized as metropolitan counties and counties coded as 4 (urban population of 20,000 or more, adjacent to a metro area) to 9 (completely rural or less than 2,500 urban population, not adjacent to a metro area) are categorized as nonmetropolitan counties. I used the RUCC as both an ordinal variable (1-9) and a dichotomous variable (Metropolitan vs. Nonmetropolitan) in this dissertation. Specifically, for the analyses on patterns of IPH, the RUCC was used as an ordinal variable (1-9); for the analyses on trends of IPH, the RUCC was used as a dichotomous variable (Metropolitan vs. Nonmetropolitan) in calculating states' percentage metropolitan counties.

3.3.3 American Community Survey

The American Community Survey (ACS) data (United States Census Bureau, 2020) were used to provide estimates of state/year population, percentage of adult poverty, and percentage of college graduates. Sex and race/ethnicity-specific estimates were obtained to examine their associations with the sex and race/ethnicity-specific IPH rate. The non-IPH adult homicide rate per state/year was also used as a control variable. Specifically, the non-IPH adult homicide rate was calculated using the non-IPH homicide count data from the NVDRS and estimates of population number from the ACS.

3.3.4 State Policies

Information on policies, including DV arrest policies (i.e., discretionary/preferred/ mandatory), firearm restriction laws, and social welfare benefit levels (TANF) by state/year was obtained from LexisNexis, existing literature (Zeoli et al., 2011a, 2011b) and state law resources on firearm restriction laws (Siegel, 2020) and welfare rules (Urban Institute, 2020). These policy indicators were selected by consulting the existing literature (Dugan et al., 2003; Zeoli & Webster, 2010).

3.5 Sample

Figure 4.1 presents the IPH case samples used in this study. A total of 8,396 IPV-relevant deaths from 2005 to 2017 (13 years) in the 16 continuing participant states in the NVDRS were identified (Table 3.1). These deaths included homicide cases signaled with circumstances related to jealousy, distress over a current or former intimate partner's relationship, suspected relationship with another person leading up to the incident, and immediate or ongoing conflict or violence between current or former intimate partners. Therefore, these deaths do not only include IPHs but also corollary homicides.

3.5.1 Patterns of IPHs

Consistent with prior studies (Dugan et al., 2003; Zeoli & Webster, 2010), IPH is defined as deaths classified as homicides (e.g., murders or non-negligent manslaughters) committed by the victim's current or former intimate partner (e.g., spouse, ex-spouse, boyfriend, girlfriend, ex-boyfriend or ex-girlfriend). Furthermore, this study analyzed IPHs in which the victim was identified as female and the perpetrator was identified as male (female IPHs) and the reverse (male IPHs) separately based on findings from the existing literature in which it is found that the source of strain and motives differ by the suspect's sex (Daly & Wilson, 1988a, 1988b; Eriksson & Mazerolle, 2013; Serran & Firestone, 2004; Websdale, 2010; Wilson & Daly, 1996, 1998; Wilson et al., 1995),

Female IPHs and male IPHs in the NVDRS-RAD for victim ages 18 and over for all incidents occurring from the year of 2005 to 2017 in the 16 included states were examined. In total, 5,771 IPHs (female IPH n = 4,530; male IPH n = 1,241) were analyzed.

3.5.2 Trends of IPHs

IPH rates among 16 states—Alaska, Colorado, Georgia, Kentucky, Maryland, Massachusetts, New Jersey, New Mexico, North Carolina, Oklahoma, Oregon, Rhode Island, South Carolina, Utah, Virginia and Wisconsin (see Table 3.1)—from 2005 to 2017 were calculated and analyzed. IPH data from 2003 and 2004 were not used because fewer states participated in the NVDRS in the first 2 years. The sample was limited to states that consistently reported from 2005 to 2017. IPHs in the NVDRS-RAD (2005-2017) for victim ages 18 and over were used to calculate the IPH rates.

3.6 Variables

3.6.1 Patterns of IPHs

Table 3.2 presents definitions of the 13 indicator variables used in the analysis investigating the patterns among IPH cases. The selection of these variables was guided by the studies examining typologies of IPH cases (Banks et al., 2008; Salari & Sillito, 2016) and the availability of the data. These indicators were dichotomous and include characteristics of the incident (e.g., whether the incident involved multiple homicide victim deaths), the suspect (e.g., whether there was a known history of abuse of victim by the suspect), and the victim (e.g., weather the victim was 65 years old or older). Some indicator variables were created using information from more than one variable in the NVDRS dataset. For example, the variable Victim Had a Known Mental Health Issue was coded as “yes” if the victim was diagnosed with a mental health problem, the victim had a history of being treated for a mental health problem, or the victim was perceived to be depressed at the time of injury.

3.6.2 Trends of IPHs

Table 3.3 presents definitions of the state/year level variables used in the analysis investigating the trend of the IPH rates. The state policies examined included DV arrest policies (i.e., discretionary/preferred/mandatory), number of firearm restriction laws, and TANF benefit levels, measured by state/year. State/year-level control variables included Percentage Metropolitan Counties, Percentage College Graduates, Percentage Adults Below Poverty, and Non-IPH Adult Homicide Rate. These variables were selected by consulting the previous studies (Gallup-Black, 2005; Iyengar, 2009; Raissian, 2016; Zeoli & Webster, 2010). For example, the variable Non-IPH Homicide Rate was selected because it represents the state crime rate likely to be associated with the IPH rate (Dugan et al., 1999; Zeoli & Webster, 2010).

The sex and race/ethnicity specific IPH rates were obtained in order to examine the differential associations between social policies and the IPH rate disaggregated by sub population groups. The control variables Percentage College Graduates, Percentage Adult Poverty, and Non-IPH Adult Homicide Rate disaggregated by sex and race/ethnicity were obtained when conducting analysis for the sex- and race/ethnicity- specific IPH rates. For example, the estimate of percentage college graduates among Black/AA women was used when investigating factors of the IPH rate among Black/AA women.

3.7 Data Analysis

3.7.1 Patterns of IPHs

LCA, a person-centered analytic approach focusing on identifying unobserved classes (Collins & Lanza, 2010), was used to identify classes (mutually exclusive groups) with distinct patterns of IPH case characteristics. To guide model selection (appropriate number of classes) and assess model fit, multiple statistics and statistical tests were performed including the Akaike's information criterion (AIC), Bayesian information criterion (BIC), Lo–Mendell–Rubin likelihood ratio (LMR LR) test, adjusted Lo–Mendell–Rubin likelihood ratio (ALMR LR) test, and bootstrap likelihood ratio test (BLRT; Wang & Wang, 2012). In applying these tests, smaller values indicate better model fit and a significant *p value* ($p < 0.05$) of the LMR LR or BLRT test indicates that a model with one additional class is a better fit than a model with one less class (Wang & Wang, 2012). LCA was conducted with Mplus 8 (Muthén & Muthén, 1998-2017).

To conduct LCA, 13 binary indicator variables were created to capture the characteristics of IPHs. The selection of indicator variables was guided by prior studies and the availability of data. For example, the NVDRS-RAD did not systematically code the suspect's motivations. Therefore, that characteristic was not included in the LCA indicators. LCA procedures were then applied to identify patterns of the IPHs. To properly label the latent classes, the item-response probabilities over sample means were signaled in bold in highlighting the differences between the classes (see Table 4.4). I also contrast the probabilities between the male sample and the female sample to determine the class characteristics. For example, although the *Physical Fight and Substance Use* class *and the History of IPV and Substance Use* class in the male and female sample were similar in most case characteristics, the probability of endorsing the indicator physical fight or argument was higher for the male sample (male IPHs: 0.82, female IPHs: 0.60), whereas the probability of endorsing the indicator history of IPV was higher for the female sample (male IPHs: 0.17, female IPHs: 0.41). Acknowledging this difference, I named this class the *Physical Fight and Substance Use* class for male IPHs, and the *History of IPV and Substance Use* class for female IPHs.

Lastly, three-step latent class modeling, a widely used analytic approach in LCA analysis, was adopted to further investigate the association between latent class membership and demographics (Asparouhov & Muthén, 2014; Bakk et al., 2013; Bolck et al., 2004; Vermunt, 2017). More specifically, I conducted equality tests of means (for continuous variables) and probabilities (for categorical variables) across classes by using the auxiliary *DCON* and *DCAT* commands in the Mplus software package to investigate the association between latent class membership and victims' demographic variables (Asparouhov & Muthén, 2014). The *DCON/DCAT* approach, originally developed by Lanza et al. (2013) and later incorporated into Mplus (Asparouhov & Muthén, 2014), uses Bayes theorem and the model-based approach to estimate the conditional distribution of distal, observed outcome by class membership.

I used the complete cases that did not miss on the 13 binary indicator variables for the LCA, resulting in all IPH LCA sample n = 1,173, female IPH LCA sample n = 897, and male IPH LCA sample n = 276. As the analytic sample sizes were noticeably smaller, I also used the full information maximum likelihood (FIML) approach to handle missing data when performing LCA, which resulted in similar patterns. Additional analyses that compared the analytic sample and the excluded sample for male IPHs (see Table 4.6.1) and female IPHs (see Table 4.6.2) were also conducted. The results indicated similarity between the analytic sample and the excluded sample but also identified several significant differences by samples. For example, the percentage of suspects attempting suicide was higher in the excluded sample for both male and female IPH samples.

3.7.2 Trends of IPHs

Two-level random intercept modeling was performed to investigate the association between state policy and the IPH rate over time. Mixed-effects modeling was used because the state data of multiple years (16 states, 13 years) were nested within states and were needed to control for the clustering effects, evidenced by the high unconditional intraclass correlation statistics (ICC, see Table 4.10.1–4.10.10; Guo, 2005; Rabe-Hesketh & Skrondal, 2012). In order to accurately model the impacts of social policy on the IPH rate, which is often skewed, models were estimated with the rank-based inverse normal transformation (INT) of the IPH rate (McCaw et al., 2020) and 1-year lagged effect of policy. Histograms were conducted to check the normality of the transformed variables (Figure 4.2). The results of histograms raised concerns about normality among four out of the 10 transformed variables (i.e., Black IPH Rate, Black Female IPH Rate, Hispanic IPH Rate, and Hispanic Female IPH Rate). Random-intercept negative binomial models were thus conducted using the original outcome variables for these 4 outcomes.

For the mixed-effects linear modeling using the INT outcome variables, the mixed package in Stata was used. For the mixed-effects negative binomial modeling using the original outcome variables, the menbreg package was used. Robust standard errors were requested for the significance test. For mixed-effects linear models, the ICC statistics and R-squared were calculated following guidance from Rabe-Hesketh and Skrondal (2012). For mixed-effects negative binomial regression models, the *p* values of likelihood-ratio test that compared the mixed-effects Poisson regression model and negative binomial regression model were presented to indicate the need of using mixed-effects negative binomial regression models (vs. mixed-effects Poisson regression models).

All models were estimated with four steps. In Step 1, bivariate associations between policy and control variables were estimated with random intercept models using single independent variable. In Step 2, single policy variable and significant control variables in the Step 1 ($p < 0.05$) were used. In Step 3, all policy variables and significant control variables in the Step 2 ($p < 0.05$) were used. In the last Step 4, models in Step 3 were re-estimated after eliminating the variables with a *p* value > 0.80 in Step 3. Analyses were conducted with Stata 15 (StataCorp, 2017).

Chapter 4: Results

4.1 What Are the Patterns among IPH Cases?

4.1.1 Descriptive Analysis

Sample Characteristics of IPV-relevant Deaths. A total of 8,396 IPV-relevant deaths reported by the 16 included states from 2005 to 2017 were identified (Figure 4.1). Table 4.1 presents characteristics of the 8,396 IPV-relevant deaths. Among these deaths, about 73% of the victims (*n* = 6,160) were identified as an intimate partner of the suspect, whereas 27% of the victims (*n* = 2,236) were not an intimate partner of the suspect. Other victim-suspect relationships included acquaintance (16.06%; *n* = 1,348), parent (1.12%; *n* = 94), child (0.70%; *n* = 59) and other family member (1.38%; *n* = 116).

Sample Characteristics of Male IPHs and Female IPHs. Table 4.2 presents sample characteristics of 5,771 IPHs. About eight out of 10 victims were female (*n* = 4,530 female IPHs; 78.50%), whereas the remaining were male (*n* = 1,241 male IPHs; 21.50%). Female IPHs and male IPHs appeared differently in most incident-related variables. Female IPHs were more likely to involve multiple homicides (9.36% vs. 1.05%), have a suspect attempting suicide after the incident (32.76% vs. 6.12%), and involve a firearm as the primary weapon (57.40% vs. 49.80%) than male IPHs. Furthermore, female IPHs were less likely to report a physical fight or argument before the incident (33.89% vs. 46.01%), victim's use of alcohol preceding the incident (15.94% vs. 33.60%), and victim's use of weapon during the course of the incident (1.19% vs. 6.85%).

Victims and suspects of female IPHs and male IPHs were also different in demographic, interpersonal, and behavioral health variables. A higher percentage of female IPH victims were

White (54.44% vs. 44.64), Asian/Pacific Islander (PI) (2.41% vs. 0.97%), multiracial (3.18% vs. 1.45%), Hispanic (9.67% vs. 5.80%), foreign-born (9.74% vs. 3.14%), ever-married (64.81% vs. 59.71%), high-school graduate (49.01% vs. 46.33%), reported having mental health issues (4.97% vs. 3.55%) and a history of abuse by the suspect (18.28% vs. 7.82%). In contrast, a higher percentage of male IPH victims were Black/AA (44.24% vs. 27.97%), reported having substance abuse issues (13.94% vs. 9.14%), and had been involved in some other crime either by themselves or by the suspect (18.21% vs. 12.43%). The percentage of 65 years and older was higher among male suspects (7.84% vs. 3.55%). As to the contextual variables, a higher percentage of male IPH victims lived in a nonmetropolitan county (24.98% vs. 20.49%) and a county with more than 20% adult poverty rate (16.44% vs. 11.5%).

4.1.2 Latent Class Analysis

Table 4.3 presents fit statistics for latent Classes 1–7 using complete cases (i.e., no missing on the 13 LCA indicator variables) of female IPHs (n = 897) and male IPHs (n = 276). As shown, the lowest BIC was for the 3-class model with female IPHs (10777) and the 1-class model with male IPHs (3059.704) suggesting support for a 3-class model with female IPHs and a 1-class model with male IPHs (Nylund et al., 2007). Results of the LMR LR and ALMR LR test also suggested that the 3-class model performed better than the 2-class model with female IPHs (LMR: $p < 0.001$; ALMR: $p < 0.001$) and that the 2-class model did not perform better than the 1-class model with male IPHs (LMR: $p = 0.059$; ALMR: $p = 0.062$). However, with male IPHs, given that the BIC statistics of the 1-class model, the 2-class model, and the 3-class model were very close (1-class: 3059.704; 2-class: 3060.634; 3-class: 3059.992) and that the LMR and ALMR tests were near significant for the 2-class model (LMR: $p = 0.059$; ALMR: $p = 0.062$), we determined the 2-class model with male IPHs. Entropy, an index for assessing the precision of assigning latent class membership (Celeux & Soromenho, 1996; Ramaswamy et al., 1993), was 0.70 for the 3-class solution with female IPHs and 0.78 for the 2-class solution with male IPHs, suggesting good LCA models.

Patterns of IPH Characteristics. Table 4.4 presents the 3-class LCA model for female IPH (*n* = 897 female IPHs) and the 2-class LCA model for male IPH (*n* = 276 male IPHs) based on the estimated probabilities of endorsing the 13 LCA indicators. In this analysis, IPHs were placed in classes with distinct patterns of IPH case characteristics.

Male IPHs. With the sample of male IPHs, the classes identified were (a) *Physical Fight and Substance Use* (16.73%) and (b) *Justice-Involved* (83.27%). Class 1, the *Physical Fight and Substance Use* Class, comprised 17% of male IPHs and was characterized by higher probabilities of endorsing the indicator of reporting physical fight or argument (0.82 vs. sample mean: 0.66) and indictors related to substance use, including victim had known substance use issues (0.52 vs. sample mean: 0.23), victim used alcohol preceding the incident (0.85 vs. sample mean: 0.33), and suspect used alcohol or substance preceding the incident (0.74 vs. sample mean: 0.16). This class also had higher probabilities of endorsing the indicator IPV history (0.17 vs. sample mean: 0.05) and the indicator related to mental health (e.g., suspect's attack was related to a mental illness: 0.14 vs. sample mean: 0.05; victim had a known mental health issue: 0.10 vs. sample mean: 0.05).

Class 2, the *Justice-Involved* Class, comprised 83% of male IPHs, and was characterized by a higher probability of endorsing the indicator victim or suspect was involved in some crime (0.31 vs. sample mean: 0.28). This class also had a higher probability of endorsing the indicator firearm being the primary weapon (0.58 vs. sample mean: 0.56) and the indicator victim was suspect's (ex) boy/girlfriend (0.65 vs. sample mean: 0.62).

Female IPHs. With the sample of female IPHs, the classes identified were (a) *Multiple Homicides Followed by Suicides* (21.40%), (b) *History of IPV and Substance Use* (19.49%), and (c) *Justice-Involved* (59.11%). Class 1, *Multiple Homicides Followed by Suicides*, comprised 21% of female IPHs, and was characterized by higher probabilities of endorsing the indicator multiple homicides (0.15 vs. sample mean: 0.10) and the indicator suspect attempted suicide after the death of the victim (0.74 vs. sample mean: 0.35). This class also had a higher probability of endorsing the indicator firearm being primary weapon (0.90 vs. sample mean: 0.60) and the indicators related to mental health (e.g., suspect's attack was related to a mental illness: 0.12 vs. sample mean: 0.07; victim had a known mental health issue: 0.10 vs. sample mean: 0.09). Furthermore, this class had the lowest probability of endorsing the indicator suspect being victim's (ex) boy/girlfriend (0.05 vs. sample mean: 0.53) among the three classes.

Class 2, *History of IPV and Substance Use*, comprised 19% of the sample, and was characterized by higher probabilities of endorsing the indicator history of IPV against victim by suspect (0.41 vs. sample mean: 0.21) and the indicators related to substance use, such as, victim had known substance use issues (0.38 vs. sample mean: 0.13), victim used alcohol preceding the incident (0.58 vs. sample mean: 0.18), and suspect used alcohol or substance preceding the incident (0.76 vs. sample mean: 0.18). This class also had a higher probability of endorsing the indicator physical fight or argument before the incident (0.60 vs. sample mean: 0.45), the indicators related to mental health (e.g., suspect's attack was related to a mental illness: 0.11 vs sample mean: 0.07; victim had a known mental health issue: 0.15 vs. sample mean: 0.09), and the indicator suspect being victim's (ex) boy/girlfriend (0.67 vs. sample mean: 0.53).

Lastly, Class 3, *Justice-Involved*, comprised 59% of the sample and was characterized by higher probabilities of endorsing the indicator suspect being victim's (ex) boy/girlfriend (0.65 vs.

sample mean: 0.53) and the indicator victim or suspect was involved in some crime (0.23 vs. sample mean: 0.18).

4.1.3 Comparison Between Latent Classes

Table 4.5 summarizes results of the associations between latent class membership and victims' demographic variables using the *DCON/DCAT* method. The *DCON/DCAT* method analyzed the available cases depending on missingness on the auxiliary variables (i.e., victims' and suspects' demographic variables), resulting in different sample sizes presented in Table 4.5.

Male IPHs. With the sample of male IPHs, male victims' foreign-born status ($p < 0.01$), education level ($p < 0.001$) and race/ethnicity ($p < 0.001$) were different by class membership. The mean RUCC of victim's residence county also differed by class membership ($p < 0.05$). Specifically, the percentage of male victims who were U.S.-born (100% vs. 95%), high-school graduates (100% vs. 76%), and White (76% vs. 2%) were higher in the *Physical Fight and Substance Use* class than the *Justice-Involved* class. In contrast, the percentage of Black/AA victims (87% vs. 11%) were higher in the *Justice-Involved* class. The mean RUCC (2.66 vs. 3.35) was lower in the *Justice-Involved* class, indicating a higher level of urbanity. The percentage of economically disadvantaged counties (20% vs. 7%) was higher in this class although the difference between the two classes was only near significant ($p = 0.055$).

