Self-defense Regulations and Crime: Evidence from the Stand Your Ground Law

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Abstract

This study investigates the potential unintended consequences of relaxed self-defense regulations through a combination of game-theoretic modeling and empirical analysis. While such policies aim to empower victims and deter crime, our model demonstrates how they can inadvertently lead to an escalation of violence. By analyzing both the intensity and frequency of self-defense responses, we show that relaxed regulations can embolden both existing and previously reluctant defenders, potentially increasing their risk of harm. This effect is hypothesized to be more pronounced in spontaneous encounters where victims may perceive a lower threat level from less prepared offenders, potentially escalating the situation. Empirical analysis of stand-your-ground (SYG) laws provides support for this hypothesis, revealing a causal relationship between the implementation of SYG laws and an increase in murder rates, particularly in cases of second-degree (unplanned) murder, consistent with the model's predictions.

Keywords: Self-defense regulations, stand-your-ground laws, murder.

JEL Classification: I18, K14.

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1 Introduction

This paper investigates the potential link between relaxed self-defense regulations and an increase in violent crime. The motivating example is the "stand-your-ground" (SYG) laws, which eliminate the "duty to retreat" in public spaces. Currently enacted in 30 states, SYG laws have sparked legislative proposals at both state and federal levels to expand their implementation[1]. These laws authorize individuals to use force in self-defense without attempting escape upon perceiving a threat (e.g., §776.012, Fla. Stat. (2005)[2]; A.R.S. §13-418[3]). Proponents argue that SYG laws empower victims, deter crime, and ultimately reduce violence (e.g., Governor Jeb Bush's speech, 2016[4]). However, this perspective overlooks the potential countervailing effect: increased access to firearms and the emboldening of self-defense under SYG laws could exacerbate minor conflicts, leading to more frequent and severe violent encounters. This crime escalation could lead to murder, which, according to McCollister, French and Fang (2010), incurs a societal cost of $8,982,907 in 2008 dollars - over 30 times greater than the cost of rape, the second most costly index crime[5]. Increased murders also devastate families and raise serious ethical questions about society's responsibility to prevent the loss of life.

While there have been several empirical studies of the effects of SYG laws on homicide rates – many of which find increases in homicides – there are no theoretical underpinnings for the likely effects of SYG on homicides. A key contribution of this paper is the development of a novel game-theoretical framework, the first to analyze the potential for increased crime resulting from changes in self-defense regulations. It models interactions between criminals and two distinct victim types: those who retreat and those who fight back. In addition, the study differentiates between planned and unplanned attacks both theoretically and empirically. Another contribution to the empirical literature utilizes difference-in-differences (DiD) and event study techniques to assess both the immediate and long-term effects of these regulatory changes.

Our theoretical models analyze the interactions between victims and offenders in both planned and unplanned attacks. In planned attacks, we assume the decisions of the offender and victim

[1] For an example, please see H.R.3142 - 118th Congress (2023-2024): Stand Your Ground Act of 2023. (2023, May 9). https://www.congress.gov/bill/118th-congress/house-bill/3142 and S.1445 - 118th Congress (2023-2024): Stand Your Ground Act of 2023. (2023, May 4). https://www.congress.gov/bill/118th-congress/senate-bill/1445.

[2] Click here for the link to the Florida statute.

[3] Click here for the link to the Arizona statute.

[4] Click here for the link to a news article covering Jeb Bush's speech.

[5] See Appendix A for details.

are made sequentially, whereas in unplanned attacks, they are made simultaneously. Sequential decision-making begins with the victim, who decides their level of self-defense based on their predictions of how the offender will respond. Upon the passage of the self-defense law, some victims anticipate facing reduced penalties for defending themselves violently, which leads them to switch from retreating to fighting. Offenders in turn intensify their efforts to avoid injuries to themselves. In unplanned attacks, since both the offender and the victim make decisions simultaneously, they lack knowledge of each other's planned actions. With the self-defense law in effect, the victim may be more inclined to believe that they can outmaneuver an offender, leading to a potential "escalation of violence." A victim who uses violent self-defense can inadvertently become the aggressor as well.

We investigate the hypothesized mechanisms by empirically assessing the impact of SYG laws on murder rates using DiD and event study analyses. Our study leverages the variation in the timing of SYG law adoption across states. This study employs murder rate data sourced from the FBI's Uniform Crime Reporting program (UCR), specifically the Offenses Known and Clearances by Arrest (OKCA) and Supplementary Homicide Report (SHR) datasets. To further refine our analysis and distinguish between first- and second-degree murder, we incorporate data from the Murder Cases in 33 Large Urban Counties in the United States, 1988 (MC) dataset.

Our empirical analysis reveals a statistically significant increase in both first- and second-degree murder rates following the implementation of SYG laws. This increase aligns with our theoretical predictions in that there is a larger increase in second-degree murders. It also shows a growing trend over time. Our findings also shed light on other dimensions of these laws. We observe that in the majority of states, new SYG laws represent a shift from case law interpretations to statutory provisions, rather than introducing significant changes to self-defense rules. The observed increase in both first- and second-degree murder rates following the implementation of these laws may partly stem from misconceptions about their implications. Victims and offenders may misinterpret SYG laws as removing limitations on self-defense, potentially leading to excessive force in homicide cases without proper consideration of over-defense scenarios (McAdams, 2015). This misinterpretation could amplify the effects predicted by our model, as evidenced by a gradual escalation over time.

This paper is organized as follows: Section 2 provides a review of relevant literature, followed by the game-theoretical models in Sections 3. To provide context, Section 4 gives an in-depth overview of SYG laws. We then turn to the empirical aspects: Section 5 details the data sources and presents summary statistics, followed by preliminary analysis in Section 6. Section 7 then explains the

empirical methodology, which informs the findings presented in Section 8. Finally, we discuss the policy implications in Section 9 and offer concluding remarks in Section 10.

2 Related Work

The literature has devoted significant attention to modeling crime dynamics. While several studies have empirically examined SYG laws, none have specifically analyzed changes in murder rates over time or differentiated between planned and unplanned murders.