Female IPHs. With female IPHs, female victims' education level ($p < 0.005$), age ($p < 0.001$), and race/ethnicity ($p < 0.001$) were different by class membership. The mean RUCC of victim residence county also differed by class membership ($p < 0.001$). Specifically, the percentage of female victims who were high school graduates (92% vs. Class 2: 81%, Class 3: 84%) and White (81%) were highest in the *Multiple Homicides Followed by Suicides* class, although the percentage of high school graduates were not significantly higher than the Class 2

(81%) or Class 3 (84%) in pairwise comparisons. The mean age (75.03 vs. Class 2: 37.84, Class 3: 37.89) was also highest in the *Multiple Homicides Followed by Suicides* class. In contrast, the percentage of female victims who were Black/AA (47% vs. Class 1: 10%, Class 2: 6%) and Hispanic (14% vs. Class 1: 6%, Class 2: 13%) were highest in the *Justice-Involved* class. The mean RUCC (2.23 vs. Class 1: 2.74, Class 2: 3.07) was lowest in the *Justice-Involved* class, indicating a higher level of urbanity. Lastly, the percentage of victims reported as other race/ethnicity (AI/AN, Asian/PI, Other; 12% vs. Class 1: 2%, Class 3: 5%) and multiracial (4% vs. Class 1: 2%, Class 3: 0%) were highest in the *History of IPV and Substance Use* class. The percentage of Hispanic victims (13% vs. Class 1: 6%, Class 3: 14%) was also high in the *History of IPV and Substance Use* class.

4.2 How Are State Policies Associated with the IPH Rate?

4.2.1 Descriptive Analysis

IPH Rates. Table 4.7.1, 4.7.2, and 4.7.3 presents the descriptive statistics of overall IPH rates, male IPH rates, and female IPH rates, respectively. On average, 39.54 IPV-relevant deaths (e.g., IPHs and corollary homicides; 10.44 per 1,000,000 adults) occurred per state/year with a greater variance between states than variance within states over years (between SD = 4.48, within SD = 2.25). Among these deaths, 27.75 per state/year were IPHs that occurred between a suspect and a victim in an intimate relationship (7.17 per 1,000,000 adults); among these IPHs, 15.47 per state/year used a firearm as the primary weapon (3.93 per 1,000,000 adults). The average IPH rate was highest for victims who were multiracial (rate = 16.12 per 1,000,000 adults, count = 0.78), then victims who were Black/AA (rate = 13.13 per 1,000,000 adults, count = 8.73), then victims who were AI/AN (rate = 7.83 per 1,000,000 adults, count = 0.60), then victims who were

Hispanic (rate = 6.05 per 1,000,000 adults, count = 2.24), and last victims who were White (rate = 5.46 per 1,000,000 adults, count = 14.52).

Male IPH Rates. Table 4.7.2 presents the descriptive statistics of male IPH rates. On average, 5.97 male IPHs (3.13 per 1,000,000 adults) occurred per state/year with comparable between-states and within-state variances (between *SD* = 1.77, within *SD* = 1.60). The average male IPH rate was highest for male victims who were Black/AA (rate = 9.48 per 1,000,000 adults, count = 2.64), then multiracial (rate = 3.86 per 1,000,000 adults, count = 0.09), then victims who were AI/AN (rate = 3.53 per 1,000,000 adults, count = 0.16), then victims who were White (rate = 2.20 per 1,000,000 adults, count = 2.66), and last victims who were Hispanic (rate = 1.90 per 1,000,000 adults, count = 0.35).

Female IPH Rates. Table 4.7.3 presents the descriptive statistics of female IPH rates. On average, 21.78 female IPHs occurred (11.05 per 1,000,000 adults) occurred per state/year with a slightly greater variance between states than variance within states over time (between *SD* = 4.21, within *SD* = 3.68). The average female IPH rate was highest for female victims who were multiracial (rate = 27.93 per 1,000,000 adults, count = 0.69), then Black/AA (rate = 16.70 per 1,000,000 adults, count = 6.09), then victims who were AI/AN (rate = 12.10 per 1,000,000 adults, count = 0.44), then victims who were Hispanic (rate = 10.75 per 1,000,000 adults, count = 2.11), and last victims who were White (rate = 8.58 per 1,000,000 adults, count =11.86).

Policy (2004–2016). Table 4.8 presents the descriptive statistics for policy variables. Among the 16 states, the mean of firearm restriction laws per state/year was 27.8 with a greater variance between states than variance within states over time (between *SD* = 26.81, within *SD* = 2.21). The mean TANF benefit for a family of three per month was $453.54 (between *SD* = 184.14, within *SD* = 22.06). As to the DV arrest policy, on average, 38% of states/year adopted discretionary DV arrest policies, 6% adopted preferred arrest laws, and the other 56% adopted mandatory arrest.

Control Variables (2005-2017). Table 4.9 presents the descriptive statistics of control variables at the state level. On average, each state/year had 48% metropolitan counties, 38% college graduates, and 12% adults living in poverty. The mean non-IPH adult homicide rate was 51.18 per 1,000,000 adults. Disparities appeared in the control variables by race/ethnic groups. The Percentage College Graduates variable was highest among Whites (White: 34%, White female: 33%), then Blacks/AAs (Black: 20%, Black female: 21%), and last Hispanics (Hispanic: 15%, Hispanic female: 17%). The Percentage Adult Poverty variable was lowest among Whites (White: 9%, White female: 10%). Blacks/AAs (Black: 20%, Black female: 23%) and Hispanics (Hispanic: 19%, Hispanic female: 23%) appeared to have a similar level of adult poverty rate. The rate of non-IPH adult homicide was highest among Blacks/AAs (Black: 197.53 per 1,000,000, Black female: 37.11 per 1,000,000), then Hispanics (Hispanic: 56.40 per 1,000,000, Black female: 11.46 per 1,000,000), and last Whites (White: 23.55 per 1,000,000, White female: 10.64 per 1,000,000).

4.2.2 Random-Intercept Models

Modeling IPV-relevant Deaths and IPHs. Table 4.10.1 and 4.10.2 presents results of random-intercept models predicting the rate of IPV-relevant death (e.g., IPHs and corollary homicides; Table 4.10.1) and the rate of IPH (Table 4.10.2). Most variables were significantly associated with the rate of IPV-relevant death and the rate of IPH in the bivariate models (Step 1). The preferred arrest policy, the mandatory arrest law, the number of firearm restriction laws, the percentage of metropolitan counties, and the percentage of college graduates were associated with a decrease in IPV-relevant death and IPH. In contrast, the rate of non-IPH adult homicide was associated with an increase in IPV-relevant death and IPH. However, the associations between policy variables and the rate of IPV-relevant death and the rate of IPH became nonsignificant in multivariate models from Step 2, suggesting that the control variables shared a significant proportion of the variance. In the final model predicting the rate of IPV-relevant death (Table 4.10.1, Step 4), only percentage of college graduates (-) and non-IPH adult homicide rate (+) were significant. In the final model predicting the IPH rate (Table 4.10.2, Step 4), only percentage of metropolitan counties (-) and non-IPH adult homicide rate (+) were significant.

Modeling Male IPHs and Female IPHs. Table 4.10.3 and 4.10.4 presents results of random-intercept models predicting the rate of male IPH (Table 4.10.3) and female IPH (Table 4.10.4). In the bivariate models (Step 1), the preferred arrest law, the mandatory arrest law, the number of firearm restriction laws, the percentage of metropolitan counties, the percentage of college graduates, and non-IPH adult homicide rate were associated with a decrease in male IPH, whereas the preferred arrest policy, the number of firearm restriction laws, and the percentage of metropolitan counties were significantly associated with the female IPH rate. In the final model, policy variables were nonsignificant for both the male IPH rate and the female IPH rate, suggesting that the control variables shared a significant proportion of the variance. The non-IPH adult homicide rate (+) was significantly associated with the male IPH rate (Table 4.10.3, Step 3), whereas no variables were significantly associated with the female IPH rate (Table 4.10.4, Step 4).

Modeling White IPHs, Black/AA IPHs, and Hispanic IPHs. Table 4.10.5, 4.10.6, and 4.10.7 presents results of random-intercept models predicting the White IPH rate, the Black IPH rate, and the Hispanic IPH rate. In the bivariate models (Step 1) predicting the White IPH rate, significant variables included the preferred arrest law (-), the mandatory arrest law (-), the number of firearm restriction laws (-), percentage of metropolitan counties (-), percentage of adult poverty (+), and non-IPH adult homicide (-). In contrast, the preferred arrest law (-) was the only variable associated with the Black IPH rate, and non-IPH homicide rate was the only variable associated with the Hispanic IPH rate in the bivariate models. In the multivariate final models, the preferred arrest law (-), TANF benefit level (-), and percentage of metropolitan counties (-) were associated with the White IPH rate; the non-IPH adult homicide rate (+) was associated with the White IPH rate and the Hispanic IPH rate, but not the Black IPH rate.

Modeling White Female IPHs, Black/AA Female IPHs, and Hispanic Female IPHs. Table 4.10.8, 4.10.9, and 4.10.10 presents results of random-intercept models predicting the White female IPH rate, the Black female IPH rate, and the Hispanic female IPH rate. The preferred arrest law (-), the mandatory arrest law (-),the number of firearm restriction laws (-), percentage of metropolitan counties (-), percentage of adult poverty (+), and non-IPH adult homicide (-) were associated with the White female IPH rate in the bivariate model. The preferred arrest law (-) was the only variable associated with the Black female IPH rate, and no variable was associated with the Hispanic female IPH rate. In the multivariate final models, the preferred arrest law (-), TANF benefit level (-), percentage metropolitan counties (-), and non-IPH adult homicide rate (+)were associated with the White female IPH rate, whereas no variables were associated with the Black female IPH rate and the Hispanic female IPH rate.

Chapter 5: Discussion

This study investigated the patterns and trends among IPH cases with a focus on differences within and between victims' sex and race/ethnicity subgroups. In the first part of the analysis, I employed a person-centered analytic approach to investigate patterns of IPHs and their associations with victim's race/ethnicity. In the second part of the analysis, I investigated the differential associations between social policy and the IPH rate disaggregated by sex- and race/ethnicity. In contrast to prior IPH studies that only focused on the White and Black populations, this study calculated the IPH rates by victim's sex and race/ethnicity and presents descriptive results of IPH rates that were not presented in the existing literature—the multiracial IPH rate, AI/AN IPH rate, and Hispanic IPH rate. This study adds to the literature by providing a fuller picture of typologies of IPH cases, by presenting racial/ethnic disparities in IPH, and by examining factors that contribute to sex and racial/ethnic disparities in IPH.

5.1 Patterns of IPHs

Echoing prior studies that attempted to differentiate or categorize IPH cases (Banks et al., 2008; Belknap et al., 2012; Salari & Sillito, 2016; Websdale, 2010), analysis results of this study suggest heterogeneity among IPH cases. As hypothesized, patterns of IPH were identified. Consistent with the studies that compared primarily homicidal IPHs to primarily suicidal IPHs (Banks et al., 2008; Salari & Sillito, 2016), this study also found that the suspects and victims in the *Multiple Homicides Followed by Suspects' Suicides* class were older, were more likely to be in a current or former marital relationship, and were less likely to have a known substance issue. IPHs in the *Multiple Homicides Followed by Suspects' Suicides* class were also more likely to involve a firearm as the primary weapon.

This study adds to the literature by furthering knowledge about patterns of IPH by victim's sex. Firstly, findings of this study suggested that the *Multiple Homicides Followed by Suspects' Suicides* class was identified only for female IPHs, but not for male IPHs. Furthermore, although both male and female IPHs shared two similar classes (e.g., the *Physical Fight/History of IPV and Substance Use* class and the *Justice-Involved* class), some differences existed across samples. One obvious difference is the probability of endorsing the indicator physical fight or argument and the indicator history of IPV for the *Physical Fight and Substance Use* class in male IPHs and the similar *History of IPV and Substance Use* class in female IPHs. As these two classes were similar in most case characteristics, the probability of endorsing the indicator physical fight or argument was higher for the male sample (male IPHs: 0.82, female IPHs: 0.60), whereas the probability of endorsing the indicator history of IPV was higher for the female sample (male IPHs: 0.17, female IPHs: 0.41). Additionally, the demographic characteristics also appeared to differ across the female and male samples for similar classes. For example, for the *Physical Fight and Substance Use* class with male IPHs, all (100%) victims were U.S.-born and high school graduates, whereas no class in female IPHs had 100% of victims who were U.S.-born or high school graduates. Similar to the *Justice-Involved* class with the male sample, female victims in the *Justice-Involved* class were more likely to live in urban counties, but there appeared to be less difference among classes with regard to adult poverty rate in the female sample.

This study also found significant difference in victim's race/ethnicity by class with both samples, suggesting distinct types of risks and needs by different population groups. For male IPHs, victims who were White and other race/ethnicity were more likely to be in the *Physical Fight and Substance Use* class, whereas victims who were Black/AA and Hispanic were more likely to be in the *Justice-Involved* class. For female IPHs, White victims were more likely to be in the *Multiple Homicides Followed by Suicides* class. Black/AA victims were more likely to be in the *Justice-Involved* class. Victims who were other race/ethnicity and multiracial were more likely to be in the *History of IPV and Substance Use* class. Lastly, Hispanic victims were equally likely to be in the *History of IPV and Substance Use* class and the *Justice-Involved* class.

As the results indicated significant differences in victims' demographic variables, it is important to note that the importance of not essentializing race or reinforcing stereotypes and the importance of putting these findings into context. For example, the results suggested that Black/AA individuals were more likely to be in the *Justice-Involved* class. Viewing this finding in the context, it is highly possible that this finding is generated by systematic racism that makes Black/AA individuals more likely to have a criminal record in the legal systems (Richie, 1996, 2012). Implications of the findings should be made with acknowledging systematic racism in the U.S. legal systems.

5.2 Trends of IPHs

The analysis results on the trend of IPH highlight the utility of the intersectionality frame in social policy analysis. Consistent with the prior studies (Fridel & Fox, 2019; Koppa & Messing, 2019; Petrosky et al., 2017), this study found that women are more likely than men to experience IPH. Furthermore, this study found that minority groups—particularly multiracial, Black/AA, and AI/AN—had a higher IPH rate. Furthermore, the analysis results suggest distinct factors of the IPH rate by victim's sex and race/ethnicity.

As existing literature suggested (Dugan et al., 1999; Zeoli & Webster, 2010), this study found that DV arrest policy, firearm restriction law, and welfare benefit level were likely to prevent IPH and IPV-relevant death as they were associated with a decrease in IPH in bivariate models. However, most policy variables became nonsignificant after adding the control variables, suggesting that the control variables shared a considerable proportion of variance. The non-IPH adult homicide rate and percentage metropolitan counties appeared to be more robust factors of the IPH rate. As expected, the non-IPH homicide rate was associated with an increase in IPH and an increase in IPV-relevant death, whereas percentage metropolitan counties was associated with a decrease in IPH.

The analysis results suggested distinct factors of IPH rate by victim's sex. In bivariate models predicting the IPH rate, the variables preferred arrest policy, mandatory arrest policy, and firearm restriction law were significant for male victims, whereas only preferred arrest policy and firearm restriction law were significant for female victims. The mandatory arrest policy was nonsignificant for female victims although the preferred arrest policy was significant for them. In the final model, only the non-IPH adult homicide rate was significant with the IPH rate for male victims, whereas only percentage metropolitan counties were near significant ($p = 0.099$) for female victims. Some studies (e.g., Arnold & Ake, 2013) have pointed out the unintended consequences of criminalization efforts responding to DV for women. The mandatory arrest policy, particularly, has been criticized for increasing women's risk of being arrested and disempowering women in the legal systems (Goodmark, 2012; Meloy & Miller, 2011). Given that the mandatory arrest policy was associated with male IPH but not female IPH in bivariate models and that the preferred arrest policy was associated with the IPH rate for both groups in the analysis, it is possible that the mandatory arrest policy does offset some desired effects in addressing DV for women. Furthermore, that the non-IPH homicide rate was only significant for male victims is intriguing, suggesting that the state-level crime trend matters more for male IPHs than female IPHs.

The results also suggest distinct factors of the IPH rate by victim's race/ethnicity and the intersection of sex and race/ethnicity, highlighting the utility of the intersectionality frame (Crenshaw, 1991, 2017; Murphy et al., 2009). Specifically, in bivariate analysis, the preferred arrest policy, mandatory arrest policy, and firearm restriction law were significant in models predicting IPH for Whites and White women, whereas only preferred arrest policy was significant for Black/AA and Black/AA women, and no policy variable was significant for Hispanic and Hispanic women. In multivariate analysis models, the preferred arrest law, TANF benefit level, and percentage of metropolitan counties were significant for Whites and White women but not for other victims. Additionally, the non-IPH homicide rate was significant for White, White women, and Hispanic, but not for Black/AA, Black/AA women, and Hispanic women. These findings have several implications.

Firstly, the finding that mandatory arrest policy was significant for White victims in the bivariate model but not for Blacks/AAs and Hispanics offers some quantitative evidence supporting narratives (Coker, 2001; Richie, 1996, 2012) regarding the disproportionately negative effects of mandatory arrest policy for minority groups. Richie (1996, 2012), for example, points out that the antiviolence movement's emphasis on punitive interventions coincided with the buildup of America's prison nation which might contribute to the ongoing escalation of male violence against Black/AA women as Black/AA men encounter more difficulties. Furthermore, because Black/AA women from low-income communities were more likely to resort to "fighting back" as a coping strategy for IPV, they are more likely to be seen as not fitting the dominant portrait of victim, resulting in unsupportive responses and being punished by the legal systems, which leaves victims in great danger (Richie, 1996, 2012).

Second, the finding that TANF benefit level was significant after adding the control variables suggests that welfare benefit level has unique effects on preventing IPHs—although it was only significant for Whites and White women but not for other victims. Additionally, the finding that the preferred arrest policy and TANF were significant for White women but not significant for Black women or Hispanic women in the final models is intriguing. This discrepancy, probably, can be explained by the different context women experience. In light of the finding that White women were more likely to be in the Multiple Homicide and Suicide class in LCA and that the rurality and poverty variables were more salient for White women but not for Black and Hispanic women in mixed-effects modeling, it is possible that economic support and the preferred arrest policy—which deems DV as a crime but also gives women some extent of autonomy in the legal system—might be working particularly well for preventing female IPHs in the context of economically disadvantaged, rural areas. The results also highlight that we do not know much about how to prevent IPH with minority groups and the need for future research.

Lastly, consistent with the results from the LCA analysis investigating IPH patterns, the finding that percentage metropolitan counties was significant for Whites and White women suggests a link of rurality with IPH among victims who were White.