2.1 Modeling Crime

Economists have rigorously analyzed crime using game-theoretical models ever since Gary Becker's groundbreaking contribution on the topic (Becker, 1968). It focuses on how potential criminals evaluate the gains and losses associated with illegal activity. This foundation has spurred research on victim self-protection, explored in various contexts (Skogh, 1973; Shavell, 1991; Ben-Shahar and Harel, 1995, 1996; Donohue and Levitt, 1998; Guha and Guha, 2012; Baumann, Denter and Friehe, 2019). Our study distinguishes itself by pioneering the examination of the effects of relaxed over-defense regulations on the actions of perpetrators and victims in both premeditated and spontaneous attacks.

We conceptualize the interaction between the offender and the victim as a contest, where the victim can exert defense efforts to thwart the attack, while the offender's efforts increase the likelihood of a successful attack. In the Economics of Crime literature, several studies model the probability of a successful attack using a Tullock contest framework, where offenders invest effort to increase this probability and victims invest efforts to decrease it. For instance, Goyal and Vigier (2014) analyze a contest between attackers and a central planner who optimizes resource allocation for defending against attacks in a network. Hong and Neilson (2020) treat the interaction between cybercriminals and victims as a contest, exploring optimal punishments for cybercrimes.

Our paper is also closely aligned with a body of literature that compares simultaneous moves in a Cournot–Nash framework with sequential moves in a Stackelberg framework (Dixit, 1987; Baik and Shogren, 1992; Leininger, 1993; Yildirim, 2005). We find that, in a one-shot Cournot-Nash game, relaxing punishment for over-defense decreases the fighting victim's total cost. In contrast, the impact of such relaxed punishment on the fighting victim's total cost is ambiguous in a Stackelberg setting, as the offender can anticipate the victim's actions.

2.2 Empirical Studies

To empirically evaluate the prediction of the theoretical models, this study examines the impact of SYG laws on crime rates, since crime results from a successful attack. Existing research on this topic includes both nationwide and regional analyses. Utilizing data from all 50 states, Cheng and Hoekstra (2013) initiates this line of inquiry, employing the Uniform Crime Report (UCR) dataset to demonstrate that the enactment of SYG laws is associated with an increase in murder rates. In addition to murders, they also examine burglary, robbery, and aggravated assault, and do not find a statistically significant change in those crimes. Unlike Cheng and Hoekstra (2013), this paper focuses solely on murder.

Subsequent research by McClellan and Tekin (2017), leveraging health records data, corroborates the findings of the inaugural paper, further strengthening the evidence linking SYG laws to increased murders. Addressing concerns about endogeneity, Gius (2016) utilizes a two-stage fixed effects model, instrumenting SYG adoption with the percentage of Republican voters. After effectively mitigating the potential for reverse causality, their study similarly concludes that SYG laws contribute to elevated murder rates. Miller and Pepper (2020) use partial identification methodologies to arrive at a similar conclusion.

Guettabi and Munasib (2018) employs the synthetic control method to examine variations in the impact of SYG laws in various states. Their findings indicate that the implementation of SYG laws is associated with significant increases in gun death rates in Alabama, Florida, and Michigan. In addition, Ren, Zhang and Zhao (2015) analyzes the deterrent effect of Texas' castle doctrine, examining the impact of the subsequent Horn shooting on burglaries in Houston and Dallas. Employing time-series ARIMA models, they find a reduction in burglaries in nearby Houston but not in far-away Dallas following this widely publicized incident.

This study departs from previous research in three key ways. First, we differentiate between planned and unplanned murder cases to analyze the varying effects of SYG laws. Second, we employ event-study methodology to capture the changes in murder rates over time. Finally, our analysis incorporates more recent data, offering updated insights on this policy. Importantly, since this paper focuses on aggregate-level behavioral responses to these laws, our analysis incorporates all states rather than comparing and contrasting a subset of states.

3 Theoretical Model

Our model builds upon the seminal work of Becker (1968), but introduces a key distinction: we represent planned attacks as sequential games and unplanned attacks as simultaneous games between offenders and victims. Specifically, in a planned attack, the victim makes the initial move by selecting a costly defense level, s. The offender then responds, after observing s, by deciding whether or not to commit a crime and, if so, how much costly effort, x, to expend. Unplanned attacks, on the other hand, involve victims and offenders making their choices independently and simultaneously.

The success of the attack is determined by the relative efforts of the offender and the victim, governed by the Tullock contest success function $p(x, s) = \frac{x}{x+s}$. This function specifies that as the offender's effort x increases, the likelihood of success rises, whereas increases in the victim's defense effort s reduces this likelihood. Additionally, we assume there is a minimum level of effort required from the offender during an attack. In addition, there are two types of victims: those who retreat to a safe place and those who engage with the offender. The two types differ in that the latter might do damage to the offender while suffer the probability of breaking the law for over-defense.

3.1 Contest between Offender and Victim

The offender, being risk neutral, decides whether to commit a crime and determines the effort they will exert if they do. Their expected utility from attempting the crime is given by

$$O(x) = p(x, s)B - x - (1 - p(x, s))D \tag{1}$$

where B represents the net benefit (criminal benefit minus expected penalties) conditional on a successful attack, and x denotes the cost associated with the effort. If the offender fails, they don't enjoy any benefit. We assume the victim can choose to retreat or fight when facing the attack. If the victim fights rather than retreats, the offender risks injury or death if the attack fails, reducing their expected payoff by D; otherwise, the victim retreat from the scene and there won't be a damage to the offender, $D = 0$.

On the defender's side, the victim incurs a loss L if the crime succeeds but can reduce the offender's probability of success by exerting a costly defense effort s. The victim's expected loss is given by

$$V(s) = p(x, s)L + s + (1 - p(x, s))\alpha \tag{2}$$

Here, the victim bears the cost of defense effort s, which reduces the probability of incurring the loss L. The marginal cost of the victim's defense effort compared to the offender's attacking effort is also normalized to 1. If the victim retreats, there won't be over-defense, $\alpha = 0$. If the victim fights back and successfully prevents the offense, they may face punishment for over-defense, with an expected value of $\alpha > 0$. The victim may discount this α based on perception.