5.3 Limitations

This study had several limitations. First, some key variables were not available in the data of NVDRS-RAD, such as victim/suspect's income level and suspect's motivations to commit IPH. The lack of measures of suspect's motivations helps explain why this study did not identify the typology described as self-defense or self-help (e.g., IPH committed by IPV survivors to end long-term abuse) in the prior literature (Belknap et al., 2012; Peterson, 1999; Serran & Firestone, 2004). Second, although NVDRS provides richer information than FBI-SHR and the data quality is considered as better (Dobash & Dobash, 2015), there is still some missing documentation in the NVDRS-RAD. The documentation is limited to information known to the system. Unknown, unavailable information for certain variables (e.g., mental health issue) can be categorized with "no" in the NVDRS-RAD, compromising the accuracy in interpretation of findings. Third, the sample size of LCA analytic samples (male LCA IPH n = 276, female LCA IPH n = 897) are much smaller than the full samples (male IPH n = 1,241; female IPH n = 4,530). Additional analysis that compared the LCA analytic sample to the excluded sample identified several significant differences. Therefore, the findings should be interpreted with caution regarding generalizability. Fourth, given that one of the study aims was to model IPV-relevant death, this study employed the NVDRS dataset instead of the FBI-SHR dataset, resulting in a narrower time span and fewer included states in the analysis (16 states, 13 years). Relatedly, some multivariate models investigating the trends of IPH had multicollinearity issues—particularly for the firearm restriction variable (see VIFs across Table 4.10.1 – Table 4.10.10). This issue is not uncommon for policy analysis. Therefore, I adopted the four-step modeling and reported the results of each step to assess the policy effects. Last, in the analysis on the trend of IPH, due to the data nature of rare events, I could not model the IPH rate for multiracial and AI/AN victims and assess policy effects for these victims. However, this study still adds to the literature by presenting descriptive statistics of IPH rate for these minority groups.

5.4 Implications for Practice and Policy

5.4.1 Heterogeneity in IPHs

The analysis of patterns of IPH suggest heterogeneity in IPH cases and that the effective measures to prevent IPH cases differ by the patterns identified. Consistent with prior studies that found offenders and victims in suicide–homicide cases were older than homicide-only cases

(Banks et al., 2008; Salari & Sillito, 2016), the current analysis also found that victims and suspects in the *Multiple Homicides Followed by Suspects' Suicides* class were older than in other classes. Additionally, the results suggest that the victims and suspects in the *Multiple Homicides Followed by Suspects' Suicides* class had a higher probability of endorsing indicators related to mental health. Taken together, the findings suggest unmet needs and mental health issues among older adults. Given that older populations may use health services more often, it is likely that implementing screening for IPV and training health service workers to discuss with service users their relational health may be helpful in preventing IPHs in this class. On the other hand, as such screening is already in place (O'Doherty et al., 2015) existing research indicates barriers to screening for IPV in healthcare settings including the lack of screening protocol and insufficient training among health service providers (O'Campo et al., 2011; Sprague et al., 2012). Furthermore, it is possible that health service providers may skip older adults due to untested assumptions such as that older adults are not in an intimate relationship or that they do not experience IPV.

The finding regarding the *Physical Fight/History of IPV and Substance Use* class (higher probabilities of endorsing physical fight, history of IPV, substance use, mental health) suggest the complexity of IPV issues and a need for comprehensive, evidence-based services to address survivors' mental health and maladaptive coping simultaneously. In addition, given that this class has a higher probability of endorsing IPV history, individuals in this class are most likely to have been aware of potential danger of lethality and to have sought help from formal services (Koppa & Messing, 2019). Typical services and assessment tools with IPV survivors such as risk assessment, safety planning, and empowerment, would be helpful to prevent IPH cases in this class (Cattaneo & Goodman, 2015; Hamby, 2012-2014; Messing & Thaller, 2015). However, it is important to note that some research indicates that the current services to address IPV have a tendency to neglect the difficult and complex situations survivors face—particularly for more vulnerable populations including racial/ethnic minorities (Davies & Lyon, 2014). Providing more survivor-centered, culturally sensitive services are needed in practice (Davies & Lyon, 2014; Hamby, 2014).

Furthermore, the findings related to the *Justice-Involved* class suggest that the legal systems might be the only system these individuals had interacted with before the incident. In contrast to implementing IPV screening in the healthcare setting, systematic racism and the mandatory arrest policy for DV make screening for IPV in the legal systems not realistic and not helpful. For instance, if screening would lead to an arrest, it is highly possible that individuals in an abusive relationship would be reluctant to share such information with the system (Iyengar, 2009). Considering the lack of effectiveness in current interventions addressing DV offender recidivism (Cheng et al., 2019), more innovative, holistic approaches to address relational health at earlier stage are needed (Pitts et al., 2009). It is also important to rethink the role of the legal systems in addressing IPV. Instead of centering on penalization, using a more holistic approach to focus on DV recidivism and offenders' wellbeing might be helpful. Relatedly, the recent discussions on "defunding the police" in the U.S. suggest two possible approaches in addressing IPV and other community needs: (a) strengthening the collaboration between social workers and the legal system or the "police social work" model (McClain, 2020; Patterson & Swan, 2019), (b) developing community-driven, innovative strategies that do not rely on the legal system's response (Abrams & Detlaff, 2020; Jacobs et al., 2021). Further evaluations are needed to assess the feasibility, effectiveness, and perceived helpfulness of these initiatives. Lastly, the probabilities of endorsing the firearm was the primary weapon indicator were > 0.45 across all classes with male IPHs and > 0.50 with female IPHs, suggesting the needs to examine and implement firearm restriction laws (Zeoli et al., 2017).

5.4.2 Distinct Factors of the IPH Rate by Victim's Identity Markers

Echoing the findings on patterns of IPHs, the analysis results on trends of IPHs identify distinct factors of the IPH rate by victim's identity markers. For example, mandatory arrest policies were never significantly associated with a decrease in IPH for victims who belong to a minority group, although they were a significant factor for all victims and White victims in bivariate analysis. This finding provides evidence on supporting narratives regarding the negative effects of criminalization efforts responding to DV particularly for individuals who belong to a minority group (Coker, 2001; Meloy & Miller, 2011; Richie, 1996, 2012). This finding underscores the utility of intersectionality frame in analyzing social policies and its effects and consequences (Manuel, 2007; McPhail, 2003).

Furthermore, the finding highlights the importance of policies that support families' wellbeing in preventing IPHs. The results of multivariate models suggest that welfare benefit level has unique effects on preventing IPHs as it was the only significant policy variable after adding control variables to models predicting the IPH rate among Whites and White women. Echoing literature that highlights the role financial stress plays in IPH (Salari & Sillito, 2016; Websdale, 2010), the finding suggests that in addition to holding IPV offenders accountable through criminal justice efforts, policies and practice should also identify measures to support and promote wellbeing among individuals and families involved in IPV. Relatedly, the finding that the percentage of college graduates (-) and the percentage of adult poverty (+) were significantly associated with the IPH rate in some models suggests that, in overall, education and economic safety are preventive of IPH.

5.5 Implications for Future Research

In light of the findings on differences in patterns and factors of IPH by victim's sex and race/ethnicity, future studies should continue exploring survivors' experiences of IPV and their help-seeking experiences by sex and racial/ethnic groups. Further studies should, particularly, explore women's experiences of IPV and their help-seeking actions, particularly among racial/ethnic minority groups. Analysis of the current study found that TANF benefit level was significantly associated with a decrease in IPH for Whites and White females but not for other victims. More research needs to be conducted to explore why this occurred. Furthermore, due to the small sample sizes of these groups, the analysis on patterns of IPH collapsed certain racial/ethnic groups together. The group "other" included AI/AN, Asian, PI, and other. Similarly, the analysis on trends of IPH cannot model IPH for AI/AN, multiracial, and other racial/ethnic groups. Research should further explore the IPV and IPH experiences of these groups.

The study could not include variables measuring suspects' motivations to verify prior research that discussed the motivations of people who commit IPH (Peterson, 1999; Serran & Firestone, 2004; Websdale, 2010; Wilson & Daly, 1996) due to the unavailability of data in NVDRS-RAD. Future studies should use different sources of data (e.g., case files) that include measures of suspects' motivations to examine patterns and trends of IPH. Relatedly, I used the NVDRS-RAD because it allowed me to investigate factors of the rate of IPV-relevant death (e.g., IPHs and corollary homicides) and to model the IPH rate disaggregated by victim's race/ethnicity beyond Black vs. White. This data choice, however, also limited my analyses to 16 states throughout 13 years. Future research should explore how results vary and how models can be improved particularly for the multicollinearity issues if using a different data set (FBI-SHR) and if including more states and years. In light of the finding from the patterns of IPH that found victims and suspects in the *Multiple Homicides Followed by Suspects' Suicides* class were older than in other classes, future research should also explore the trends of IPH disaggregated by victim's age groups. Relatedly, it is worth exploring the possibilities of linking the NVDRS-RAD to the other administrative or surveillance datasets to expand the understanding of the contexts of the IPH incidents.

Furthermore, the analysis on patterns of IPH identified a significant proportion of IPH cases with known other crimes. For both male IPHs and female, the *Justice-Involved* class had a lower probability of endorsing the indicator history of IPV against victim by suspect, suggesting that the legal systems might be the only system in touch with the suspect or victim in this class. This result highlights the importance to further investigate IPH cases with no known IPV history but a known criminal history to inform intervention efforts—with the awareness of systematic racism embedded in the U.S. legal systems that contributes to racially biased criminal history known to the system (Richie, 1996, 2012).

The analysis suggests the importance of working across systems and using different policy measures to prevent lethal IPV. One potential approach is to help workers across systems to talk to and work with individuals on their relational health using a more holistic perspective. More studies need to be conducted to examine possible tools and approaches to achieve this goal. Furthermore, in addition to criminal justice efforts to hold IPV offenders accountable, policies and practice that can support and promote wellbeing among individuals and families involved in IPV are equally important. Future research should continue to identify such policies.

Last, the analysis on patterns and trends of IPH is consistent with research that highlights the importance of examining rurality in IPH (Gallup-Black, 2005; Jennings & Piquero, 2008). Future research should further explore the role of rurality in IPH and investigate how effective preventive measures for IPH vary across places.

5.6 Conclusion

Overall, the analysis indicates the complexity of IPV issues and their connectedness with multiple systems including health systems, legal systems, welfare resources, and social service. To create a safer environment for IPV survivors it is important to work across systems to screen, identify, and intervene. The study's findings highlight the utility of the intersectionality frame in analyzing social policies and their effects (Manuel, 2007; McPhail, 2003). To implement evidence-based policy making (Sanderson, 2002), researchers and policy makers should be aware of and assess the differential effects of policies on subpopulation groups.

Tables

Table 3.1 States Participating in NVDRS (2003-2017)

State	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Alaska	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Arizona													X	X	X
California															X
Colorado		X	X	X	X	X	X	X	X	X	X	X	X	X	X
Connecticut													X	X	X
Delaware															X
District of Columbia															X
Georgia		X	X	X	X	X	X	X	X	X	X	X	X	X	X
Hawaii													X	X	
Illinois														X	X
Indiana														X	X
Iowa														X	X
Kansas													X	X	X
Kentucky			X	X	X	X	X	X	X	X	X	X	X	X	X
Maine													X	X	X
Maryland	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Massachusetts	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Michigan												X	X	X	X
Minnesota													X	X	X
Nevada															X
New Hampshire													X	X	X
New Jersey	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
New Mexico			X	X	X	X	X	X	X	X	X	X	X	X	X
New York													X	X	X
North Carolina		X	X	X	X	X	X	X	X	X	X	X	X	X	X
Ohio									X	X	X	X	X	X	X
Oklahoma		X	X	X	X	X	X	X	X	X	X	X	X	X	X
Oregon	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Pennsylvania														X	X
Puerto Rico															X
Rhode Island		X	X	X	X	X	X	X	X	X	X	X	X	X	X
South Carolina	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Utah			X	X	X	X	X	X	X	X	X	X	X	X	X
Vermont													X	X	X

Virginia	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Washington														X	X
West Virginia															X
Wisconsin		X	X	X	X	X	X	X	X	X	X	X	X	X	X

Table 3.2 LCA Indicator Variable

Incident	
Multiple homicides	Whether the incident involved multiple homicide victim deaths (versus single homicide victim death).
Suspect attempted suicide after the death of the victim	Whether the suspect attempted suicide (fatally or nonfatally) after the death of the victim (versus no, not available, unknown).
Firearm was the primary weapon	Whether a firearm was used as the primary weapon or means to inflict the fatal injury (versus other weapons/means, such as, sharp, blunt instrument, and hanging).
Physical fight or argument before the incident	Whether there was a physical fight, an argument, or a conflict immediately before the violent death (versus no, not available, unknown).
Suspect	
Suspect's attack was related to a mental illness	Whether the suspect's attack on the victim was believed to be the direct result of a mental illness (e.g., suspect that had been ordered to receive a psychological evaluation by a court; versus no).
Suspect used alcohol or substance preceding the incident	Whether the suspect was suspected of alcohol use or substance use in the hours preceding the incident based on investigator reports or circumstantial evidence (e.g., Law enforcement's notes; versus no).
Victim	
Victim was 65 years old or older	Weather the victim was 65 years old or older at the time of incident (versus < 65 years).
Victim had a known mental health issue	Whether the victim had a known mental health issue (e.g., being diagnosed, being perceived to be depressed, in treatment for a mental problem; versus no, not available, unknown).
Victim had a known substance use issue	Whether the victim had a known substance use issue (e.g., alcohol dependence, alcohol problem, nonalcohol related substance abuse problem; versus no, not available, unknown).
Victim used alcohol preceding the incident	Whether the victim was suspected of alcohol use in the hours preceding the incident based on investigator reports or circumstantial evidence (e.g., Law enforcement's notes; versus no).
Victim or suspect was involved in some crime	Whether the victim or suspect was involved in some crime other than this death incident (e.g., being a gang member, precipitating crime in progress; versus no, not available, unknown).
Suspect and Victim	
Victim was suspect's (ex) boy/girlfriend	Whether the victim was the suspect's boy/girlfriend or ex boy/girlfriend (versus spouse or ex-spouse).
History of IPV against victim by suspect	Whether there was a known history of abuse of victim by this suspect (versus no).

Note. *n* = 1,173 heterosexual IPH complete cases.

Table 3.3 State/year Level Variable

DV Arrest Policy	
Arrest Type	
Discretionary	The State's DV arrest policy was considered as discretionary (e.g., a police officer has full discretion power in making the decision to arrest).
Preferred	The State's DV arrest policy was considered as preferred (e.g., the phrase "preferred response … is arrest" was used in the statues).
Mandatory	The State's DV arrest policy was considered as mandatory (e.g., the phrase "shall arrest" was used in the statues).
Firearm Restriction Policy	
Number of restrictions	Number of the presence of 134 provisions of firearm restriction laws (e.g., purchase of long guns from licensed dealers restricted to age 21 and older).
TANF	
$ Monthly benefit	Maximum monthly TANF benefit for a family of three with no income.
Demographic Variables	
% Metropolitan counties	= Number of counties categorized as metropolitan counties (i.e., 1-3 in RUCC) / Number of all counties
% College graduates[1]	= Individuals with an associate's or bachelor's degree or above (≥ 25 yrs.) / Population number (≥ 25 yrs.)
% Adults below poverty line[1]	= Individuals with income below poverty level in the past 12 months (≥ 18 yrs.) / Population number (≥ 18 yrs.)
Non-IPH adult homicide rate[1]	Non-IPH adult homicide per 1,000,000 adults (≥ 18 yrs.)

Note. n = 16 states, year 2005-2017.[1] Sex- and race/ethnicity- specific estimates were obtained for analyses on the sex- and race/ethnicity- specific IPH rates.

Table 4.1 Sample Characteristics of IPV-Relevant Deaths

	Freq.	%
Relationship of the victim to the suspect[1]		
Spouse	2,612	31.11
Ex-spouse	245	2.92
Girlfriend or boyfriend	2,475	29.48
Ex-girlfriend or ex-boyfriend	581	6.92
Girlfriend or boyfriend, unspecified	247	2.94
Other person, known to victim (e.g., acquaintance, friend)	1,348	16.06
Parent or stepparent (including intimate partner of suspect's parent)	94	1.12
Child or stepchild (including child of suspect's boyfriend/girlfriend)	59	0.70
Other family member (e.g., sibling, cousin, in-law)	116	1.38
Roommate (not intimate partner), schoolmate, work relationship	44	0.52
Victim was law enforcement officer	9	0.11
Stranger	113	1.35
Rival gang member	7	0.08
Relationship unknown	446	5.31

Note. n = 8,396. IPV-relevant deaths refer to homicide cases signaled with circumstances related to jealousy, distress over a current or former intimate partner's relationship, suspected relationship with another person leading up to the incident, immediate or ongoing conflict or violence between current or former intimate partners.

[1] Per NVDRS documentation, the following sentence can be used as a guide for understanding the appropriate description of the relationship: "The victim is the______ of the suspect." For example, when a parent kills a child, the relationship categorized in this table is "Child" not "Parent." ("The victim is the child of the suspect.")

Table 4.2 Sample Characteristics of Heterosexual IPHs

	Heterosexual IPHs (*n* = 5,771, 100%)		Female IPHs (*n* = 4,530, 78.50%)		Male IPHs (*n* = 1,241, 21.50%)	
	n	%	*n*	%	*n*	%
Incident						
Incident type[1***]	0[2]	0.00	0	0.00	0	0.00
Single homicide	5,334	92.43	4,106	90.64	1,228	98.95
Multiple homicides	437	7.57	424	9.36	13	1.05
Suspect attempted suicide (fatally or nonfatally) after the incident[***]	1,668	28.9	1,191	26.29	477	38.44
No	2,543	44.07	1,855	40.95	688	55.44
Yes	1,560	27.03	1,484	32.76	76	6.12
Primary weapon used to inflict the fatal injury[***]	145	2.51	135	2.98	10	0.81
Sharp, blunt instrument, hanging, other (e.g., burn, motor vehicle)	2,408	41.73	1,795	39.62	613	49.40
Firearm	3,218	55.76	2,600	57.40	618	49.80
Physical fight or argument occurred before the incident[***]	0	0.00	0	0.00	0	0.00
No, not available, unknown	3,665	63.51	2,995	66.11	670	53.99
Yes	2,106	36.49	1,535	33.89	571	46.01
Suspect’s attack on the victim was believed to be the direct result of a mental illness	2,972	51.50	2,353	51.94	619	49.88
No	2,597	45	2,016	44.5	581	46.82
Yes	202	3.5	161	3.55	41	3.3
Suspect was suspected of using alcohol or substance preceding the incident	4,323	74.91	3,415	75.39	908	73.17
No	1,207	20.91	927	20.46	280	22.56
Yes	241	4.18	188	4.15	53	4.27
Victim used a weapon during the course of the incident[***]	0	0.00	0	0.00	0	0.00
No, not available, unknown	5,632	97.59	4,476	98.81	1,156	93.15
Yes	139	2.41	54	1.19	85	6.85
Victim was suspected of using alcohol preceding the incident[***]	1,097	19.01	868	19.16	229	18.45
No	3,535	61.25	2,940	64.9	595	47.95
Yes	1,139	19.74	722	15.94	417	33.60
Victim						
Victim’s race/ethnicity[***]	3	0.05	3	0.07	0	0.00
White, non-Hispanic	3,020	52.33	2,466	54.44	554	44.64
Black/AA, non-Hispanic	1,816	31.47	1,267	27.97	549	44.24
AI/AN, non-Hispanic	125	2.17	92	2.03	33	2.66
Asian/PI, non-Hispanic	121	2.10	109	2.41	12	0.97
Other/Unspecified, non-Hispanic	14	0.24	11	0.24	3	0.24
Two or more races, non-Hispanic	162	2.81	144	3.18	18	1.45

	Heterosexual IPHs (*n* = 5,771, 100%)		Female IPHs (*n* = 4,530, 78.50%)		Male IPHs (*n* = 1,241, 21.50%)	
Hispanic	510	8.84	438	9.67	72	5.80
Born in the U.S.***	277	4.80	225	4.97	52	4.19
Not born in the U.S.	480	8.32	441	9.74	39	3.14
Born in the U.S., including US territory (e.g., Puerto Rico)	5,014	86.88	3,864	85.3	1,150	92.67
Victim's age	0	0.00	0	0.00	0	0.00
< 65	5,370	93.05	4,228	93.33	1,142	92.02
≥ 65	401	6.95	302	6.67	99	7.98
Education Level***	2,215	38.38	1,771	39.09	444	35.78
No high school degree	761	13.19	539	11.90	222	17.89
High school, GED, or above	2,795	48.43	2,220	49.01	575	46.33
Victim's marital status**	60	1.04	41	0.91	19	1.53
Never married, single, widowed	2,034	35.25	1,553	34.28	481	38.76
Ever married, including civil union and domestic partnership	3,677	63.72	2,936	64.81	741	59.71
Victim had a known mental health issue*	0	0.00	0	0.00	0	0.00
No, not available, unknown	5,502	95.34	4,305	95.03	1,197	96.45
Yes	269	4.66	225	4.97	44	3.55
Victim had a known substance use issue***	0	0.00	0	0.00	0	0.00
No, not available, unknown	5,184	89.83	4,116	90.86	1,068	86.06
Yes	587	10.17	414	9.14	173	13.94
Victim's residency county						
Metropolitan vs. nonmetropolitan county[3]**	0	0.00	0	0.00	0	0.00
Metropolitan	4,533	78.55	3,602	79.51	931	75.02
Nonmetropolitan	1,238	21.45	928	20.49	310	24.98
Adult poverty (%)***	0	0.00	0	0.00	0	0.00
< 20%	5,046	87.44	4,009	88.5	1,037	83.56
≥ 20%	725	12.56	521	11.5	204	16.44
Suspect[4]						
Suspect's race/ethnicity***	322	5.58	224	4.94	98	7.90
White, non-Hispanic	2,570	44.53	2,083	45.98	487	39.24
Black/AA, non-Hispanic	1,861	32.25	1,410	31.13	451	36.34
AI/AN, non-Hispanic	96	1.66	63	1.39	33	2.66
Asian/PI, non-Hispanic	91	1.58	79	1.74	12	0.97
Other/Unspecified, non-Hispanic	321	5.56	221	4.88	100	8.06
Two or more races, non-Hispanic	55	0.95	47	1.04	8	0.64
Hispanic	455	7.88	403	8.90	52	4.19
Suspect's age***	742	12.86	491	10.84	251	20.23
< 65	4,630	80.23	3,684	81.32	946	76.23
≥ 65	399	6.91	355	7.84	44	3.55
Relationship of the victim to the suspect***	0	0.00	0	0.00	0	0.00
Spouse or ex-spouse	2,720	47.13	2,224	49.09	496	39.97
Girl/boyfriend or ex-girl/boyfriend	3,051	52.87	2,306	50.91	745	60.03

	Heterosexual IPHs (n = 5,771, 100%)		Female IPHs (n = 4,530, 78.50%)		Male IPHs (n = 1,241, 21.50%)	
History of abuse of victim by Suspect***	1,192	20.65	942	20.79	250	20.15
No	3,654	63.32	2,760	60.93	894	72.04
Yes	925	16.03	828	18.28	97	7.82
Victim or suspect was involved in some crime other than this death incident***	0	0.00	0	0.00	0	0.00
No, not available, unknown	4,982	86.33	3,967	87.57	1,015	81.79
Yes	789	13.67	563	12.43	226	18.21

Note. n = 5,771.