SYG laws can reduce α, the punishment for over-defense perceived by victims, for several reasons. As McAdams (2015) specifies, first, it allows victims to defend themselves without the requirement to retreat, thereby lowering the burden of proof and decreasing the likelihood of being penalized for over-defense. Second, the law's informational impact alters public perceptions of over-defense. Some may mistakenly believe that SYG statutes remove limitations on using self-defense against charges of murder, granting individuals the right to meet force with force. Legislative statements, such as the preamble to the Florida SYG bill, proclaims that "no person or victim of crime should . . . be required to needlessly retreat in the face of intrusion or attack" and reinforce these beliefs. Additionally, high profile acquittals in murder cases like *Florida v. Zimmerman*[6] may encourage deadly defensive force in situations where alternatives exist. Media coverage of the law's passage, subsequent incidents, prosecutions, and acquittals has amplified these legal perspectives. Legislatures are attuned to public sentiment, and acquittals by juries may be viewed as reflections of broader societal attitudes towards self-defense laws.

3.2 Unplanned Attack - Retreating vs Fighting Victims

An unplanned attack involves an intentional crime committed without premeditation. We model this scenario using a simultaneous game where neither the offender nor the victim observes the other's choice of effort. By taking the first-order condition for Equations (1) and (2) and solving them simultaneously, we obtain the optimal effort for the offender and the fighting victim, the probability that the crime succeeds, the victim's total loss, and the offender's net benefit. They are

[6] https://www.justice.gov/opa/pr/federal-officials-close-investigation-death-trayvon-martin

listed below.

$$x^{**} = \frac{(B+D)^2(L-\alpha)}{(B+D+L-\alpha)^2} \tag{3}$$

$$s^{**} = \frac{(B+D)(L-\alpha)^2}{(B+D+L-\alpha)^2} \tag{4}$$

$$p^{**} = \frac{x^{**}}{x^{**}+s^{**}} = \frac{B+D}{B+D+L-\alpha} \tag{5}$$

$$V^{**} = \frac{L(B+D)^2 + 2L(B+D)(L-\alpha) + \alpha(L-\alpha)^2}{(B+D+L-\alpha)^2} \tag{6}$$

$$O^{**} = \frac{B(B+D)^2 - 2D(B+D)(L-\alpha) - D(L-\alpha)^2}{(B+D+L-\alpha)^2} \tag{7}$$

If the victim retreats, there are no punishment to over-defense (α) or damage to the offender (D). Therefore, the optimal efforts for the offender and retreating victim, the offender's probability of success, the victim's total loss, and the offender's net benefit are as below.

$$x^* = \frac{B^2 L}{(B+L)^2} \tag{8}$$

$$s^* = \frac{BL^2}{(B+L)^2} \tag{9}$$

$$p^* = \frac{x^*}{x^*+s^*} = \frac{B}{B+L} \tag{10}$$

$$V^* = \frac{BL(B+2L)}{(B+L)^2} \tag{11}$$

$$O^* = \frac{B^3}{(B+L)^2} \tag{12}$$

We derive a number of partial derivatives (listed in Appendix C), and we are discussing the important ones here. First, $\frac{\partial p^{**}}{\partial \alpha} > 0$ means that when the punishment for over-defense decreases after the SYG laws, the probability of success for the offender who encounters the fighting victim will also decrease. This is because, for the fighting victim, a reduction in the penalty for over-defense diminishes the marginal cost of a victim's fighting effort. Consequently, victims who choose to engage with offenders are incentivized to exert greater effort, thereby reducing the probability of the offender's success. This is an advantage for the fighting victims on the intensive margin.

Another consequence of reduced penalties for over-defense is a decrease in the fighting victim's overall costs and a decrease in the offender's overall benefits. The model demonstrates this through $\frac{\partial V^{**}}{\partial \alpha} > 0$ and $\frac{\partial O^{**}}{\partial \alpha} > 0$. These are two additional advantages for the fighting victims on the intensive margin.

Proponents of the SYG laws highlight the above advantages for the fighting victim when the penalty for over-defense is reduced. However, the fact that fighting victims are benefiting on the

intensive margin is not the whole picture. Comparison of the fighting and retreating victim scenarios reveals $p^{**} > p^*$, indicating a higher probability of success for an offender who encounters a fighting victim. Although this finding may appear counterintuitive, it likely arises because offenders facing a fighting victim experience heightened fear of injury, prompting them to intensify their efforts and thus increasing their probability of success. This is evidenced by the fact that $\frac{\partial x^{**}}{\partial \alpha} < 0$.

Consequently, the fighting victim incurs a strictly greater cost than the retreating victim due to the elevated probability of injury. This is evidenced by the fact that $V^{**} > V^*$. By focusing on the fact that $\frac{\partial V^{**}}{\partial \alpha} > 0$, the retreating-turning-fighting victim can end up making a choice that is not rational and not ideal. Also due to $p^{**} > p^*$, the net benefit to the offender after they encounter the fighting victim may be larger than that after they encounter the retreating victim, evidenced by the fact that O^{**} is potentially larger than O^*.

In summary, SYG laws create a complex set of incentives for both victims and offenders in an unplanned attack scenario. For victims already inclined to fight back (the intensive margin), SYG laws offer a potential benefit. Freed from the fear of legal repercussions for harming an attacker, these victims may respond more forcefully, potentially reducing the offender's likelihood of success. However, SYG laws also introduce a risk for victims who might previously have chosen to retreat but now opt to fight (the extensive margin). This shift could expose these victims to increased danger, as offenders, motivated to avoid injury, might escalate their efforts and become more likely to succeed. Therefore, while SYG laws may empower some victims by encouraging more robust self-defense, they simultaneously increase risk for others. Moreover, an incorrect assessment of the acceptable level of force (represented by parameter α), can still result in penalties for excessive force, adding to the crime tally. Consequently, determining the overall impact of SYG laws - whether the benefits for those already inclined to fight outweigh the costs for this group and the risks for those newly inclined to fight - requires robust empirical analysis.

The results from the fighting victims hinge on α being less than L. This is because if the penalty from self-defense is larger than the potential loss from the crime, the victim is unlikely to fight. The victim may fight if they perceive α to be smaller than L.