[1] Chi-square statistics were performed to investigate difference between male IPHs and female IPHs. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

[2] Numbers in the first row for each variable indicate missing n and missing %.

[3] The categorization of metropolitan versus nonmetropolitan counties was made by following the 2013 Rural-urban Continuum Codes. Counties coded as 1 (counties in metro areas of 1 million population or more) to 3 (counties in metro areas of fewer than 250,000 population) were categorized into metropolitan counties; counties coded as 4 (urban population of 20,000 or more, adjacent to a metro area) to 9 (completely rural or less than 2,500 urban population, not adjacent to a metro area) were categorized into nonmetropolitan counties.

[4] Primary suspect if there were two or more suspects.

Table 4.3 Comparisons of Different LCA Models

Model	AIC	BIC	ABIC	Entropy	LMR LR Test *p* value	ALMR LR Test *p* value	BLRT *p* value	Absolute frequency for smallest class	Relative frequency for smallest class
Female IPHs (*n* = 897)									
1-class LCA	11086	11149	11107	–	–	–	–	–	–
2-class LCA	10753	10882	10797	0.676	0.000	0.000	0.000	230.43	0.26
3-class LCA	10580	10777	10646	0.699	0.004	0.004	0.000	174.84	0.19
4-class LCA	10523	10787	10612	0.698	0.166	0.169	0.000	123.51	0.14
5-class LCA	10494	10825	10606	0.775	0.143	0.145	0.000	86.11	0.10
6-class LCA	10469	10867	10603	0.745	0.033	0.034	0.000	59.60	0.07
7-class LCA	10467	10933	10624	0.758	0.565	0.565	0.565	55.65	0.06
Male IPHs (*n* = 276)									
1-class LCA	3013	3060	3018	–	–	–	–	–	–
2-class LCA	2963	3061	2975	0.775	0.059	0.062	0.000	46.17	0.17
3-class LCA	2912	3060	2930	0.699	0.159	0.163	0.000	46.95	0.17
4-class LCA	2908	3107	2933	0.710	0.100	0.102	0.100	33.12	0.12
5-class LCA	2908	3158	2939	0.735	0.208	0.213	0.255	14.89	0.05
6-class LCA	2911	3211	2948	0.775	0.060	0.062	0.260	15.15	0.05
7-class LCA	2913	3264	2957	0.818	0.279	0.283	0.200	14.93	0.05

Note. – = not applicable; AIC = Akaike's information criterion; BIC = Bayesian information criterion; ABIC = Adjusted BIC; LMR LR test = Lo–Mendell–Rubin likelihood ratio test; ALMR LR test = Adjusted Lo–Mendell–Rubin likelihood ratio test; BLRT = Bootstrap likelihood ratio test.

Table 4.4 Item-response Probabilities

Variable	Latent class			Sample mean
Male IPHs (*n* = 276)		Class 1: Physical Fight and Substance Use (*n* = 46, 16.73%)	Class 2: Justice-Involved (*n* = 230, 83.27%)	
Multiple homicides		**0.03**	0.02	0.02
Suspect attempted suicide after the death of the victim		0.07	0.07	0.07
Firearm was the primary weapon		0.46	**0.58**	0.56
Physical fight or argument before the incident		**0.82**	0.63	0.66
Victim was suspect's (ex) boy/girlfriend		0.51	**0.65**	0.62
History of IPV against victim by suspect		**0.17**	0.03	0.05
Suspect's attack was related to a mental illness		**0.14**	0.03	0.05
Suspect used alcohol or substance preceding the incident		**0.74**	0.04	0.16
Victim was 65 years old or older		**0.10**	0.08	0.08
Victim had a known mental health issue		**0.10**	0.05	0.05
Victim had a known substance use issue		**0.52**	0.17	0.23
Victim used alcohol preceding the incident		**0.85**	0.23	0.33
Victim or suspect was involved in some crime		0.08	**0.31**	0.28
Female IPHs (*n* = 897)	Class 1: Multiple Homicides Followed by Suspects' Suicides (*n* = 192, 21.40%)	Class 2: History of IPV and Substance Use (*n* = 174, 19.49%)	Class 3: Justice-Involved (*n* = 530, 59.11%)	
Multiple homicides	**0.15**	0.06	0.10	0.10
Suspect attempted suicide after the death of the victim	**0.74**	0.32	0.21	0.35
Firearm was the primary weapon	**0.90**	0.52	0.51	0.60
Physical fight or argument before the incident	0.21	**0.60**	**0.49**	0.45
Victim was suspect's (ex) boy/girlfriend	0.05	**0.67**	**0.65**	0.53
History of IPV against victim by suspect	0.13	**0.41**	0.18	0.21
Suspect's attack was related to a mental illness	**0.12**	**0.11**	0.04	0.07
Suspect used alcohol or substance preceding the incident	0.08	**0.76**	0.02	0.18
Victim was 65 years old or older	**0.35**	0.01	0.00	0.08
Victim had a known mental health issue	**0.10**	**0.15**	0.06	0.09
Victim had a known substance use issue	0.00	**0.38**	0.10	0.13
Victim used alcohol preceding the incident	0.03	**0.58**	0.10	0.18
Victim or suspect was involved in some crime	0.14	0.09	**0.23**	0.18

Note.
[a] Class counts and proportions for latent classes are based on estimated posterior probabilities. Class counts based on probabilities were rounded to the nearest integer to reflect the original sample size.
[b] Item-response probabilities > sample means were signaled in bold to facilitate interpretation.

Table 4.5 Comparison Between Latent Classes

Male IPHs (*n* = 276)

Variable	*n*	Sample mean	Class 1: Physical Fight and Substance Use (16.73%)	Class 2: Justice-Involved (83.27%)	Overall test *p* value
Victim					
Born in US	271	96%	100%	95%	$p < 0.01$
High school, GED, or above	268	79%	100%	76%	$p < 0.001$
Age in years	276	43.15	42.60	43.26	$p = 0.772$
Race/Ethnicity	276				$p < 0.001$
White		45%	76%	2%	
Black/AA		42%	11%	87%	
Other (AI/AN, Asian/PI, Other)		5%	8%	0%	
Two or more races		1%	2%	1%	
Hispanic		7%	4%	11%	
Victim's residence county					
RUCC (ranged from 1-9)	276	2.79	3.35	2.66	$p < 0.05$
Counties with ≥ 20% adult poverty rate	276	16%	7%	20%	$p = 0.055$
Suspect					
Age in years	231	37.83	38.79	37.62	$p = 0.571$

Female IPHs (*n* = 897)

Variable	*n*	Sample mean	Class 1: Multiple Homicides Followed by Suicides (21.40%)	Class 2: History of IPV and Substance Use (19.49%)	Class 3: Justice-Involved (59.11%)	Overall test *p* value
Victim						
Born in US	882	89%	89%^{a}	92%^{a}	88%^{a}	$p = 0.640$
High school, GED, or above	864	85%	92%^{a}	81%^{a}	84%^{a}	$p < 0.05$
Age in years	897	40.69	75.03^{a}	37.84^{b}	37.89^{b}	$p < 0.001$
Race/Ethnicity	897		^{a}	^{b}	^{c}	$p < 0.001$
White		53%	81%	65%	35%	
Black/AA		27%	10%	6%	47%	
Other (AI/AN, Asian/PI, Other)		6%	2%	12%	5%	
Two or more races		2%	2%	4%	0%	
Hispanic		12%	6%	13%	14%	
Victim's residence county						
RUCC (ranged from 1-9)	897	2.49	2.74^{a}	3.07^{a}	2.23^{b}	$p < 0.001$
Counties with ≥ 20% adult poverty rate	897	9%	6%^{a}	10%^{a}	10%^{a}	$p = 0.414$
Suspect						
Age in years	809	49.81	76.02^{a}	40.13^{b}	40.80^{b}	$p < 0.001$

Note. Equality tests of means/probabilities across classes were estimated using the DCON/DCAT method.
Subscripts indicate significance differences in pairwise comparisons at p < .05.
RUCC = Rural-urban Continuum Codes (2013).

Table 4.6.1 Comparison Between the Male LCA Analytic Sample and the Excluded Sample

	Analytic sample n = 276 (22.24%)		Excluded sample n = 965 (77.76%)	
Incident	n/m	%/SD	n/m	%/SD
Multiple homicides	5	1.81	8	0.83
Suspect attempted suicide after the incident*	18	6.52	58	11.89
Firearm was the primary weapon*	154	55.80	464	48.59
Physical fight or argument occurred before the incident***	182	65.94	389	40.31
Suspect				
Victim was suspect's (ex) boy/girlfriend	172	62.32	573	59.38
History of IPV against victim by suspect**	15	5.43	82	11.47
Suspect's attack was related to a mental illness	13	4.71	28	8.09
Suspect used alcohol or substances preceding the incident	44	15.94	9	15.79
Age in years*	37.83	11.86	39.77	13.42
Victim				
Victim was 65 years old or older	22	7.97	77	7.98
Victim had a known mental health issue	15	5.43	29	3.01
Victim had a known substance use issue***	63	22.83	110	11.40
Victim used alcohol preceding the incident***	91	32.97	326	44.29
Victim or suspect was involved in some other crime***	76	27.54	150	15.54
Born in U.S.	261	96.31	889	96.84
High school, GED, or above***	213	79.48	362	68.43
Age in years	43.15	14.44	43.03	14.20
Victim's race/ethnicity				
White	124	44.93	430	44.56
Black/AA	116	42.03	433	44.87
Other (AI/AN, Asian/PI, Other)	13	4.71	35	3.63
Two or more races	4	1.45	14	1.45
Hispanic	19	6.88	53	5.49
Victim's residency county				
RUCC (ranged from 1-9)	2.79	2.08	2.67	2.11
Counties with ≥ 20% adult poverty rate	45	16.30	159	46.48

Note. n = 1,241.

[1] % calculated based on nonmissing n.

[2] Chi-square statistics were performed to investigate difference between the analytic sample and excluded sample. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

[3] Numbers in the first row for each variable indicate missing n and missing %.

[4] Primary suspect if there were two or more suspects.

RUCC = Rural-urban Continuum Codes (2013).

Table 4.6.2 Comparison Between the Female LCA Analytic Sample and the Excluded Sample

	Analytic sample n = 897 (19.80%)		Excluded sample n = 3,633 (80.20%)	
Incident				
Multiple homicides	92	10.26	332	9.14
Suspect attempted suicide after the incident***	310	34.56	1,174	48.08
Firearm was the primary weapon	534	59.53	2,066	59.06
Physical fight or argument occurred before the incident***	404	45.04	1,131	31.13
Suspect				
Victim was suspect's (ex) boy/girlfriend	471	52.51	1,835	50.51
History of IPV against victim by suspect	189	21.07	639	23.75
Suspect's attack was related to a mental illness	65	7.25	96	7.50
Suspect used alcohol or substances preceding the incident	160	17.84	28	12.84
Age in years	49.81	15.49	42.93	14.68
Victim				
Victim was 65 years old or older	68	7.58	234	6.44
Victim had a known mental health issue***	78	8.70	147	4.05
Victim had a known substance use issue***	118	13.15	296	8.15
Victim used alcohol preceding the incident	158	17.61	564	20.40
Victim or suspect was involved in some other crime***	162	18.06	401	11.04
Born in U.S.	782	88.66	3,082	90.04
High school, GED, or above***	735	85.07	1,485	78.36
Age in years	40.69	14.97	40.02	13.35
Victim's race/ethnicity***				
White	479	53.40	1,987	54.74
Black/AA	246	27.42	1,021	28.13
Other (AI/AN, Asian/PI, Other)	54	6.02	158	4.35
Two or more races	14	1.56	130	3.58
Hispanic	104	11.59	334	9.20
Victim's residency county				
RUCC (ranged from 1-9)	2.49	1.98	2.44	1.94
Counties with ≥ 20% adult poverty rate*	82	9.14	439	12.08

Note. n = 4,530.

[1] Chi-square statistics were performed to investigate difference between male IPHs and female IPHs. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

[2] Numbers in the first row for each variable indicate missing n and missing %.

[3] Primary suspect if there were two or more suspects.

RUCC = Rural-urban Continuum Codes (2013).

Table 4.7.1 Descriptive Statistics of Overall Intimate Partner Homicide Rate

	Effects	Mean	SD
Overall Estimates			
IPV-relevant deaths[4] per 1,000,000 adults	Overall[1]	10.44	5.04
	Between[2]		4.48
	Within[3]		2.55
IPV-relevant death count	Overall	39.54	28.70
	Between		28.48
	Within		7.73
Adult population number	Overall	3956638.00	2136893.00
	Between		2192654.00
	Within		193102.90
IPH per 1,000,000 adults	Overall	7.17	3.53
	Between		2.92
	Within		2.11
IPH count	Overall	27.75	20.67
	Between		20.19
	Within		6.56
Adult population number	Overall	3956638.00	2136893.00
	Between		2192654.00
	Within		193102.90
Firearm IPH per 1,000,000 adults	Overall	3.93	2.35
	Between		1.93
	Within		1.41
Firearm IPH count	Overall	15.47	13.33
	Between		12.97
	Within		4.39
Adult population number	Overall	3956638.00	2136893.00
	Between		2192654.00
	Within		193102.90
Race/Ethnicity-Specific Estimates			
IPH per 1,000,000 adults (White)	Overall	5.46	2.88
	Between		2.22
	Within		1.91
IPH count (White)	Overall	14.52	10.18
	Between		9.63
	Within		4.05
Adult population number (White)	Overall	2753929.00	1391359.00
	Between		1431423.00
	Within		75417.34
IPH per 1,000,000 adults (Black/AA)	Overall	13.13	11.99
	Between		7.21
	Within		9.73
IPH count (Black/AA)	Overall	8.73	11.03

	Effects	Mean	SD
	Between		10.77
	Within		3.53
Adult population number (Black/AA)	Overall	581641.60	647345.00
	Between		664385.10
	Within		56894.13
IPH per 1,000,000 adults (Hispanic)	Overall	6.05	6.26
	Between		2.59
	Within		5.73
IPH count (Hispanic)	Overall	2.45	2.79
	Between		2.34
	Within		1.63
Adult population number (Hispanic)	Overall	370532.80	282435.60
	Between		285114.70
	Within		56497.59
IPH per 1,000,000 adults (AI/AN)	Overall	7.83	16.29
	Between		10.29
	Within		12.88
IPH count (AI/AN)	Overall	0.60	1.19
	Between		0.93
	Within		0.77
Adult population number (AI/AN)	Overall	43276.87	49484.35
	Between		50665.04
	Within		5528.43
IPH per 1,000,000 adults (Multiracial)	Overall	16.12	30.35
	Between		14.39
	Within		26.95
IPH count (Multiracial)	Overall	0.78	1.17
	Between		0.68
	Within		0.97
Adult population number (Multiracial)	Overall	72373.76	43237.70
	Between		40334.71
	Within		18355.44

Data source. Estimates of adult population number were estimated using the ACS 1-year estimates (2005-2017), except that the variable Adult Population Number for AI/AN individuals for the year of 2006 and 2007 was estimated using the ACS 5-year estimates (2005-2009) due to missingness in the ACS 1-year estimates. The counts of IPH were estimated using the NVDRS-RAD.
Note. 16 states, year 2005-2017.
[1] Overall $n = 208$. [2] Between $n = 16$. [3] Within $n = 13$. [4] IPV-relevant deaths refer to homicide cases signaled with circumstances related to jealousy, distress over a current or former intimate partner's relationship or suspected relationship with another person leading up to the incident, and/or immediate or ongoing conflict or violence between current or former intimate partners.

Table 4.7.2 Descriptive Statistics of Male Intimate Partner Homicide Rates

	Effects	Mean	SD
IPH per 1,000,000 adults (Male)	*Overall*[1]	3.13	2.35
	Between[2]		1.77
	Within[3]		1.60
IPH count (Male)	*Overall*	5.97	5.54
	Between		5.04
	Within		2.60
Adult population number (Male)	*Overall*	1917752.00	1023183.00
	Between		1049917.00
	Within		92094.54
IPH per 1,000,000 adults (White male)	*Overall*	2.20	2.25
	Between		1.51
	Within		1.70
IPH count (White male)	*Overall*	2.66	2.68
	Between		2.19
	Within		1.64
Adult population number (White male)	*Overall*	1336927.00	670490.60
	Between		689665.70
IPH per 1,000,000 adults (Black/AA male)	*Overall*	9.48	12.79
	Between		6.85
	Within		10.92
IPH count (Black/AA male)	*Overall*	2.64	3.44
	Between		3.09
	Within		1.68
Adult population number (Black/AA male)	*Overall*	268833.10	293070.10
	Between		300752.60
	Within		26106.77
IPH per 1,000,000 adults (Hispanic male)	*Overall*	1.90	6.06
	Between		1.56
	Within		5.87
IPH count (Hispanic male)	*Overall*	0.35	0.69
	Between		0.42
	Within		0.56
Adult population number (Hispanic male)	*Overall*	193110.80	142034.50
	Between		143994.00
	Within		25327.99
IPH per 1,000,000 adults (AI/AN male)	*Overall*	3.53	10.01
	Between		6.00
	Within		8.14
IPH count (AI/AN male)	*Overall*	0.16	0.44
	Between		0.27
	Within		0.35
Adult population number (AI/AN male)	*Overall*	21016.17	23529.67

	Effects	Mean	SD
	Between		24059.53
	Within		2888.18
IPH per 1,000,000 Adults (Multiracial male)	*Overall*	3.86	19.33
	Between		7.01
	Within		18.09
IPH count (Multiracial male)	*Overall*	0.09	0.33
	Between		0.18
	Within		0.28
Adult population number (Multiracial male)	*Overall*	35203.78	20989.42
	Between		19520.06
	Within		9033.94

Data source. Estimates of adult population number were estimated using the ACS 1-year estimates (2005-2017), except that the variable Adult Population Number for AI/AN individuals for the year of 2006 and 2007 was estimated using the ACS 5-year estimates (2005-2009) due to missingness in the ACS 1-year estimates. The counts of IPH were estimated using the NVDRS-RAD.
Note. 16 states, year 2005-2017
[1] Overall n = 208. [2] Between n = 16. [3] Within n = 13.

Table 4.7.3 Descriptive Statistics of Female Intimate Partner Homicide Rate

	Effects	Mean	SD
IPH per 1,000,000 Adults (Female)	Overall[1]	11.05	5.50
	Between[2]		4.21
	Within[3]		3.68
IPH count (Female)	Overall	21.78	15.84
	Between		15.25
	Within		5.65
Adult population number (Female)	Overall	2038886.00	1114277.00
	Between		1143287.00
	Within		101402.40
IPH per 1,000,000 Adults (White female)	Overall	8.58	4.69
	Between		2.98
	Within		3.69
IPH count (White female)	Overall	11.86	8.23
	Between		7.58
	Within		3.69
Adult population number (White female)	Overall	1417002.00	721240.80
	Between		742116.40
	Within		37124.53
IPH per 1,000,000 Adults (Black/AA female)	Overall	16.70	19.45
	Between		8.96
	Within		17.40
IPH count (Black/AA female)	Overall	6.09	8.13
	Between		7.76
	Within		3.06
Adult population number (Black/AA female)	Overall	312808.50	354345.30
	Between		363695.30
	Within		30894.22
IPH per 1,000,000 Adults (Hispanic female)	Overall	10.75	11.91
	Between		4.65
	Within		11.02
IPH count (Hispanic female)	Overall	2.11	2.37
	Between		1.97
	Within		1.40
Adult population number (Hispanic female)	Overall	177422.00	141124.10
	Between		141709.60
	Within		31600.11
IPH per 1,000,000 adults (AI/AN female)	Overall	12.10	28.40
	Between		15.77
	Within		23.92
IPH count (AI/AN female)	Overall	0.44	0.93
	Between		0.69
	Within		0.64

	Effects	Mean	SD
Adult population number (AI/AN female)	Overall	22260.69	25992.72
	Between		26617.68
	Within		2862.39
IPH per 1,000,000 adults (Multiracial female)	Overall	27.93	53.83
	Between		23.20
	Within		48.90
IPH count (Multiracial female)	Overall	0.69	1.05
	Between		0.54
	Within		0.92
Adult population number (Multiracial female)	Overall	37169.98	22343.48
	Between		20851.72
	Within		9467.98

Estimates of adult population number were estimated using the ACS 1-year estimates (2005-2017), except that the variable Adult Population Number for AI/AN individuals for the year of 2006 and 2007 was estimated using the ACS 5-year estimates (2005-2009) due to missingness in the ACS 1-year estimates. The counts of IPH were estimated using the NVDRS-RAD.

Note. 16 states, year 2005-2017.

[1] Overall n = 208. [2] Between n = 16. [3] Within n = 13.

Table 4.8 Descriptive Statistics of Policy Variable

Continuous Variable	Effects	Mean	SD
Number of firearm restriction laws	Overall[1]	27.80	26.12
	Between[2]		26.81
	Within[3]		2.21
TANF for a family of three ($)	Overall	453.54	180.08
	Between		184.14
	Within		22.06
Categorical Variable		**Freq (%)**	**Freq (%)**
Arrest Type		Overall	Between
Discretionary		78 (38%)	6 (38%)
Preferred		13 (6%)	1 (6%)
Mandatory		117 (56%)	9 (56%)

Data source. Information of DV arrest policy, firearm restriction, and social welfare benefit (TANF) level by state/year was obtained by conducting legal research using LexisNexis, existing literature (Zeoli et al., 2011a, 2011b), and state law data sources on firearm laws (Siegel, 2020), and welfare rules (Urban Institute, 2020).
Note. 16 states, year 2004-2016.
[1] Overall n = 208. [2] Between n = 16. [3] Within n = 13.

Table 4.9 Descriptive Statistics of Control Variable

Continuous Variable	Effects	Mean	SD
Percentage Metropolitan Counties			
% Metropolitan counties	Overall[1]	48%	27%
	Between[2]		28%
	Within[3]		2%
Percentage College and Above			
All			
% College graduates (All)	Overall	38%	5%
	Between		5%
	Within		2%
% College graduates (Male)	Overall	37%	6%
	Between		6%
	Within		1%
% College graduates (Female)	Overall	39%	5%
	Between		5%
	Within		3%
Non-Hispanic White			
% College graduates (White)	Overall	34%	6%
	Between		6%
	Within		2%
% College graduates (White female)	Overall	33%	6%
	Between		6%
	Within		2%
Black/AA			
% College graduates (Black/AA)	Overall	20%	5%
	Between		4%
	Within		2%
% College graduates (Black/AA female)	Overall	21%	5%
	Between		4%
	Within		3%
Hispanic			
% College graduates (Hispanic)	Overall	15%	4%
	Between		4%
	Within		2%
% College graduates (Hispanic female)	Overall	17%	4%
	Between		4%
	Within		2%
Percentage Adult Poverty			
All			
% Adult poverty (All)	Overall	12%	3%
	Between		3%
	Within		1%
% Adult poverty (Male)	Overall	10%	3%

Continuous Variable	Effects	Mean	SD
	Between		2%
	Within		1%
% Adult poverty (female)	Overall	13%	3%
	Between		3%
	Within		1%
Non-Hispanic White			
% Adult poverty (White)	Overall	9%	2%
	Between		2%
	Within		1%
% Adult poverty (White female)	Overall	10%	3%
	Between		3%
	Within		1%
Black/AA			
% Adult poverty (Black/AA)	Overall	20%	5%
	Between		5%
	Within		3%
% Adult poverty (Black/AA female)	Overall	23%	6%
	Between		6%
	Within		3%
Hispanic			
% Adult poverty (Hispanic)	Overall	19%	5%
	Between		5%
	Within		3%
% Adult poverty (Hispanic female)	Overall	23%	6%
	Between		6%
	Within		3%
Non-IPH Adult Homicide			
All			
Non-IPH adult homicide per 1,000,000 (All)	Overall	51.18	23.60
	Between		22.69
	Within		8.46
Non-IPH adult homicide per 1,000,000 (Male)	Overall	89.78	43.28
	Between		41.84
	Within		14.95
Non-IPH adult homicide per 1,000,000 (Female)	Overall	14.69	7.69
	Between		6.08
	Within		4.93
Non-Hispanic White			
Non-IPH adult homicide per 1,000,000 (White)	Overall	23.55	12.56
	Between		11.81
	Within		5.14
Non-IPH adult homicide per 1,000,000 (White female)	Overall	10.64	6.51
	Between		4.78
	Within		4.58

Continuous Variable	Effects	Mean	SD
Black/AA			
Non-IPH adult homicide per 1,000,000 (Black/AA)	Overall	197.53	82.78
	Between		63.24
	Within		55.55
Non-IPH adult homicide per 1,000,000 (Black/AA female)	Overall	37.11	38.60
	Between		13.45
	Within		36.32
Hispanic			
Non-IPH adult homicide per 1,000,000 (Hispanic)	Overall	56.40	31.08
	Between		19.92
	Within		24.33
Non-IPH adult homicide per 1,000,000 (Hispanic female)	Overall	11.46	13.81
	Between		4.31
	Within		13.16

Data source. Estimates of control variables were estimated using the ACS 1-year estimates (2005-2017), except that the variable Percentage Adult Poverty for Black individuals in Alaska was estimated using the ACS 5-year estimates (2005-2009, 2008-2012, 2013-2017) due to missingness in the ACS 1-year estimates. The counts of adult homicides were estimated using the NVDRS-RAD.

Note. 16 states, year 2005-2017.

[1] Overall n = 208. [2] Between n = 16. [3] Within n = 13.

Table 4.10.1 Results of Random-Intercept models[1]: IPV-relevant Deaths per 1,000,000 Adults

		Step 1[3]		Step 2[4]						Step 3[5]		Step 4[6]	
		Bivariate		Arrest		Firearm		TANF		Model 1		Model 2	
		Coef.	*p* value[7]	Coef.	*p* value	Coef.	*p* value	Coef.	*p* value	Coef.	*p* value	Coef.	*p* value
Policy variable													
Arrest law (Ref: Discretionary)													
Preferred		-2.040	0.000	-0.054	0.792					0.570	0.180	0.570	0.182
Mandatory		-0.717	0.043	0.166	0.434					0.125	0.487	0.111	0.631
Firearm restriction law		-0.023	0.000			-0.008	0.111			-0.012	0.211	-0.012	0.151
TANF benefit level		-0.002	0.194					0.000	0.741	0.000	0.918		
Control variable													
% Metropolitan counties		-2.058	0.000	-1.346	0.000	-0.847	0.046	-1.382	0.000	-0.735	0.186	-0.702	0.214
% College graduates		-6.009	0.000	-4.567	0.000	-3.756	0.013	-4.225	0.002	-3.881	0.002	-3.895	0.002
% Adult poverty		-4.108	0.227										
Non-IPH adult homicide per 1,000,000		0.018	0.003	0.019	0.000	0.017	0.000	0.018	0.000	0.019	0.000	0.019	0.000
Variance													
Constant variance	0.702[10]			0.123		0.114		0.134		0.106		0.105	
Residual variance	0.281			0.252		0.252		0.251		0.252		0.252	
ICC[8]	0.714												
R-squared				0.619		0.628		0.608		0.636		0.637	
p value of LR test[9] (mixed vs. standard)	0.000												
Mean VIF[11]				1.79		2.16		1.40		3.66		3.47	

Notes. $\bar{X}$ = 10.44[2], overall *SD* = 5.04. ICC = intraclass correlation.

Since the rank-based inverse normal transformation outcome variable was used, the regression coefficient should be multiplied the *SD* of the original variable when interpreting the results. For example, IPV-relevant deaths were 10.28 (= -2.040*5.04; -2.040: regression coefficient, 5.04: *SD* of the original variable) units lower in states that adopted the preferred arrest laws, compared to the states that adopted discretionary arrest laws.

[1]Random intercept models were estimated using mixed in Stata with 1-year lagged effect of policy variables and the rank-based inverse normal transformation outcome variable (McCaw et al., 2019).

[2]Sample statistics of the original IPH variable.

[3]The models were estimated using a single policy variable.

[4]The model was estimated using a single policy variable plus significant control variables at $p < 0.05$ in the Step 1 bivariate models.

[5]This model was estimated using all three policy variables plus significant control variables at $p < 0.05$ in the Step 2 model.

[6]This model was estimated after eliminating variables with a *p* value > 0.80 in the Step 3.
[7]Robust standard errors were used.
[8]ICC and R-squared was calculated following Rabe-Hesketh & Skrondal (2012)
[9]A significant *p* value of the likelihood-ratio test shows there is enough variability to favor a mixed-effects model over a standard regression model.
[10]Unconditional model.
[11]Mean VIF was estimated after regression for multivariate models. A VIF greater 2.5 indicates the multicollinearity issue.

Table 4.10.2 Results of Random-Intercept models[1]: IPHs per 1,000,000 Adults

		Step 1[3]		Step 2[4]						Step 3[5]		Step 4[6]	
		Bivariate		Arrest		Firearm		TANF		Model 1		Model 2	
		Coef.	*p* value[7]	Coef.	*p* value	Coef.	*p* value	Coef.	*p* value	Coef.	*p* value	Coef.	*p* value
Policy variable												NA	
Arrest law (Ref: Discretionary)													
Preferred		-1.933	0.000	-0.247	0.242					0.235	0.562		
Mandatory		-0.720	0.030	0.043	0.823					-0.016	0.917		
Firearm restriction law		-0.020	0.000			-0.008	0.124			-0.011	0.163		
TANF benefit level		-0.002	0.195					-0.001	0.497	0.000	0.625		
Control variable													
% Metropolitan counties		-1.846	0.000	-1.349	0.000	-0.927	0.016	-1.456	0.000	-0.958	0.027		
% College graduates		-4.354	0.019	-2.505	0.135	-1.857	0.341	-2.148	0.179				
% Adult poverty		0.062	0.987										
Non-IPH adult homicide per 1,000,000		0.016	0.001	0.018	0.000	0.018	0.000	0.017	0.000	0.018	0.000		
Variance													
Constant variance	0.616[10]			0.087		0.077		0.095		0.078			
Residual variance	0.367			0.358		0.357		0.355		0.358			
ICC[8]	0.627												
R-squared				0.548		0.559		0.543		0.557			
p value of LR test[9] (mixed vs. standard)	0.000												
Mean VIF[11]				1.79		2.16		1.40		3.60			

Notes. $\bar{X}$ = 7.17[2], overall *SD* = 3.53. ICC = intraclass correlation. NA = not applicable.

Since the rank-based inverse normal transformation outcome variable was used, the regression coefficient should be multiplied the *SD* of the original variable when interpreting the results. For example, IPHs were 6.82 (= -1.933*3.53; -1.933: regression coefficient, 3.53: *SD* of the original variable) units lower in states that adopted the preferred arrest laws, compared to the states that adopted discretionary arrest laws.

[1]Random intercept models were estimated using mixed in Stata with 1-year lagged effect of policy variables and the rank-based inverse normal transformation outcome variable (McCaw et al., 2019).

[2]Sample statistics of the original IPH variable.

[3]The models were estimated using a single policy variable.

[4]The model was estimated using a single policy variable plus significant control variables at $p < 0.05$ in the Step 1 bivariate models.

[5]This model was estimated using all three policy variables plus significant control variables at $p < 0.05$ in the Step 2 model.

[6]This model was estimated after eliminating variables with a *p* value > 0.80 in the Step 3.
[7]Robust standard errors were used.
[8]ICC and R-squared was calculated following Rabe-Hesketh & Skrondal (2012)
[9]A significant *p* value of the likelihood-ratio test shows there is enough variability to favor a mixed-effects model over a standard regression model.
[10]Unconditional model.
[11]Mean VIF was estimated after regression for multivariate models. A VIF greater 2.5 indicates the multicollinearity issue.

Table 4.10.3 Results of Random-Intercept models[1]: Male IPHs per 1,000,000 Adults

		Step 1[3]		Step 2[4]						Step 3[5]		Step 4[6]	
		Bivariate		Arrest		Firearm		TANF		Model 1		Model 2	
		Coef.	*p* value[7]	Coef.	*p* value	Coef.	*p* value	Coef.	*p* value	Coef.	*p* value	Coef.	*p* value
Policy variable												NA	
Arrest law (Ref: Discretionary)													
Preferred		-1.637	0.000	-0.067	0.775					0.497	0.203		
Mandatory		-0.870	0.002	-0.107	0.532					-0.091	0.629		
Firearm restriction law		-0.017	0.000			-0.004	0.438			-0.009	0.246		
TANF benefit level		-0.002	0.140					-0.001	0.202	-0.0004	0.438		
Control variable													
% Metropolitan counties		-1.370	0.001	-0.930	0.000	-0.694	0.081	-1.008	0.000	-0.537	0.222		
% College graduates		-6.652	0.000	-3.920	0.012	-3.682	0.024	-3.564	0.022	-2.972	0.062		
% Adult poverty		-6.782	0.085										
Non-IPH adult homicide per 1,000,000		0.009	0.007	0.009	0.000	0.009	0.000	0.008	0.000	0.009	0.000		
Variance													
Constant variance	0.491[10]			0.051		0.050		0.046		0.041			
Residual variance	0.464			0.463		0.462		0.461		0.459			
ICC[8]	0.514												
R-squared				0.461		0.463		0.470		0.476			
p value of LR test[9] (mixed vs. standard)	0.000												
Mean VIF[11]				1.88		2.16		1.43		3.91			

Notes. $\bar{X}$ = 3.13[2], overall *SD* = 2.35. ICC = intraclass correlation. NA = not applicable.

Since the rank-based inverse normal transformation outcome variable was used, the regression coefficient should be multiplied the *SD* of the original variable when interpreting the results. For example, ,ale IPHs were 3.85 (= -1.637*2.35; -1.637: regression coefficient, 2.35: SD of the original variable) units lower in states that adopted the preferred arrest laws, compared to the states that adopted discretionary arrest laws.

[1]Random intercept models were estimated using mixed in Stata with 1-year lagged effect of policy variables and the rank-based inverse normal transformation outcome variable (McCaw et al., 2019).

[2]Sample statistics of the original IPH variable.

[3]The models were estimated using a single policy variable.

[4]The model was estimated using a single policy variable plus significant control variables at $p < 0.05$ in the Step 1 bivariate models.

[5]This model was estimated using all three policy variables plus significant control variables at $p < 0.05$ in the Step 2 model.

[6]This model was estimated after eliminating variables with a *p* value > 0.80 in the Step 3.
[7]Robust standard errors were used.
[8]ICC and R-squared was calculated following Rabe-Hesketh & Skrondal (2012)
[9]A significant *p* value of the likelihood-ratio test shows there is enough variability to favor a mixed-effects model over a standard regression model.
[10]Unconditional model.
[11]Mean VIF was estimated after regression for multivariate models. A VIF greater 2.5 indicates the multicollinearity issue.

Table 4.10.4 Results of Random-Intercept models[1]: Female IPHs per 1,000,000 Adults

		Step 1[3]		Step 2[4]						Step 3[5]		Step 4[6]	
		Bivariate		Arrest		Firearm		TANF		Model 1		Model 2	
		Coef.	*p* value[7]	Coef.	*p* value	Coef.	*p* value	Coef.	*p* value	Coef.	*p* value	Coef.	*p* value
Policy variable												NA	
Arrest law (Ref: Discretionary)													
Preferred		-1.738	0.000	-1.100	0.000					-0.468	0.288		
Mandatory		-0.594	0.065	-0.436	0.110					-0.349	0.146		
Firearm restriction law		-0.019	0.000			-0.012	0.011			-0.008	0.446		
TANF benefit level		-0.002	0.291					-0.001	0.194	-0.001	0.601		
Control variable													
% Metropolitan counties		-1.836	0.000	-1.452	0.000	-0.994	0.089	-1.815	0.000	-1.065	0.099		
% College graduates		-2.719	0.190										
% Adult poverty		4.595	0.185										
Non-IPH adult homicide per 1,000,000		0.018	0.094										
Variance													
Constant variance	0.522[10]			0.205		0.230		0.248		0.191			
Residual variance	0.461			0.459		0.460		0.454		0.457			
ICC[8]	0.531												
R-squared				0.324		0.298		0.286		0.340			
p value of LR test[9] (mixed vs. standard)	0.000												
Mean VIF[11]				1.20		2.49		1.00		3.77			

Notes. $\bar{X}$ = 11.05[2], overall *SD* = 5.50. ICC = intraclass correlation.

Since the rank-based inverse normal transformation outcome variable was used, the regression coefficient should be multiplied the *SD* of the original variable when interpreting the results. For example, female IPHs were -9.56 (= -1.738*5.50; -1.738: regression coefficient, 5.50: *SD* of the original variable) units lower in states that adopted the preferred arrest laws, compared to the states that adopted discretionary arrest laws.

[1]Random intercept models were estimated using mixed in Stata with 1-year lagged effect of policy variables and the rank-based inverse normal transformation outcome variable (McCaw et al., 2019).