3.3 Planned attack - Retreating vs Fighting Victims

In the planned attack, the victim moves first, setting up their defense. The offender moves next, carrying out their attack. When the victim retreats, the optimal efforts of the offender and victim, the offender's probability of success, the victim's total loss, and the offender's net benefit are given

by:

$$x^{\dagger} = \frac{B^2}{4L} \tag{13}$$

$$s^{\dagger} = \frac{B}{2} - \frac{B^2}{4L} \tag{14}$$

$$p^{\dagger} = \frac{B}{2L} \tag{15}$$

$$V^{\dagger} = B - \frac{B^2}{4L} \tag{16}$$

$$O^{\dagger} = \frac{B^2}{4L} \tag{17}$$

Conversely, if the victim chooses to fight, these values change to:

$$x^{\dagger\dagger} = \frac{(B+D)^2}{4(L-\alpha)} \tag{18}$$

$$s^{\dagger\dagger} = \frac{B+D}{2} - \frac{(B+D)^2}{4(L-\alpha)} \tag{19}$$

$$p^{\dagger\dagger} = \frac{B+D}{2(L-\alpha)} \tag{20}$$

$$V^{\dagger\dagger} = (B+D) - \frac{(B+D)^2}{4(L-\alpha)} + \alpha \tag{21}$$

$$O^{\dagger\dagger} = \frac{(B+D)^2)}{4(L-\alpha)} - D \tag{22}$$

Similar to the unplanned attack situation for the fighting victim, as punishment to over-defense decreases, the offender's probability of success decreases, and the net benefit for the offender who encounters the fighting victim decreases. See Equations 56 and 58 in Appendix C for more details. Again, these effects are highlighted by SYG law proponents. However, even at its lowest point, the offender's probability of success is higher in the fighting-victim scenario than in the retreating-victim scenario. Again, this outcome results from the offender's motivation for self-preservation, particularly when the victim resists. See the discussion following Equations 64 and 65 in Appendix C.

Comparing the unplanned and the planned murder cases, the magnitude of the difference between p^{**} and p^{*} is greater than that between $p^{\dagger\dagger}$ and $p^{\dagger}$. This outcome suggests that the offender in the unplanned murder case experiences more perceived threat from the fighting victim than the offender in the planned murder case. This is due to victim uncertainty in the planned attack case regarding both the impact of a decrease in α on their loss and the relationship between $V^{\dagger\dagger}$ and $V^{\dagger}$. In other words, victims may not take up arms in response to incentives when attackers' actions are hidden. Therefore, the change in p is likely greater in the unplanned attack case than in the planned attack case.

4 Background of the Stand Your Ground Laws in the U.S.

The framework presented here is motivated by the characteristics of SYG legislation. These laws eliminate the common law requirement for an individual to retreat before using force, even in a public setting when the opportunity to safely withdraw exists. Under SYG statutes, a victim's use of force against a perceived attacker–for instance, a shooting in response to a threat of serious bodily harm–may be deemed justifiable. This justification is typically contingent upon the victim proving a reasonable fear of harm, or it may stem from a rebuttable presumption of self-defense against the prosecution.

The foundation of the U.S. legal system is rooted in English common law principles, which historically imposed a "duty to retreat" before an individual could justifiably use lethal force in self-defense (Wolf, 2014). By the late nineteenth century, however, many American jurisdictions began to abandon this duty in public settings (Epps, 1992).[7]

This shift was significantly propelled by state supreme court decisions. The landmark 1876 Ohio Supreme Court decision in *Erwin v. State* was pivotal, establishing the right to stand one's ground.[8] The ruling stated: "... but a true man, who is without fault, is not obliged to fly from an assailant, who, by violence or surprise, maliciously seeks to take his life or do him enormous bodily harm." This rule was affirmed across the country. For instance, the Indiana Supreme Court similarly asserted in 1877 that when a faultless person in a lawful place is violently assaulted, "he may, without retreating, repel force by force..." [9]

SYG laws codify this absence of a duty to retreat and in essence expand self-defense principles beyond the confines of one's home and yard[10]. Instead, they apply this principle to any public space where an individual has a right to be. Under SYG provisions, lethal force becomes legally

[7]Before the spate of "stand your ground" laws, the Florida Supreme Court noted that, while it is required to retreat, "a majority of jurisdictions do not impose a duty to retreat before a defendant may resort to deadly force when threatened with death or great bodily harm." *Weiand v. State*, 732 So.2d 1044, 1049 (Fla.1999). See also *Gillis v. United States*, 400 A.2d 311, 312 (D.C. 1979) "[P]robably the majority [of states] have adopted the rule that one is not required to retreat but may stand his ground and defend himself. This has been called the American rule, and in at least two cases, the Supreme Court has indicated approval of it." The two cases are *Beard v United States*, 158 US550 (1985) and *Rowe v United States*, 164 US 546 (1896).

[8]Erwin v. State, 29 Ohio St. 186 (O.H. Sup. Ct. 1876).
https://www.ravellaw.com/opinions/cbfa395dc51f8884111941c298f52407

[9]Runyan v. State, 57 Ind. 80 (I.N. Sup. Ct. 1877).
https://cite.case.law/ind/57/80/

[10]The traditional "castle doctrine," which, in some states extends to one's vehicle and workplace

justifiable if a person reasonably believes it is necessary to defend against imminent death, great bodily harm, or a forcible felony such as kidnapping and robbery. Florida extends this justification to individuals engaged in unlawful activity[11]. Refer to Appendix B for details on law passage dates and key features.

While these laws grant individuals the legal right to use lethal force against attackers, they spark significant debate regarding their potential consequences. Critics argue that these laws may embolden individuals to resort to deadly force even when safer alternatives, such as retreat, are viable. However, understanding the historical evolution of self-defense laws is essential for properly evaluating SYG legislation. Although the enactment of SYG laws didn't drastically change the core self-defense doctrine in many states, they have incrementally broadened the scope of acceptable forceful responses. Beyond their legal impact, SYG laws have shifted public perception of acceptable self-defense, influencing how people perceive and react to perceived threats. Furthermore, they risk fostering a growing misinterpretation of the law, resulting in individuals holding increasingly inflated perceptions of their legal entitlements.