[2]Sample statistics of the original IPH variable.

[3]The models were estimated using a single policy variable.

[4]The model was estimated using a single policy variable plus significant control variables at $p < 0.05$ in the Step 1 bivariate models.

[5]This model was estimated using all three policy variables plus significant control variables at $p < 0.05$ in the Step 2 model.

[6]This model was estimated after eliminating variables with a *p* value > 0.80 in the Step 3.
[7]Robust standard errors were used.
[8]ICC and R-squared was calculated following Rabe-Hesketh & Skrondal (2012)
[9]A significant *p* value of the likelihood-ratio test shows there is enough variability to favor a mixed-effects model over a standard regression model.
[10]Unconditional model.
[11]Mean VIF was estimated after regression for multivariate models. A VIF greater 2.5 indicates the multicollinearity issue.

Table 4.10.5 Results of Random-Intercept models[1]: White IPHs per 1,000,000 Adults

		Step 1[3]		Step 2[4]						Step 3[5]		Step 4[6]	
		Bivariate		Arrest		Firearm		TANF		Model 1		Model 2	
		Coef.	*p* value[7]	Coef.	*p* value	Coef.	*p* value	Coef.	*p* value	Coef.	*p* value	Coef.	*p* value
Policy variable													
Arrest law (Ref: Discretionary)													
Preferred		-1.733	0.000	-0.644	0.000					-0.299	0.398	-0.362	0.011
Mandatory		-0.739	0.020	-0.265	0.113					-0.130	0.331	-0.117	0.422
Firearm restriction law		-0.019	0.000			-0.006	0.159			-0.001	0.847		
TANF benefit level		-0.002	0.152					-0.001	0.001	-0.001	0.050	-0.001	0.029
Control variable													
% Metropolitan counties		-1.909	0.000	-0.986	0.000	-0.656	0.177	-1.414	0.000	-1.036	0.052	-1.120	0.000
% College graduates		0.456	0.852										
% Adult poverty		6.669	0.049	-0.137	0.963	0.900	0.760	-5.695	0.061				
Non-IPH adult homicide per 1,000,000		0.039	0.000	0.029	0.000	0.032	0.000	0.031	0.000	0.028	0.000	0.028	0.000
Variance													
Constant variance	0.522[10]			0.048		0.053		0.015		0.031		0.031	
Residual variance	0.457			0.453		0.456		0.460		0.452		0.452	
ICC[8]	0.533												
R-squared				0.488		0.480		0.515		0.507		0.506	
p value of LR test[9] (mixed vs. standard)	0.000												
Mean VIF[11]				1.66		2.13		1.95		3.66		1.68	

Notes. $\bar{X}$ = 5.46[2], overall *SD* = 2.88. *ICC* = intraclass correlation. *NA* = not applicable.
Since the rank-based inverse normal transformation outcome variable was used, the regression coefficient should be multiplied the *SD* of the original variable when interpreting the results. For example, White IPHs were -4.99 (= -1.733*2.88; -1.733: regression coefficient, 2.88: *SD* of the original variable) units lower in states that adopted the preferred arrest laws, compared to the states that adopted discretionary arrest laws.
[1]Random intercept models were estimated using mixed in Stata with 1-year lagged effect of policy variables and the rank-based inverse normal transformation outcome variable (McCaw et al., 2019).
[2]Sample statistics of the original IPH variable.
[3]The models were estimated using a single policy variable.
[4]The model was estimated using a single policy variable plus significant control variables at $p < 0.05$ in the Step 1 bivariate models.
[5]This model was estimated using all three policy variables plus significant control variables at $p < 0.05$ in the Step 2 model.

[6]This model was estimated after eliminating variables with a p value > 0.80 in the Step 3.
[7]Robust standard errors were used.
[8]ICC and R-squared was calculated following Rabe-Hesketh & Skrondal (2012)
[9]A significant p value of the likelihood-ratio test shows there is enough variability to favor a mixed-effects model over a standard regression model.
[10]Unconditional model.
[11]Mean VIF was estimated after regression for multivariate models. A VIF greater 2.5 indicates the multicollinearity issue.

Table 4.10.6 Results of Random-Intercept models[1]: Black/AA IPHs per 1,000,000 Adults

		Step 1[3]		Step 2[4]						Step 3[5]		Step 4[6]	
		Bivariate		Arrest		Firearm		TANF		Model 1		Model 2	
		IRR	*p* value[7]	IRR	*p* value	IRR	*p* value	IRR.	*p* value	IRR	*p* value	IRR	*p* value
Policy variable													
Arrest law (Ref: Discretionary)													
Preferred		0.536	0.005	0.536	0.005					0.683	0.223	0.678	0.132
Mandatory		0.810	0.470	0.810	0.470					0.936	0.812	0.936	0.812
Firearm restriction law		0.996	0.225			0.996	0.225			1.000	0.986		
TANF benefit level		0.999	0.066					0.999	0.066	0.999	0.093	0.999	0.091
Control variable													
% Metropolitan counties		0.878	0.730										
% College graduates		0.007	0.059										
% Adult poverty		4.478	0.622										
Non-IPH adult homicide per 1,000,000		1.002	0.449										
Constant variance	0.175[10]			0.146		0.161		0.149		0.137		0.137	
p value of LR test[8] (mixed vs. standard)	0.003												
p value of LR test[9] (menbreg vs. mepoison)	0.000												
Mean VIF[11]										1.81		1.32	

Notes. $\bar{X}$ = 13.13[2], overall *SD* = 11.99. *ICC* = intraclass correlation. *IRR* = incidence rate ratio. *NA* = not applicable.

[1]Random intercept negative binomial models were estimated using menbreg in Stata with 1-year lagged effect of policy variables and the original IPH rate outcome variables.

[2]Sample statistics of the original IPH variable.

[3]The models were estimated using a single policy variable.

[4]The model was estimated using a single policy variable plus significant control variables at $p < 0.05$ in the Step 1 bivariate models.

[5]This model was estimated using all three policy variables plus significant control variables at $p < 0.05$ in the Step 2 model.

[6]This model was estimated after eliminating variables with a *p* value > 0.80 in the Step 3.

[7]Robust standard errors were used.

[8]A significant *p* value of the likelihood-ratio test shows there is enough variability to favor a mixed-effects model over a standard regression model.

[9]A likelihood-ratio test comparing the mixed-effects negative binomial model to the mixed-effects Poisson model was performed. The test can be performed because the mixed-effects Poisson model is nested within the mixed-effects negative binomial model. A significant *p* value suggests favoring the mixed-effects negative binomial model over the mixed-effects Poisson model.

[10]Unconditional model.

[11]Mean VIF was estimated after regression for multivariate models. A VIF greater 2.5 indicates the multicollinearity issue.

Table 4.10.7 Results of Random-Intercept models1: Hispanic IPHs per 1,000,000 Adults

		Step 1[3]		Step 2[4]						Step 3[5]		Step 4[6]	
		Bivariate		Arrest		Firearm		TANF		Model 1		Model 2	
		IRR	*p* value[7]	IRR	*p* value	IRR	*p* value	IRR.	*p* value	IRR	*p* value	IRR	*p* value
Policy variable												NA	
Arrest law (Ref: Discretionary)													
Preferred		0.915	0.648	0.899	0.563					1.002	0.998		
Mandatory		0.786	0.318	1.128	0.638					1.070	0.809		
Firearm restriction law		0.998	0.479			0.998	0.414			0.997	0.570	0.997	0.237
TANF benefit level		1.000	0.866					1.000	0.579	1.000	0.589	1.000	0.432
Control variable													
% Metropolitan counties		0.650	0.113										
% College graduates		9.849	0.485										
% Adult poverty		0.209	0.358										
Non-IPH adult homicide per 1,000,000		1.010	0.000	1.011	0.000	1.010	0.000	1.010	0.000	1.011	0.000	1.010	0.000
Constant variance	0.082[10]			0.022		0.021		0.025		0.005		0.008	
p value of LR test[8] (mixed vs. standard)	0.097												
p value of LR test[9] (menbreg vs. mepoison)	0.000												
Mean VIF[11]				1.23		1.00		1.01		1.76		1.07	

Notes. $\bar{X}$ = 6.05[2], overall *SD* = 6.26. *ICC* = intraclass correlation. *IRR* = incidence rate ratio. *NA* = not applicable.

[1]Random intercept negative binomial models were estimated using menbreg in Stata with 1-year lagged effect of policy variables and the original IPH rate outcome variables.

[2]Sample statistics of the original IPH variable.

[3]The models were estimated using a single policy variable.

[4]The model was estimated using a single policy variable plus significant control variables at $p < 0.05$ in the Step 1 bivariate models.

[5]This model was estimated using all three policy variables plus significant control variables at $p < 0.05$ in the Step 2 model.

[6]This model was estimated after eliminating variables with a *p* value > 0.80 in the Step 3.

[7]Robust standard errors were used.

[8]A significant *p* value of the likelihood-ratio test shows there is enough variability to favor a mixed-effects model over a standard regression model.

[9]A likelihood-ratio test comparing the mixed-effects negative binomial model to the mixed-effects Poisson model was performed. The test can be performed because the mixed-effects Poisson model is nested within the mixed-effects negative binomial model. A significant *p* value suggests favoring the mixed-effects negative binomial model over the mixed-effects Poisson model.

[10]Unconditional model.

[11]Mean VIF was estimated after regression for multivariate models. A VIF greater 2.5 indicates the multicollinearity issue.

Table 4.10.8 Results of Random-Intercept models[1]: White Female IPHs per 1,000,000 Adults

		Step 1[3]		Step 2[4]						Step 3[5]		Step 4[6]	
		Bivariate		Arrest		Firearm		TANF		Model 1		Model 2	
		Coef.	*p* value[7]	Coef.	*p* value	Coef.	*p* value	Coef.	*p* value	Coef.	*p* value	Coef.	*p* value
Policy variable													
Arrest law (Ref: Discretionary)													
Preferred		-1.488	0.000	-0.661	0.000					-0.298	0.362	-0.334	0.006
Mandatory		-0.635	0.022	-0.322	0.083					-0.180	0.212	-0.173	0.247
Firearm restriction law		-0.017	0.000			-0.005	0.291			-0.001	0.904		
TANF benefit level		-0.002	0.085					-0.002	0.001	-0.001	0.006	-0.001	0.007
Control variable													
% Metropolitan counties		-1.677	0.000	-1.050	0.000	-0.831	0.103	-1.545	0.000	-1.259	0.005	-1.307	0.000
% College graduates		0.940	0.718										
% Adult poverty		11.391	0.001	2.854	0.394	4.694	0.141	-2.940	0.357				
Non-IPH adult homicide per 1,000,000		0.032	0.008	0.027	0.028	0.028	0.013	0.030	0.009	0.027	0.038	0.027	0.034
Variance													
Constant variance	0.363[10]			0.053		0.070		0.013		0.017		0.017	
Residual variance	0.604			0.597		0.599		0.605		0.600		0.600	
ICC[8]	0.376												
R-squared				0.328		0.309		0.360		0.362		0.362	
p value of LR test[9] (mixed vs. standard)	0.000												
Mean VIF[11]				1.46		2.01		1.80		3.46		1.45	

Notes. $\bar{X}$ = 8.58[2], overall *SD* = 4.69. *ICC* = intraclass correlation. *NA* = not applicable.

Since the rank-based inverse normal transformation outcome variable was used, the regression coefficient should be multiplied the *SD* of the original variable when interpreting the results. For example, White female IPHs were -6.98 (= -1.488*4.69; -1.488: regression coefficient, 4.69: *SD* of the original variable) units lower in states that adopted the preferred arrest laws, compared to the states that adopted discretionary arrest laws.

[1]Random intercept models were estimated using mixed in Stata with 1-year lagged effect of policy variables and the rank-based inverse normal transformation outcome variable (McCaw et al., 2019).

[2]Sample statistics of the original IPH variable.

[3]The models were estimated using a single policy variable.

[4]The model was estimated using a single policy variable plus significant control variables at $p < 0.05$ in the Step 1 bivariate models.

[5]This model was estimated using all three policy variables plus significant control variables at $p < 0.05$ in the Step 2 model.

[6]This model was estimated after eliminating variables with a p value > 0.80 in the Step 3.
[7]Robust standard errors were used.
[8]ICC and R-squared was calculated following Rabe-Hesketh & Skrondal (2012)
[9]A significant p value of the likelihood-ratio test shows there is enough variability to favor a mixed-effects model over a standard regression model.
[10]Unconditional model.
[11]Mean VIF was estimated after regression for multivariate models. A VIF greater 2.5 indicates the multicollinearity issue.

Table 4.10.9 Results of Random-Intercept models[1]: Black/AA Female IPHs per 1,000,000 Adults

		Step 1[3]		Step 2[4]						Step 3[5]		Step 4[6]	
		Bivariate		Arrest		Firearm		TANF		Model 1		Model 2	
		IRR	*p* value[7]	IRR	*p* value	IRR	*p* value	IRR.	*p* value	IRR	*p* value	IRR	*p* value
Policy variable												NA	
Arrest law (Ref: Discretionary)													
Preferred		0.439	0.001	0.439	0.001					0.367	0.154		
Mandatory		0.663	0.556	0.663	0.556					0.698	0.584		
Firearm restriction law		0.997	0.698			0.997	0.698			1.004	0.737		
TANF benefit level		0.999	0.517					0.999	0.517	1.000	0.787		
Control variable													
% Metropolitan counties		1.125	0.855										
% College graduates		11007.690	0.248										
% Adult poverty		0.140	0.600										
Non-IPH adult homicide per 1,000,000		1.000	0.989										
Constant variance	1.131[10]			1.059		1.124		1.132		1.058			
p value of LR test[8] (mixed vs. standard)	0.000												
p value of LR test[9] (menbreg vs. mepoison)	0.000												
Mean VIF[11]										1.81			

Notes. $\bar{X}$ = 16.70[2], overall *SD* = 19.45. *ICC* = Intraclass correlation. *IRR* = incidence rate ratio. *NA* = not applicable.

[1]Random intercept negative binomial models were estimated using menbreg in Stata with 1-year lagged effect of policy variables and the original IPH rate outcome variables.

[2]Sample statistics of the original IPH variable.

[3]The models were estimated using a single policy variable.

[4]The model was estimated using a single policy variable plus significant control variables at $p < 0.05$ in the Step 1 bivariate models.

[5]This model was estimated using all three policy variables plus significant control variables at $p < 0.05$ in the Step 2 model.

[6]This model was estimated after eliminating variables with a *p* value > 0.80 in the Step 3.

[7]Robust standard errors were used.

[8]A significant *p* value of the likelihood-ratio test shows there is enough variability to favor a mixed-effects model over a standard regression model.

[9]A likelihood-ratio test comparing the mixed-effects negative binomial model to the mixed-effects Poisson model was performed. The test can be performed because the mixed-effects Poisson model is nested within the mixed-effects negative binomial model. A significant *p* value suggests favoring the mixed-effects negative binomial model over the mixed-effects Poisson model.

[10]Unconditional model.

[11]Mean VIF was estimated after regression for multivariate models. A VIF greater 2.5 indicates the multicollinearity issue.

Table 4.10.10 Results of Random-Intercept models[1]: Hispanic Female IPHs per 1,000,000 Adults

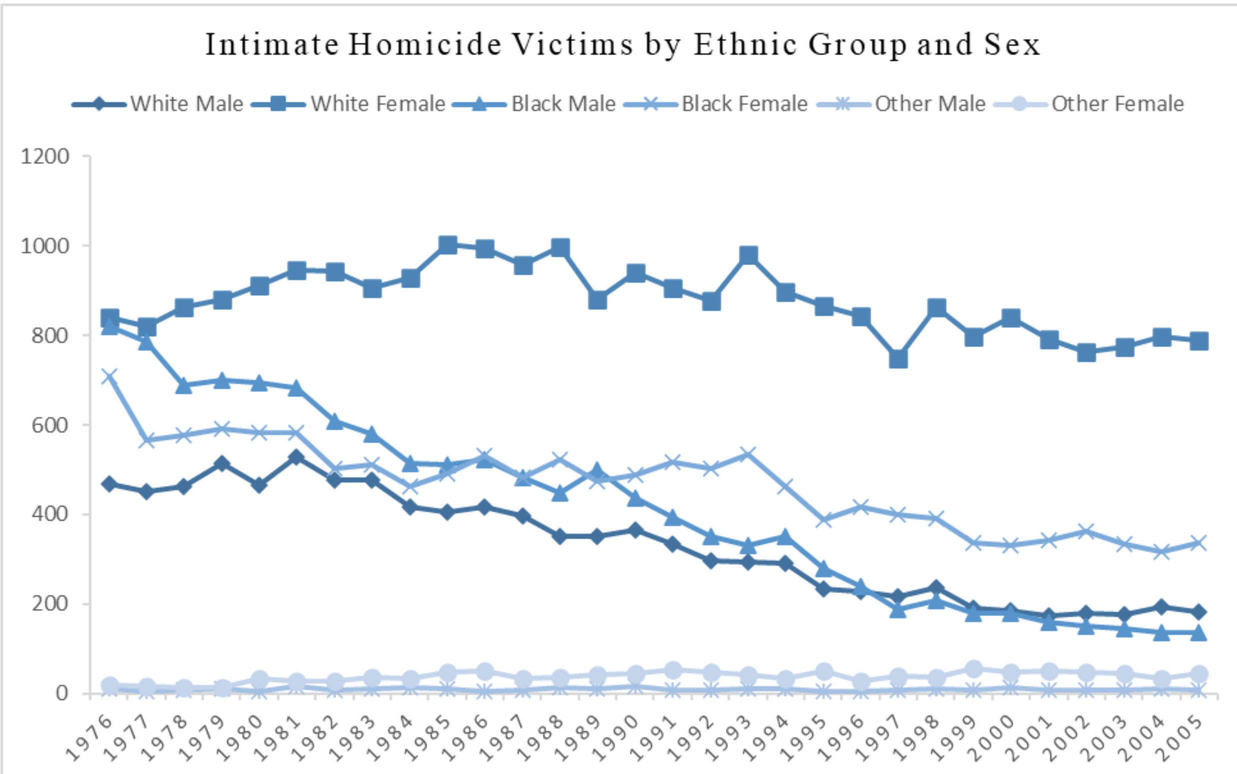
		Step 1[3]		Step 2[4]						Step 3[5]		Step 4[6]	
		Bivariate		Arrest		Firearm		TANF		Model 1		Model 2	
		IRR	*p* value[7]	IRR	*p* value	IRR	*p* value	IRR.	*p* value	IRR	*p* value	IRR	*p* value
Policy variable												NA	
Arrest law (Ref: Discretionary)													
Preferred		0.915	0.630	0.915	0.630					1.267	0.719		
Mandatory		0.772	0.253	0.772	0.253					0.830	0.547		
Firearm restriction law		0.999	0.628			0.999	0.628			0.997	0.583		
TANF benefit level		0.999	0.396					0.999	0.396	1.000	0.702		
Control variable													
% Metropolitan counties		0.696	0.089										
% College graduates		0.777	0.893										
% Adult poverty		0.526	0.633										
Non-IPH adult homicide per 1,000,000		1.005	0.475										
Constant variance	0.013[10]			0.000		0.011		0.000		0.000			
p value of LR test[8] (mixed vs. standard)	0.425												
p value of LR test[9] (menbreg vs. mepoison)	0.000												
Mean VIF[11]										1.81			

Notes. $\bar{X}$ = 10.75[2], overall *SD* = 11.91. *ICC* = intraclass correlation. *IRR* = incidence rate ratio. *NA* = not applicable.
[1]Random intercept negative binomial models were estimated using menbreg in Stata with 1-year lagged effect of policy variables and the original IPH rate outcome variables.
[2]Sample statistics of the original IPH variable.
[3]The models were estimated using a single policy variable.
[4]The model was estimated using a single policy variable plus significant control variables at $p < 0.05$ in the Step 1 bivariate models.
[5]This model was estimated using all three policy variables plus significant control variables at $p < 0.05$ in the Step 2 model.
[6]This model was estimated after eliminating variables with a *p* value > 0.80 in the Step 3.
[7]Robust standard errors were used.
[8]A significant *p* value of the likelihood-ratio test shows there is enough variability to favor a mixed-effects model over a standard regression model.
[9]A likelihood-ratio test comparing the mixed-effects negative binomial model to the mixed-effects Poisson model was performed. The test can be performed because the mixed-effects Poisson model is nested within the mixed-effects negative binomial model. A significant *p* value suggests favoring the mixed-effects negative binomial model over the mixed-effects Poisson model.