5 Data

The analytical sample spans 2000 to 2014, a period chosen because it encapsulates the introduction of the law (beginning with Florida in 2005) and extends to the latest year for which comprehensive data was available during the study. The primary data for criminal activity were drawn from the Uniform Crime Report (UCR), specifically the Offenses Known and Clearances by Arrest (OKCA) files [12] and the Supplementary Homicide Reports (SHR) files[13]. We also incorporated the Murder Cases in 33 Large Urban Counties in the United States, 1988 (MC) dataset[14] as an auxiliary source. Dates of law passage were compiled from various sources, including Wallace v. State (2015). Control variables were selected to account for relevant local conditions (at the state level), encompassing metrics like police force size, unemployment rate, poverty rate, and demographic data. These were primarily acquired from the UCR Police Employee Data (LEOKA) files[15] and other diverse data sources.

[11] § 776.012, Fla. Stat. (2005).

[12] Bureau of Justice Statistics (BJS) (2000-2015).

[13] Federal Bureau of Investigation (FBI) (2000-2015*b*).

[14] Bureau of Justice Statistics (1988).

[15] Federal Bureau of Investigation (FBI) (2000-2015*a*).

5.1 Crime Data

The OKCA files come from the UCR Data Tools website (Bureau of Justice Statistics (BJS), 2000-2015)[16]. We downloaded state-level data spanning from 2000 to 2014 and consolidated it into a panel dataset. The OKCA data comprehensively covers crimes reported to law enforcement agencies, including detailed information on the nature of offenses. Of particular interest to our study within the OKCA dataset is the category of Murders and Non-negligent Manslaughters.

The SHR data comes from the National Archive of Criminal Justice Data (NACJD) at the University of Michigan[17]. Unlike OKCA, SHR data is organized by incident, offering more granular details about homicides, including circumstances surrounding each event. We aggregated the number of cases by state, year, and circumstances under which crimes happened, merging it to create a panel dataset. The top five circumstances are listed in Table 1. We excluded data from states and years with limited observations based on recommendations associated with the dataset: Office of Juvenile Justice and Delinquency Prevention (2000-2015). See Appendix D for more details. Florida's SHR data was sourced and processed separately from Florida's own database[18] because it's not included in the national database.

Table 1: Top Five Circumstances in the SHR

Circumstance	Percentage
Other Arguments	53.6
Robbery	13.8
Juvenile Gang Killings	11.2
Drug-related Killings	8.1
Argument over Money or Property	2.9

Notes: Among offenses categorized as murder and non-negligent manslaughter by the police that are reported to the SHR during the years 2000-2014, the top five known circumstances are displayed above. Arguments that are unrelated to money or property make up more than half of the cases.

We calculated the murder rate as the number of murders per 100,000 people. Summary statistics for the murder rate across states are presented in Table 2. Louisiana recorded the highest murder rate of 14.6 per 100,000 in 2007, while North Dakota reported the lowest rate of 0.6 per 100,000 in

[16]The tool has been replaced by the FBI's Crime Data Explorer.

[17]Federal Bureau of Investigation (FBI) (2000-2015*b*).

[18]Florida Department of Law Enforcement (2000-2015).

2000.

Table 2: Summary statistics for murder rate at the state level

	Count	Max	Min	Mean	Std. Dev.
Murder Rate	850	14.6	0.6	4.5	2.3
Planned Murder Rate	838	10.3	0.3	3.2	1.7
Unplanned Murder Rate	838	2.3	0.1	0.7	0.4

Notes: The highest murder rate in the OKCA data is 14.6, and the lowest is 0.6. The highest planned murder rate in the SHR data after adjustments is 10.3, and the lowest is 0.3. The highest unplanned murder rate is 2.3, and the lowest is 0.1.

5.2 Planned and Unplanned Murder Data

The UCR's various data files do not explicitly classify murders as planned or unplanned. However, the Murder Cases in 33 Large Urban Counties in the United States, 1988 (MC) dataset provides insights into whether murders are categorized as first- or second-degree. First-degree murder necessitates a deliberate and premeditated unlawful killing (FindLaw, n.d.*a*), whereas second-degree murder involves an intentional killing that lacks premeditation (FindLaw, n.d.*b*). Therefore, we employ first-degree murder data as a proxy for planned murders and second-degree murder data as a proxy for unplanned murders.

Using the MC dataset and assuming that the proportion of first-degree murders remains relatively constant across different circumstances, we interpolate the rates of first- and second-degree murders for all states and years. This assumption is grounded in behavioral tendencies; for instance, arguments often lead to unplanned murders, whereas drug-related incidents may indicate premeditated actions. Table 3 lists the top five circumstances from the MC dataset, which closely mirror those in the SHR data (see Table 1).

Table 3: Top Five Circumstances in MC

Circumstance	Percentage
Other Arguments	45.0
Robbery	12.9
Drug-related Killings	12.1
Argument over Money or Property	9.2
Child Abuse	3.2

Notes: The top five circumstances in MC are very similar to those in SHR. See Table 1 for comparison.

Table 4 illustrates that a significant majority of first-degree murder offenders had prior relationships with their victims. This pre-existing familiarity likely serves as a critical factor in facilitating premeditation. Detailed knowledge of the victim, including their patterns of behavior and vulnerabilities, allows offenders to predict their victim's actions and thereby exert greater control over the fatal encounter.

Table 4: Prior Relations

	Prior Relationship		
	Count	Percent	Cum Percent
Yes	1495	65.80	65.80
Likely	259	11.40	77.20
No	518	22.80	100
Total	2272	100	

Notes: Among first-degree murders, 65.8% of the murderers and victims have prior relationship with each other, 11.4% are likely to have prior relationship, and 22.8% have no prior relationship. The data comes from the MC dataset.

Crucially, we leverage the MC dataset to estimate the proportions of murders that are planned versus unplanned. Table 5 details the distribution of the most serious charges levied against defendants within the MC dataset, highlighting a marked prevalence of first- and second-degree murders.