[10]Unconditional model.
[11]Mean VIF was estimated after regression for multivariate models. A VIF greater 2.5 indicates the multicollinearity issue.

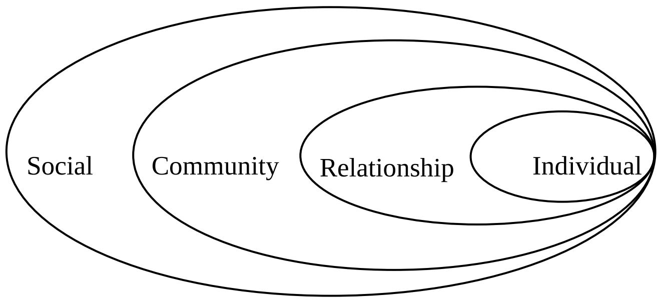
Figures

Figure 1.1 Recent Trends of IPH Rate



Note.
Data source: FBI, Supplementary Homicide Reports, 1976-2005 (as summarized in Fox & Zawitz, 2007).

Figure 3.1 Lethal Violence Against Women: An Ecological Framework



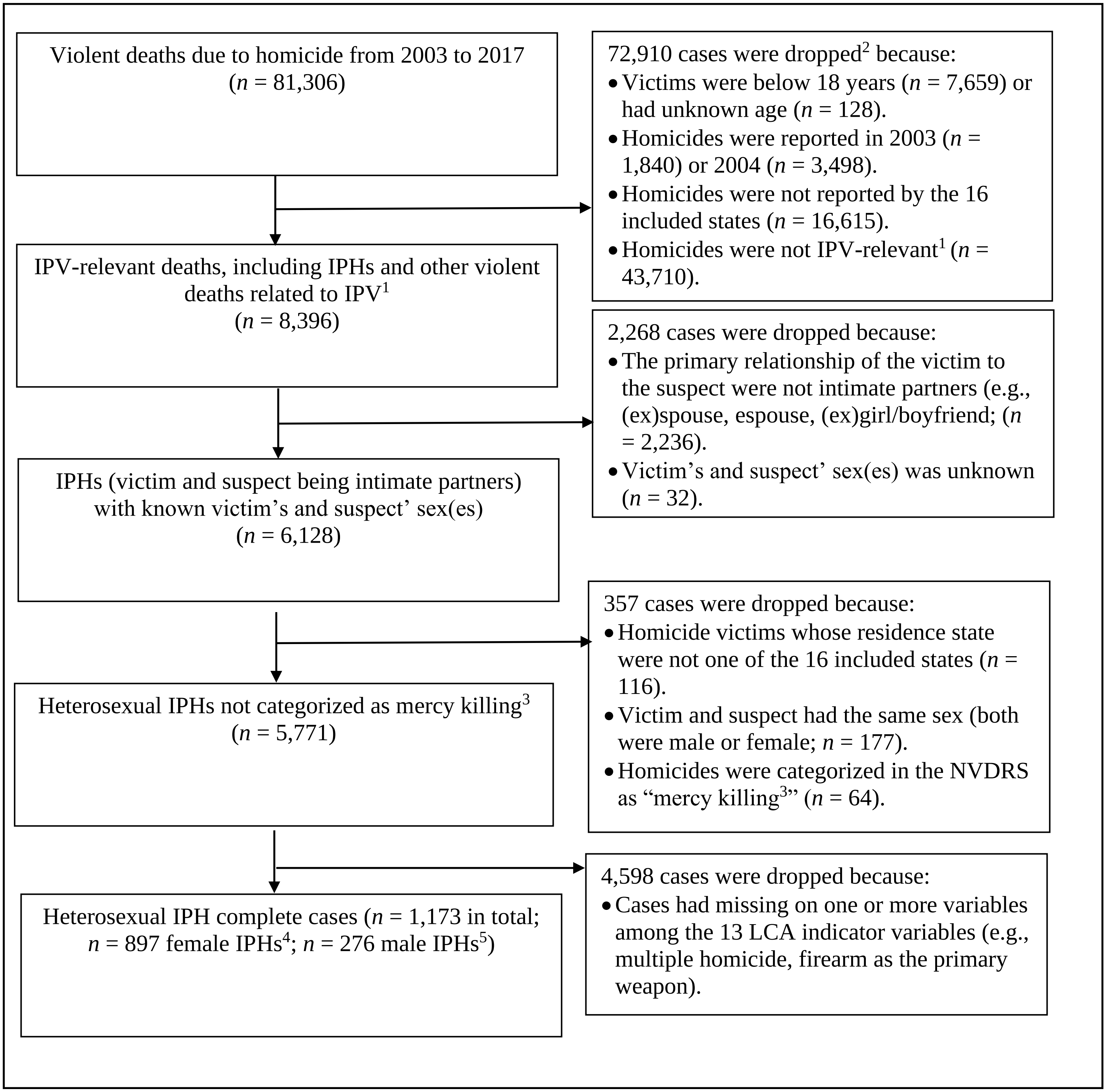
Individual
- Demographic characteristics
- Health, mental health, and substance abuse
- Life stressors

Relationship/Interaction
- History of IPV

Community
- Concentrated poverty
- Rurality
- Social disorganization

Social
- Women's social and economic status
- IPV-related policies
- Welfare benefit levels

Figure 4.1 The Sample of IPV-Relevant Deaths, IPHs, and LCA Analytic Sample



Note. IPV-relevant death *n* = 8,396, IPH *n* = 6,128, LCA analytic sample *n* = 1,173 heterosexual IPH complete cases.

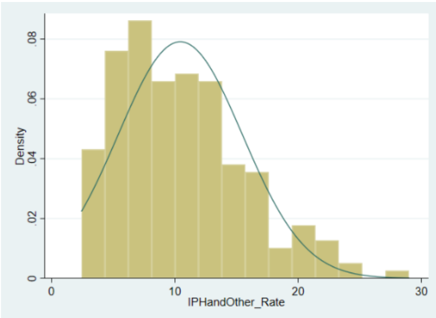
[1] IPV-relevant deaths refer to homicide cases signaled with circumstances related to jealousy, distress over a current or former intimate partner's relationship, suspected relationship with another person leading up to the incident, immediate or ongoing conflict or violence between current or former intimate partners.

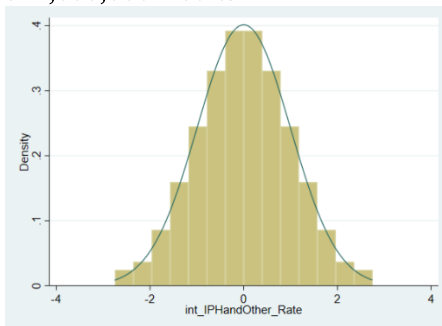
[2] Cases were dropped with a stepwise manner. The n documented here indicates based on what reason the cases were dropped.
[3] Cases were categorized as mercy killing if the NVDRS noted that the "victim was killed, at the victim's request, out of compassion in order to end his or her pain or distress."
[4] The term female IPHs indicates incidents in which the victim was identified as female and the suspect was identified as male.
[5] The term male IPHs indicates incidents in which the victim was identified as male and the suspect was identified as female.

Figure 4.2 Histograms Before and After Rank-based Inverse Normal Transformation

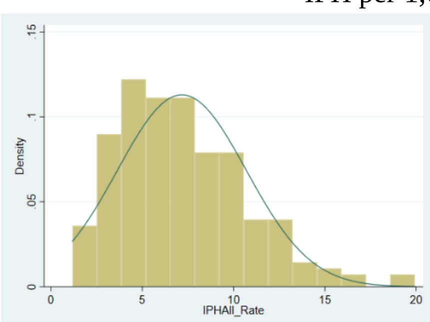
Before inverse normal transformation After inverse normal transformation

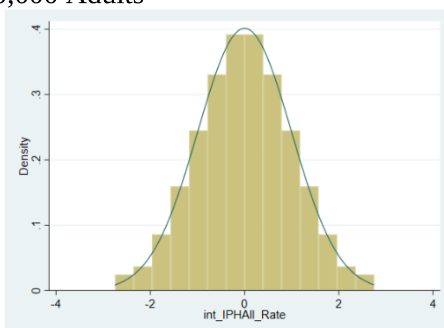
IPV-relevant deaths per 1,000,000 Adults



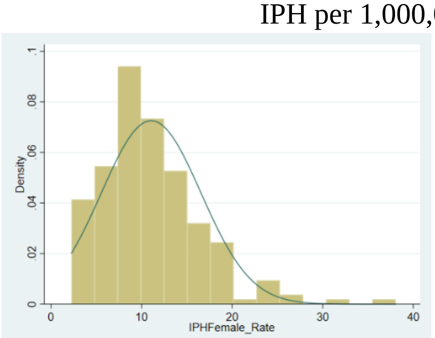


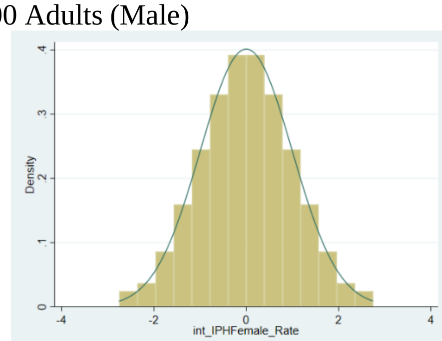
IPH per 1,000,000 Adults



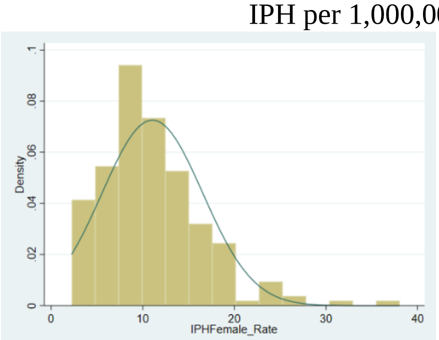


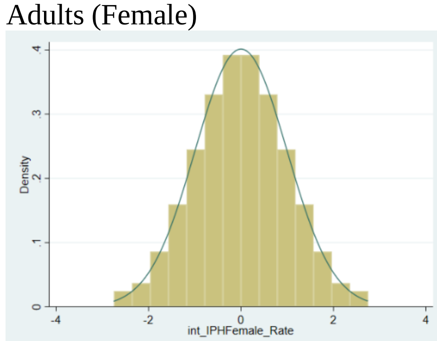
IPH per 1,000,000 Adults (Male)





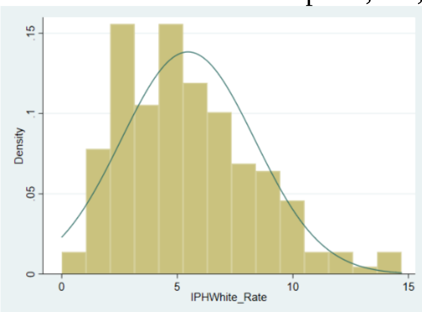
IPH per 1,000,000 Adults (Female)

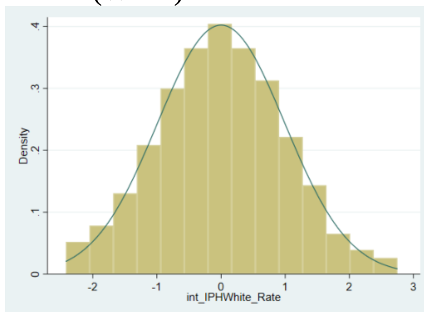




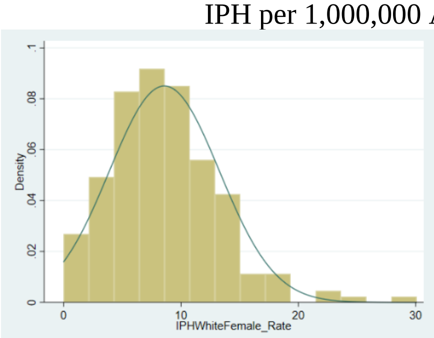
Before inverse normal transformation After inverse normal transformation

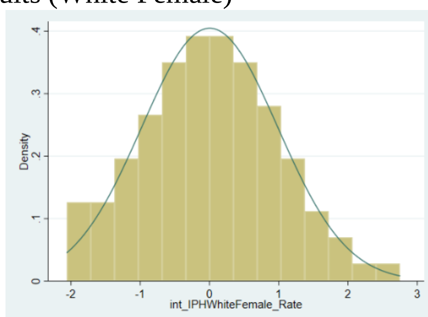
IPH per 1,000,000 Adults (White)



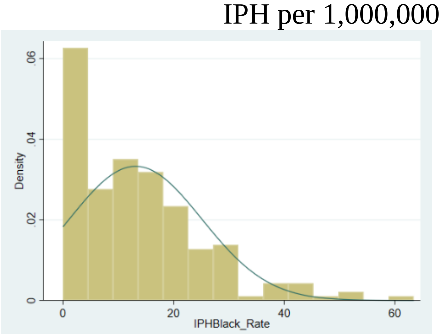


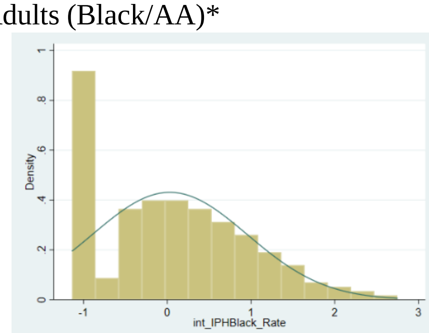
IPH per 1,000,000 Adults (White Female)



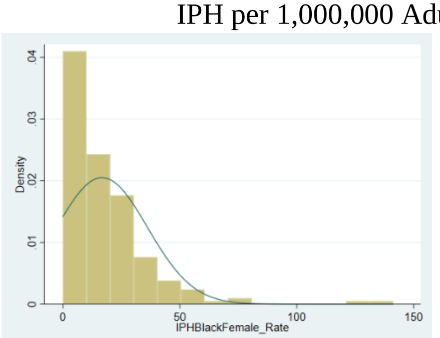


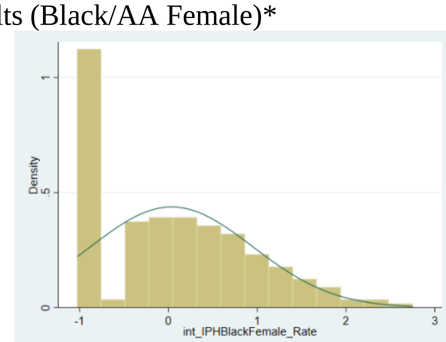
IPH per 1,000,000 Adults (Black/AA)*





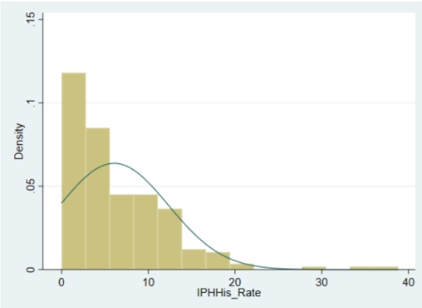
IPH per 1,000,000 Adults (Black/AA Female)*

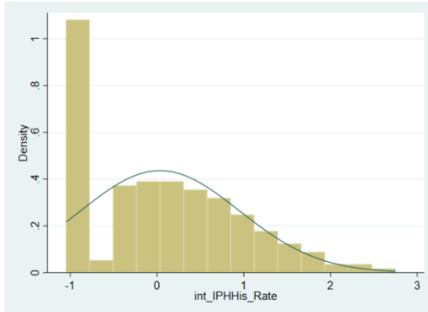




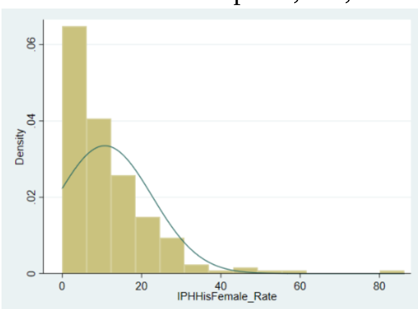
IPH per 1,000,000 Adults (Hispanic)*

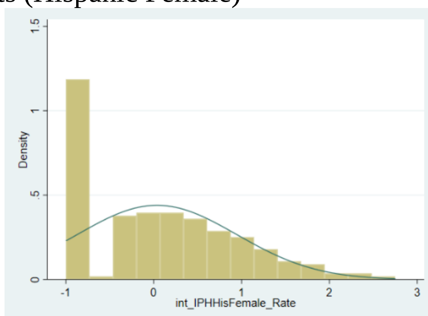
Before inverse normal transformation After inverse normal transformation





IPH per 1,000,000 Adults (Hispanic Female)*





Note. 16 states, 2005-2017.
*Random-intercept negative binomial models were conducted using the original outcome variable due to the lack of evidence of normality for the rank-based inverse normal transformation outcome variable.

References

AbiNader, M. A. (2020). Correlates of intimate partner homicide in the rural United States: Findings from a national sample of rural counties, 2009–2016. *Homicide Studies, 24*(4), 353-376.

Abrams, L. S., & Detlaff, A. (2020). An open letter to NASW and allied organizations on social work's relationship with law enforcement. https://alandettlaff.medium.com/an-open-letter-to-nasw-and-allied-organizations-on-social-works-relationship-with-law-enforcement-1a1926c71b28

Alisic, E., Groot, A., Snetselaar, H., Stroeken, T., & Putte, E. v. d. (2015). Parental intimate partner homicide and its consequences for children: Protocol for a population-based study. *BMC psychiatry, 15*, 177. https://doi.org/10.1186/s12888-015-0565-z

Arnold, G., & Ake, J. (2013). Reframing the narrative of the battered women's movement. *Violence Against Women, 19*(5), 557-578. https://doi.org/10.1177/1077801213490508

Asparouhov, T., & Muthén, B. (2014). Auxiliary variables in mixture modeling: Three-step approaches using Mplus. *Structural equation modeling: A multidisciplinary Journal, 21*(3), 329-341.

Bailey, J. E., & Kellermann, A. L. (1997). Risk factors for violent death of women in the home. *Archives of Internal Medicine, 157*(7), 777.

Bakk, Z., Tekle, F. B., & Vermunt, J. K. (2013). Estimating the association between latent class membership and external variables using bias-adjusted three-step approaches. *Sociological Methodology, 43*(1), 272-311.

Banks, L., Crandall, C., Sklar, D., & Bauer, M. (2008). A comparison of intimate partner homicide to intimate partner homicide–suicide: One hundred and twenty-four New Mexico cases. *Violence Against Women, 14*(9), 1065-1078. https://doi.org/10.1177/1077801208321983

Belknap, J., Larson, D.-L., Abrams, M. L., Garcia, C., & Anderson-Block, K. (2012). Types of intimate partner homicides committed by women: Self-defense, proxy/retaliation, and sexual proprietariness. *Homicide Studies, 16*(4), 359-379.

Beyer, K. M. M., Layde, P. M., Hamberger, L. K., & Laud, P. W. (2015, January 1, 2015). Does neighborhood environment differentiate intimate partner femicides from other femicides? *Violence Against Women, 21*(1), 49-64. https://doi.org/10.1177/1077801214564075

Bolck, A., Croon, M., & Hagenaars, J. (2004). Estimating latent structure models with categorical variables: One-step versus three-step estimators. *Political Analysis, 12*, 3-27. https://doi.org/10.1093/pan/mph001

Browne, A., & Williams, K. R. (1989). Exploring the effects of resource availability and the likelihood of female-perpetrated homicides. *Law and Society Review, 23*(1), 75-94.