Table 5: Crime types in the MC dataset

Charge	No.
first-degree murder	2,315
second-degree murder	711
third degree murder	7
voluntary manslaughter/non-negligent - manslaughter 1st	72
accessory to murder	6
accessory after the fact	6
conspiracy to murder (includes solicitation to murder)	1
attempted murder	1
use of firearm (includes felony f/a, possession of f/a)	4
aggravated battery (includes assault with a weapon)	5
burglary	1
arson	3
involuntary manslaughter/negligent - manslaughter 2nd	2
child abuse	4
child abuse with death (Albuquerque only)	2
unknown	2
Total	3,142

Notes: The majority of the cases recorded in the MC dataset are either first- or second-degree murders.

These categorizations of first- and second-degree murders are linked to specific circumstances as outlined in Table 26 of Appendix F. Notably, Robberies exhibit a higher probability of resulting in first-degree murders, whereas Turf Battles are more frequently associated with second-degree murders. Based on this information, we calculate the percentages of first- and second-degree murders under each circumstance. We obtain these state-level annual percentages by merging these data with the SHR dataset.

There may be concern that the percent of first and second-degree murder within each category is not fixed. However, when the punishment for over-defense changes, if it affects the percentages, it will also affect the prevalence of the categories themselves in the same direction. For example, if we were to assume that for the category of "Matters of opinion," the percentage of second-degree murder will increase after the SYG laws, then the overall prevalence of "Matters of opinion" compared with other categories will also rise. Therefore, assuming the fixed percentages will actually dampen the identified effects. In other words, what we find after assuming fixed percentages will be the lower

bound of the actual effects of the SYG laws.

5.3 Controls

We incorporate a set of control variables based on established research that demonstrates their causal relations with crime rates. These controls encompass factors such as the size of the police force, incarceration rates, and various socioeconomic indicators discussed below. Research by Levitt (2002) underscores the impact of police force size on crime rates. Accordingly, we include data on the number of police officers per 100,000 population, sourced from the Uniform Crime Report Police Employee Data 2000-2014[19]. The number of prisoners per 100,000 residents, which influences crime through the incapacitation effect as highlighted by Levitt (1996), is drawn from the Bureau of Justice Statistics Bulletin 1999-2014[20].

Studies such as those by Raphael and Winter-Ebmer (2001) highlight the relationship between unemployment rates and crime rates. We utilize unemployment rate data from the America Fact-Finder[21], which is now available through BLS (2000-2014*b*). Researchers have found poverty rate (Ludwig, Duncan and Hirschfield, 2001; Hipp and Yates, 2011), household income (Alba, Logan and Bellair, 1994), and demographics (Piquero and Brame, 2008; Farrington, 1986) to be associated with crime rates. This data comes from the American Community Survey (2000-2014) through the IPUMS data builder[22]. Government spending on public assistance (Hannon and DeFronzo, 1998) and welfare (Fishback, Johnson and Kantor, 2010), which are integral to poverty alleviation measures that influence crime rates, are derived from the Annual Survey of State Government Finances[23].

The correspondence between the aforementioned variables and the theoretical models can be found in Table 6. Factors such as unemployment rate, poverty rate, median household income, government spending (assistance and subsidies) per capita, and government spending (public welfare) per capita are associated with legitimate income, which correlates with gains from criminal activities. Increased legitimate income opportunities are associated with reduced reliance on criminal activities and diminished offender desperation. This decreased desperation, in turn, results in a lower likelihood of causing significant harm during criminal acts. Young black and white males play

[19]FBI (2000-2015*a*).
[20]BJS (2000-2014).
[21]BLS (2000-2014*a*).
[22]the U.S. Census Bureau (2000-2014).
[23]United States Census Bureau (2000-2014).

a significant role in driving crime rates and are associated with victimization, which encourages victims to be more cautious. Additionally, SYG laws impact the penalties faced by victims. Even though the theoretical predictions pertain to individual incentives, the incentives are generally in reaction to aggregate factors.

Table 6: Variable Comparison

Theoretical Model	Empirical Model
B - criminal benefit & D - damage to offender	unemployment rate, poverty rate, median household income, government spending (assistance and subsidies) per capita, government spending (public welfare) per capita, prisoners per 100,000 residents, and police per 100,000 residents
L - victim loss	% black male aged 15 - 24, % white male aged 15 - 24, % black male aged 25 - 44, % white male aged 25 - 44
α - punishments to the victim	SYG laws

Notes: The variables in the theoretical empirical models correspond to each other. Income-related variables affect criminal benefit and how desperate offenders are, which affects how much damage offenders incur. Percentages of young White and Black male affects how much loss victims incur. SYG laws affect punishment for over-defense for victims.

National-level summary statistics for these control variables are presented in Table 7. We do not include the percentage of the population outside of the workforce because it has a similar effect as the unemployment rate. Weighted by population, the average unemployment rate is 7.3% between the years 2000 and 2014, and the poverty rate is 13.3%. Assistance, subsidies, and public welfare spending is $1,423 per person. The proportion of White males aged 15-24 is approximately five times that of Black males aged 15-24, and the proportion of White males aged 25-44 is approximately six times that of Black males aged 25-44.

6 Preliminary Data Analysis

This section presents preliminary analysis results that motivate the subsequent panel regression models. The initial step involves partitioning the dataset into two groups: state-years with and without the law in effect. To illustrate the grouping rule, a state that never adopted the law (e.g., Massachusetts in 2000 - 2014) is consistently classified as "without the law." Conversely, for

Table 7: Descriptive Statistics

	Mean (Unweighted)	Mean (Weighted by Population)
Dependent Variables		
Planned Murder per 100,000 Population	3.1	3.7
	(1.7)	(1.4)
Unplanned Murder per 100,000 Population	.7	.8
	(.4)	(.3)
Control Variables		
Police per 100,000 residents	338.2	326.5
	(114.6)	(79.6)
Unemployment Rate (%)	6.7	7.3
	(2.0)	(2.0)
Poverty Rate (%)	12.6	13.3
	(3.4)	(3.0)
Median Household Income ($)	47,984	48,420
	(8434.5)	(7509.6)
Prisoners per 100,000 residents	429.7	447.5
	(164.1)	(145.6)
Government spending (assistance and subsidies)	120	107
per capita	(55.9)	(48.9)
Government spending (public welfare) per capita	1,261	1,316
	(460.1)	(497.6)
% Black Male Aged 15-24	.9	1.1
	(.8)	(.7)
% White Male Aged 15-24	5.5	5.29
	(1.0)	(.7)
% Black Male Aged 25-44	1.4	1.7
	(1.2)	(1.0)
% White Male Aged 25-44	10.8	10.7
	(1.6)	(1.2)
Percent suicide by gun	.5	.5
	(.1)	(.1)
N	750	750

Notes: There are around four times as many planned murders than unplanned murders. There are around five times as many white males as black males in the age group of 15-24, and around six times as many white males as black males in the age group of 25-44.

an adopting state (e.g., Florida, which enacted the law in 2005), the pre-enactment years (e.g., Florida-2000) are classified as "without the law," and post-enactment years (e.g., Florida-2014) are classified as "with the law."