Campbell, J. C., Glass, N., Sharps, P. W., Laughon, K., & Bloom, T. (2007). Intimate Partner Homicide: Review and Implications of Research and Policy. *Trauma, Violence and Abuse, 8*(3), 246-269.

Campbell, J. C., Webster, D., Koziol-McLain, J., Block, C., Campbell, D., Curry, M. A., Gary, F., Glass, N., McFarlane, J. M., Sachs, C., Sharps, P., Ulrich, Y., Wilt, S. A., Manganello, J., Xiao, X., Schollenberger, J., Frye, V., & Laughon, K. (2003). Risk factors for femicide in abusive relationships: Results from a multisite case control study. *American Journal of Public Health, 93*(7), 1089-1097.

Campbell, J. C., Webster, D. W., & Glass, N. (2009). The Danger Assessment: Validation of a lethality risk assessment instrument for intimate partner femicide. *Journal of Interpersonal Violence, 24*(4), 653-674.

Cattaneo, L. B., & Goodman, L. A. (2015). What is empowerment anyway? A model for domestic violence practice, research, and evaluation. *Psychology of Violence, 5*(1), 84.

Celeux, G., & Soromenho, G. (1996). An entropy criterion for assessing the number of clusters in a mixture model. *Journal of classification, 13*(2), 195-212.

Centers for Disease Control and Prevention. (2019). *National Violent Death Reporting System*. National Center for Injury Prevention and Control, Division of Violence Prevention, Centers for Disease Control and Prevention. Retrieved 02/08 from CDC website: https://www.cdc.gov/violenceprevention/datasources/nvdrs/index.html

Cheng, S.-Y., Davis, M., Jonson-Reid, M., & Yaeger, L. (2019). Compared to what? A meta-analysis of batterer intervention studies using nontreated controls or comparisons. *Trauma, Violence, & Abuse*. https://doi.org/10.1177/1524838019865927

Cheng, S.-Y., Wachter, K., Kappas, A., Brown, M. L., Messing, J. T., Bagwell-Gray, M., & Jiwatram-Negron, T. (2020). Patterns of help-seeking strategies in response to intimate partner violence: A latent class analysis. *Journal of Interpersonal Violence*, 0886260520966671. https://doi.org/10.1177/0886260520966671

Coker, D. (2001). Crime control and feminist law reform in domestic violence law: A critical review. *Buffalo Criminal Law Review, 4*(2), 801-860.

Collins, L. M., & Lanza, S. T. (2010). *Latent class and latent transition analysis: With applications in the social, behavioral, and health sciences*. John Wiley & Sons.

Crenshaw, K. W. (1991). Mapping the margins: Intersectionality, identity politics, and violence against women of color. *Stanford law review*, *43*(6), 1241-1299. https://doi.org/10.2307/1229039

Crenshaw, K. W. (2017). *On intersectionality: Essential writings*. The New Press.

Daly, M., & Wilson, M. I. (1988a). Evolutionary social psychology and family homicide. *Science*, *242*(4878), 519-524.

Daly, M., & Wilson, M. I. (1988b). *Homicide*. Aldine de Gruyter.

Davies, J., & Lyon, E. (2014). *Domestic violence advocacy: Complex lives/difficult choices* (2nd ed.). SAGE. https://doi.org/10.4135/9781483352916

Dewees, M. A., & Parker, K. F. (2003). Women, region, and types of homicide. *Homicide Studies*, *7*(4), 368-393. https://doi.org/10.1177/1088767903256462

Diem, C., & Pizarro, J. (2010, 2010/07/01). Social structure and family homicides. *Journal of Family Violence*, *25*(5), 521-532. https://doi.org/10.1007/s10896-010-9313-9

Dobash, R. E., & Dobash, R. P. (1979). *Violence against wives: a case against the patriarchy*. Free Press.

Dobash, R. E., & Dobash, R. P. (2015). *When men murder women*. Oxford University Press.

Dugan, L., Nagin, D. S., & Rosenfeld, M. (1999). Explaining the decline in intimate partner homicide: The effects of changing domesticity, women's status, and domestic violence resources. *Homicide Studies*, *3*(3), 187.

Dugan, L., Nagin, D. S., & Rosenfeld, R. (2003). Exposure reduction or retaliation? The effects of domestic violence resources on intimate-partner homicide. *Law and Society Review*, *37*(1), 169-198. https://doi.org/10.1111/1540-5893.3701005

Durfee, A., & Messing, J. T. (2012). Characteristics related to protection order use among victims of intimate partner violence. *Violence Against Women*, *18*(6), 701-710.

Eriksson, L., & Mazerolle, P. (2013, 2013/09/01/). A general strain theory of intimate partner homicide. *Aggression and Violent Behavior, 18*(5), 462-470. https://doi.org/10.1016/j.avb.2013.07.002

Fox, J. A., & Swatt, M. L. (2009). *Uniform Crime Reports [United States]: Supplementary Homicide Reports With Multiple Imputation, Cumulative Files 1976-2007* Inter-university Consortium for Political and Social Research [distributor]. https://doi.org/10.3886/ICPSR24801.v1

Fox, J. A., & Zawitz, M. W. (2007). *Homicide trends in the United States*. https://www.bjs.gov/content/pub/pdf/htius.pdf

Fridel, E. E., & Fox, J. A. (2019). Gender differences in patterns and trends in US homicide, 1976–2017. *Violence and gender, 6*(1), 27-36.

Frye, V., Galea, S., Tracy, M., Bucciarelli, A., Putnam, S., & Wilt, S. (2008). The role of neighborhood environment and risk of intimate partner demicide in a large urban area. *American Journal of Public Health*, *98*(8), 1473-1479.

Frye, V., & Wilt, S. (2001). Femicide and social disorganization. *Violence Against Women*, *7*(3), 335.

Fulu, E., & Miedema, S. (2015). Violence against women: Globalizing the integrated ecological model. *Violence Against Women*, *21*(12), 1431-1455.

Gallup-Black, A. (2005). Twenty years of rural and urban trends in family and intimate partner homicide: Does place matter? *Homicide Studies, 9*(2), 149-173.

Glass, N., Laughon, K., Rutto, C., Bevacqua, J., & Campbell, J. C. (2008). Young adult intimate partner femicide: An exploratory study. *Homicide Studies*, *12*(2), 177-187.

Goodmark, L. (2012). *A troubled marriage: Domestic violence and the legal system*. New York University Press.

Guo, S. (2005). Analyzing grouped data with hierarchical linear modeling. *Children and Youth Services Review*, *27*(6), 637-652.

Hamby, S. (2012-2014). *The VIGOR: A safety plan tool*. http://www.thevigor.org/the-vigor/#.WtzND8gvyUk

Hamby, S. (2014). *Battered women's protective strategies: Stronger than you know*. Oxford University Press.

Heise, L. L. (1998). Violence against women: An integrated, ecological framework. *Violence Against Women*, *4*(3), 262-290.

hooks, b. (1984). *Feminist theory: From margin to center*. South End Press.

Iyengar, R. (2009). Does the certainty of arrest reduce domestic violence? Evidence from mandatory and recommended arrest laws [Academic Journal]. *Journal of Public Economics*, *93*(1/2), 85-98.

Jacobs, L. A., Kim, M. E., Whitfield, D. L., Gartner, R. E., Panichelli, M., Kattari, S. K., Downey, M. M., McQueen, S. S., & Mountz, S. E. (2021). Defund the police: Moving towards an anti-carceral social work. *Journal of Progressive Human Services*, *32*(1), 37-62. https://doi.org/https://doi.org/10.1080/10428232.2020.1852865

Jennings, W. G., & Piquero, A. R. (2008). Trajectories of non-intimate partner and intimate partner homicides, 1980-1999: The importance of rurality. *Journal of Criminal Justice*, *36*(5), 435-443. https://doi.org/10.1016/j.jcrimjus.2008.07.002

Koppa, V., & Messing, J. T. (2019). Can justice system interventions prevent intimate partner homicide? An analysis of rates of help seeking prior to fatality. *Journal of Interpersonal Violence*, 0886260519851179.

Kurz, D. (1989). Social science perspectives on wife abuse: Current debates and future directions. *Gender and Society, 3*(4), 489-505. http://www.jstor.org/stable/189766

Lanza, S. T., Tan, X., & Bray, B. C. (2013). Latent class analysis with distal outcomes: A flexible model-based approach. *Structural equation modeling: A multidisciplinary Journal*, *20*(1), 1-26.

Manuel, T. (2007). Envisioning the possibilities for a good life: Exploring the public policy implications of intersectionality theory. *Journal of Women, Politics & Policy, 28*(3-4), 173-203.

Max, W., Rice, D. P., Finkelstein, E., Bardwell, R. A., & Leadbetter, S. (2004, Jun 2004

2015-07-18). The economic toll of intimate partner violence against women in the United States. *Violence and Victims, 19*(3), 259-272.

McCaw, Z. R., Lane, J. M., Saxena, R., Redline, S., & Lin, X. (2020). Operating characteristics of the rank-based inverse normal transformation for quantitative trait analysis in genome-wide association studies. *Biometrics*, *76*(4), 1262-1272.

McClain, A. (2020). Social workers cooperate with police forces. *The Wall Street Journal*. https://www.wsj.com/articles/social-workers-cooperate-with-police-forces-11592255480

McFarlane, J. M., Campbell, J. C., & Watson, K. (2002). Intimate partner stalking and femicide: Urgent implications for women's safety. *Behavioral Sciences and the Law, 20*(1-2), 51-68.

McPhail, B. A. (2003). A feminist policy analysis framework: Through a gendered lens. *The Social Policy Journal*, *2*(2-3), 39-61.

Meloy, M. L., & Miller, S. L. (2011). *The victimization of women: Law, policies, and politics*. Oxford University Press.

Messing, J. T., & Thaller, J. (2013). The average predictive validity of intimate partner violence risk assessment instruments. *Journal of Interpersonal Violence*, *28*(7), 1537-1558. https://doi.org/10.1177/0886260512468250

Messing, J. T., & Thaller, J. (2015). Intimate partner violence risk assessment: A primer for social workers. *British Journal of Social Work*, *45*, 1804-1820. https://doi.org/10.1093/bjsw/bcu012

Miner, E. J., Shackelford, T. K., Block, C. R., Starratt, V. G., & Weekes-Shackelford, V. A. (2012, March 01). Risk of death or life-threatening injury for women with children not sired by the abuser. *Human Nature*, *23*(1), 89-97. https://doi.org/10.1007/s12110-012-9129-9

Murphy, Y., Hunt, V., Zajicek, A. M., Norris, A. N., & Hamilton, L. (2009). *Incorporating intersectionality in social work practice, research, policy, and education*. NASW Press.

Muthén, L. K., & Muthén, B. (1998-2017). *Mplus* (8 ed.). Muthén & Muthén.

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural equation modeling: A multidisciplinary Journal*, *14*(4), 535-569.

O'Doherty, L., Hegarty, K., Ramsay, J., Davidson, L. L., Feder, G., & Taft, A. (2015). Screening women for intimate partner violence in healthcare settings. *Cochrane database of systematic reviews*(7). https://doi.org/10.1002/14651858.CD007007.pub3

O'Campo, P., Kirst, M., Tsamis, C., Chambers, C., & Ahmad, F. (2011). Implementing successful intimate partner violence screening programs in health care settings: Evidence generated from a realist-informed systematic review. *Social Science & Medicine, 72*(6), 855-866. https://doi.org/10.1016/j.socscimed.2010.12.019.

Patterson, G. T., & Swan, P. G. (2019). Police social work and social service collaboration strategies one hundred years after Vollmer. *Policing: An International Journal, 42*, 863-886. https://doi.org/10.1108/PIJPSM-06-2019-0097

Peterson, E. S. L. (1999). Murder as self-help: Women and intimate partner homicide. *Homicide Studies, 3*(1), 30.

Petrosky, E., Blair, J. M., Betz, C. J., Fowler, K. A., Jack, S. P. D., & Lyons, B. H. (2017). Racial and ethnic differences in homicides of adult women and the role of intimate partner violence—United States, 2003–2014. *Morbidity and Mortality Weekly Report, 66*(28), 741–746. https://doi.org/10.15585/mmwr.mm6628a1

Pitts, W. J., Givens, E., & McNeeley, S. (2009). The need for a holistic approach to specialized domestic violence court programming: Evaluating offender rehabilitation needs and recidivism. *Juvenile and Family Court Journal*, *60*(3), 1-21. https://doi.org/10.1111/j.1755-6988.2009.01029.x

Potter, H. (2008). *Battle cries: Black women and intimate partner abuse*. New York University Press.

Rabe-Hesketh, S., & Skrondal, A. (2012). *Multilevel and longitudinal modeling using Stata* (Third ed.). STATA press.

Raissian, K. M. (2016). Hold your fire: Did the 1996 Federal Gun Control Act expansion reduce domestic homicides? *Journal of Policy Analysis and Management, 35*(1), 67-93.

Ramaswamy, V., Desarbo, W. S., Reibstein, D. J., & Robinson, W. T. (1993). An empirical pooling approach for estimating marketing mix elasticities with PIMS data. *Marketing Science, 12*(1), 103-124.

Regoeczi, W., & Banks, D. (2014). *The nation's two measures of homicide*. U.S. Department of Justice.

Richie, B. E. (1996). *Compelled to crime: The gender entrapment of battered Black women*. Routledge.

Richie, B. E. (2012). *Arrested justice: Black women, violence, and America's prison nation*. New York University Press.

Rothenberg, B. (2003). "We don't have time for social change": Cultural compromise and the battered woman syndrome. *Gender and Society, 17*(5), 771-787. http://www.jstor.org/stable/3594709

Salari, S., & Sillito, C. L. (2016). Intimate partner homicide–suicide: Perpetrator primary intent across young, middle, and elder adult age categories. *Aggression and Violent Behavior, 26*, 26-34.

Sanderson, I. (2002, 2002/01/01). Evaluation, policy learning and evidence-based policy making. *Public Administration, 80*(1), 1-22. https://doi.org/10.1111/1467-9299.00292

Saunders, D. G. (1988). Wife abuse, husband abuse, or mutual combat? A feminist perspective on the empirical findings. In K. Yllo & M. Bograd (Eds.), *Feminist perspectives on wife abuse*. SAGE publications.

Serran, G., & Firestone, P. (2004). Intimate partner homicide: A review of the male proprietariness and the self-defense theories. *Aggression and Violent Behavior, 9*(1), 1. https://doi.org/10.1016/S1359-1789(02)00107-6

Sharps, P. W., Campbell, J., Campbell, D., Gary, F., & Webster, D. (2001). The role of alcohol use in intimate partner femicide. *American Journal on Addictions*, *10*(2), 122-135.

Sheehan, B. E., Murphy, S. B., Moynihan, M. M., Dudley-Fennessey, E., & Stapleton, J. G. (2015). Intimate partner homicide: New insights for understanding lethality and risks. *Violence Against Women*, *21*(2), 269-288. https://doi.org/10.1177/1077801214564687

Siegel, M. (2020). *State Firearm Laws Database*. http://www.statefirearmlaws.org/

Smith, S. G., Fowler, K. A., & Niolon, P. H. (2014). Intimate partner homicide and corollary victims in 16 states: National Violent Death Reporting System, 2003-2009. *American Journal of Public Health*, *104*(3), 461-466. https://doi.org/10.2105/AJPH.2013.301582

Sprague, S., Madden, K., Simunovic, N., Godin, K., Pham, N. K., Bhandari, M., & Goslings, J. C. (2012). Barriers to screening for intimate partner violence. *Women & Health*, *52*(6), 587-605.

Stark, E. (2007). *Coercive control: How men entrap women in personal life*. Oxford University Press.

StataCorp. (2017). *Stata Statistical Software: Release 15*. StataCorp LLC.

Stöckl, H., Devries, K., Rotstein, A., Abrahams, N., Campbell, J., Watts, C., & Moreno, C. G. (2013). The global prevalence of intimate partner homicide: A systematic review. *The Lancet*, *382*(9895), 859-865. https://doi.org/10.1016/S0140-6736(13)61030-2

Stout, K. D. (1989). "Intimate femicide": Effect of legislation and social services. *Affilia*, *4*(2), 21-30. https://doi.org/10.1177/088610998900400202

Taylor, R., & Jasinski, J. L. (2011, November 1, 2011). Femicide and the feminist perspective. *Homicide Studies*, *15*(4), 341-362. https://doi.org/10.1177/1088767911424541

United States Census Bureau. (2020). *American Community Survey (ACS)*. https://www.census.gov/programs-surveys/acs

United States Department of Agriculture. (2020). *Rural-Urban Continuum Codes*. https://www.ers.usda.gov/data-products/rural-urban-continuum-codes.aspx

Urban Institute. (2020). *Welfare Rules Databook*. https://wrd.urban.org/wrd/databook.cfm

Vermunt, J. K. (2017). Latent class modeling with covariates: Two improved three-step approaches. *Political Analysis*, *18*(4), 450-469. https://doi.org/10.1093/pan/mpq025

Vieraitis, L. M., Kovandzic, T. V., & Britto, S. (2008). Women's status and risk of homicide victimization: An analysis with data disaggregated by victim-offender relationship. *Homicide Studies*, *12*(2), 163-176.

Walker, L. E. A. (1979). *The battered women* Harper & Row Publishers.

Wang, J., & Wang, X. (2012). *Structural equation modeling: Applications using Mplus*. John Wiley & Sons

Websdale, N. (2010). *Familicidal hearts: The emotional styles of 211 killers*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195315417.001.0001

Wells, W., Ren, L., & DeLeon-Granados, W. (2010). Reducing intimate partner homicides: The effects of federally-funded shelter service availability in California. *Journal of Criminal Justice*, *38*(4), 512-519. https://doi.org/10.1016/j.jcrimjus.2010.04.021

Wilson, M. I., & Daly, M. (1996). Male sexual proprietariness and violence against wives. *Current Directions in Psychological Science, 5*(1), 2-7. https://doi.org/10.1111/1467-8721.ep10772668

Wilson, M. I., & Daly, M. (1998). Lethal and nonlethal violence against wives and the evolutionary psychology of male sexual proprietariness. In R. E. Dobash & R. P. Dobash (Eds.), *Rethinking violence against women* (pp. 199-230). Sage.

Wilson, M. I., Johns, H., & Daly, M. (1995). Lethal and nonlethal violence against wives. *Canadian Journal of Criminology, 37*, 331-362.

Yllö, K. A. (2004). Through a feminist lens. In D. R. Loseke, R. J. Gelles, & M. M. Cavanaugh (Eds.), *Current controversies on family violence* (pp. 19-34). SAGE Publications.

Zeoli, A. M., Frattaroli, S., Roskam, K., & Herrera, A. K. (2017). Removing firearms from those prohibited from possession by domestic violence restraining orders: A survey and analysis of state laws. *Trauma, Violence, and Abuse*, 1-12. https://doi.org/10.1177/1524838017692384

Zeoli, A. M., Malinski, R., & Turchan, B. (2016). Risks and targeted interventions: Firearms in intimate partner violence. *Epidemiologic Reviews*, *38*(1), 125-139. https://doi.org/10.1093/epirev/mxv007

Zeoli, A. M., Norris, A., & Brenner, H. (2011a). Mandatory, preferred, or discretionary: How the classification of domestic violence warrantless arrest laws impacts their estimated effects on intimate partner homicide. *Evaluation Review, 35*(2), 129-152.

Zeoli, A. M., Norris, A., & Brenner, H. (2011b). A summary and analysis of warrantless arrest statutes for domestic violence in the United States. *Journal of Interpersonal Violence, 26*(14), 2811-2833.

Zeoli, A. M., & Webster, D. W. (2010). Effects of domestic violence policies, alcohol taxes and police staffing levels on intimate partner homicide in large US cities. *Injury Prevention, 16*(2), 90-95. https://doi.org/10.1136/ip.2009.024620