The comparison of murder rates across these groups provides the first insights into the law's potential effect. Out of 825 total state-years between 2000 and 2016, 599 are classified as "without the law" and 226 as "with the law." The results, summarized in Table 8, indicate a substantial difference: state-years with the law exhibit a statistically significantly higher average murder rate (5.46 per 100,000) compared to those without the law (4.19 per 100,000). This descriptive finding suggests a positive association between the presence of the law and murder rates, warranting the rigorous causal analysis provided by the panel regressions.

Table 8: Murder Rates in State-Years With and Without SYG Laws (2000-2016)

State and Year	Summary Statistics					Comparison	
	Count	Min	Max	Mean	SD	Degrees of Freedom	t
Without Law	599	.62	13.25	4.19	2.28	823	7.28***
With Law	226	.90	14.56	5.46	2.10		

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the average murder rates (per 100,000 population) across two groups: state-years where an SYG law was in effect and state-years where the law was not in effect. For states that adopted an SYG law during a specific year (e.g., 2005), the data for that year and subsequent years are classified under the "with law" group, while the prior year (e.g., 2004) and before are classified under the "without law" group. Two-sample t-test indicates that the mean murder rate for state-years with SYG laws was 5.46 per 100,000, compared to 4.19 per 100,000 in state-years without such laws. This difference is statistically significant ($p < 0.01$). The observed rates suggest that, the presence of SYG laws is associated with a higher, rather than lower, average murder rate.

Given the potential confounding differences between states that adopt the law and those that do not, the next step of the preliminary analysis focuses exclusively on the adopting states to examine the within-state change in murder rates. Specifically, we compare the average murder rates in these states before and after the SYG law's implementation. As shown in Table 9, the average murder rate for the adopting states was 5.03 per 100,000 in the pre-implementation period, which rose to 5.50 per 100,000 in the post-implementation period. While the magnitude of this difference (0.47 per 100,000) is smaller than the cross-group difference reported in Table 8, this increase is still statistically significant at the 5% level. This finding provides further descriptive evidence suggesting that the enactment of SYG laws is associated with an increase in murder rates.

Table 9: Murder Rates in States Before and After Law (2000-2018)

State and Year	Summary Statistics					Comparison	
	Count	Max	Min	Mean	SD	Degrees of Freedom	t
Before Law	208	13.25	.62	5.03	2.56	485	2.18**
After Law	279	14.56	.90	5.50	2.16		

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents a within-state comparison of the average murder rate (per 100,000 population) exclusively for the states that adopted an SYG law. The data is partitioned into two periods: before the law's implementation and after its implementation. The mean murder rate was 5.03 (per 100,000) in the pre-adoption period, increasing to 5.50 in the post-adoption period. The observed increase is statistically significant ($p < 0.05$). This descriptive evidence suggests that, within states that adopt the law, murder rates are higher after the SYG law takes effect.

Furthermore, the descriptive statistics presented in Table 10 reveal a key difference in the circumstances of homicides: victims of second-degree murder exhibit a higher likelihood of possessing a weapon compared to victims of first-degree murder. This disparity in victim armament suggests a fundamental difference in the nature of these encounters. For first-degree murder victims, who are less frequently armed, the potential for SYG laws to apply – or to significantly alter the dynamics – may be diminished. In contrast, for second-degree murder victims, the increased prevalence of weapons suggests confrontations where the risk of escalated violence and mutual combat is higher. This observation aligns with the theoretical expectation that offenders in first-degree murder cases are more likely to demonstrate a greater degree of planning and premeditation, making the defensive elements of an SYG law less relevant to the initial offense.

Table 10: Percentage of First-Degree and Second-Degree Murder Victims with a Weapon

Murder Type	Summary Statistics			Comparison	
	Count	Mean	SD	Degrees of Freedom	t
First Degree	2014	15%	0.35	2662	1.85*
Second Degree	648	18%	0.38		

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: 15% of First-Degree Murder victims have a weapon compared to 18% of Second-Degree Murder victims. The p-value for the two-sample t-test is 0.06, which is significant at the 10% level.

Moreover, these descriptive differences extend to the characteristics of the offenders. As demon-

strated in Table 11, offenders in second-degree murder cases are statistically more likely to be under the influence of drugs at the time of the offense compared to first-degree murder offenders. This finding is critical because drug intoxication, particularly with certain substances, can be associated with heightened impulsivity, emotional disinhibition, and aggression, potentially increasing the propensity for escalated violence and spontaneous conflict (Goldstein, 1985). This contrasts with first-degree murder, where the lower incidence of drug use among offenders further supports the classification as a crime typically involving greater premeditation and cognitive control rather than drug-induced impulsive reaction.

Table 11: Percent of Offenders Under the Influence of Drugs in Offense

Murder Type	Summary Statistics			Comparison	
	Count	Mean	SD	Degrees of Freedom	t
First Degree	661	25%	0.43	867	2.10**
Second Degree	206	33%	0.47		

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the percentage of homicide perpetrators who were under the influence of drugs at the time of the offense, differentiated by the degree of murder. Specifically, 25% of first-degree murder perpetrators were under the influence of drugs, compared to 33% of second-degree murder perpetrators. The difference in the incidence of drug influence between these two groups is statistically significant ($p < 0.05$). This descriptive finding aligns with the expectation that second-degree homicides are more often associated with the impulsivity induced by drug intoxication.

Preliminary analysis using two-sample t-tests suggests a correlation: state-years that enacted the law have a statistically significantly higher mean murder rate compared to those that did not. Recognizing that this initial finding is subject to confounding variables and only indicates an association, we will proceed with a Difference-in-Difference (DiD) research design. This methodology is necessary to control for pre-existing differences and time trends, enabling us to isolate the policy's effect and establish causal inference.

These preliminary observations also reveal important distinctions: second-degree murder is more often characterized by substance use by the perpetrator and is frequently associated with victims who were armed. This foundational understanding informs our subsequent in-depth comparative analysis of the two murder types.

7 Empirical Strategy

The DiD framework is adopted to assess the distinct impacts of SYG laws on planned and unplanned murders. The states that have never enacted these laws serve as the control group, while those that have implemented SYG laws constitute the treatment group. Given the staggered adoption of SYG laws across states starting from 2005, our analysis begins from 2000 to ensure a sufficient pre-treatment period. Data availability spans from 2000 to 2014.

Our outcomes of interest are the natural logarithms of planned and unplanned murders per 100,000 population. If SYG laws lead to increased victim-initiated defense, both types of murder may see an escalation, especially for unplanned murders.

Building on the approach by Cheng and Hoekstra (2013), our baseline specification controls for state-specific murder rate trends. Equation 23 is the general specification, where i stands for the state and t stands for the year.

$$murder_{it} = \beta_0 + \beta_1 law_{it} + \beta_2 states_i + \beta_3 year_t + \beta_4 \boldsymbol{x_{it}} + \beta_5 law_{it} * year_t + \epsilon_{it} \tag{23}$$

The main variable of interest, law_{it}, varies between 0 and 1. For states that have never passed the law, the variable is equal to 0. For states that have passed the law, law_{it} transitions from 0 to 1 post-enactment, adjusted for the exact day of enactment. For example, Governor Jeb Bush signed the legislation into law in Florida on April 26, 2005. Consequently, the law variable for Florida in 2005 is assigned a value of 0.68, reflecting the proportion of the year (249/365 days) during which the law was in effect following its enactment. The years after the law is passed, the variable law_{it} would take on the value of 1.

State fixed effects $states_i$ capture time-invariant factors like cultural attitudes towards self-defense, while year fixed effects $year_{it}$ capture common time trends such as advancements in law enforcement technology. Control variables $\boldsymbol{x_{it}}$ encompass police force size, unemployment rate, poverty rate, income level, prisoner count, last year's prisoner count, demographic variables (i.e., percentage of Black and White males aged 15-24 and 25-44), and government welfare expenditures (subsidy and public welfare). These controls are crucial as they have shown correlations with murder rates in previous literature and they are closely associated with the theoretical models (see Table 6 in Section 5 for details).

Detailed specifications can be found in Appendix G. In the next section on results, Subsection 8.1 details results for overall murder rates, while Subsection 8.2 delves into the findings regarding first- and second-degree murder rates. The next subsections includes robustness checks aimed at

confirming the causal interpretation of the estimated effects and additional results.

8 Results

8.1 DiD Effects on Murder Rate

Tables 12 through 14 present the estimated DiD effects of SYG laws on murder rates. Standard errors are heteroskedasticity-robust and clustered at the year and state levels. The results consistently indicate that the years following the passage of the law experience higher murder rates compared to the pre-law years. Point estimates range between 8.4% and 9.3%, consistent with findings by Cheng and Hoekstra (2013). While we recognize the potential endogeneity of certain time-varying controls, such as police force size, the similar results obtained from specifications that omit these controls indicate that this potential bias does not meaningfully affect our primary findings.

Table 12, Column (1) shows that after controlling for state and year-fixed effects, SYG laws increase the murder rate by 9.1% more for states with the law compared to those without it. Results are statistically significant at the five percent level. Controlling for region-by-year fixed effects maintains this significance, with a slightly lower estimate of 8.4%, as shown in Column (2). Column (3) includes time-varying controls as detailed in Section 5.3. The point estimate is 8.8% while the level of significance increases to one percent. Column (4) introduces a dummy variable for the year of law passage, which minimally affects the coefficient at 8.6%. This addresses the concern that other events during the year of law passage may have caused the change in murder rate. After adding time trends in Columns (5) and (6), the coefficients increase to 9% and 9.3% while maintaining the same significance level of one percent.

Table 12: The Effect of Stand Your Ground Law on Murder (UCR & Law Year Dummy)

	(1)	(2)	(3)	(4)	(5)	(6)
Law	0.091**	0.084**	0.088***	0.086***	0.090***	0.093***
	(0.045)	(0.031)	(0.032)	(0.032)	(0.029)	(0.028)
State and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-Year Fixed Effects		Yes	Yes	Yes	Yes	Yes
Time-Varying Controls			Yes	Yes	Yes	Yes
Law Year Dummy				Yes	Yes	Yes
State-Specific Linear Time Pre-trends					Yes	Yes
State-Specific Linear Time Post-trends						Yes
N	850	850	845	845	845	845

Notes. Heteroskedasticity-robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To address the potential for reverse causality–specifically, whether the laws were enacted in response to pre-existing increases in murder rates–we introduce a pre-law dummy variable in the specifications presented in Table 13. The results show no significant increase in murder rates in the two years immediately preceding law passage compared to earlier periods. Furthermore, the estimated coefficients for the law variable remain comparable to those reported in Table 12, supporting the independence of our treatment effect.

Table 13: Robustness Check for Ashenfelter's Dip

	(1)	(2)	(3)	(4)	(5)	(6)
Law	0.091**	0.084**	0.088***	0.093**	0.099***	0.098**
	(0.045)	(0.031)	(0.032)	(0.037)	(0.037)	(0.037)
Prelaw Dummy				0.033	0.034	0.010
				(0.034)	(0.028)	(0.024)
State and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-Year Fixed Effects		Yes	Yes	Yes	Yes	Yes
Time-Varying Controls			Yes	Yes	Yes	Yes
State-Specific Linear Time Pre-trends					Yes	Yes
State-Specific Linear Time Post-trends						Yes
N	850	850	845	845	845	845

Notes. Heteroskedasticity-robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14 shows that compared to two years or more before the laws' enactment, two years or more after the laws exhibit a higher murder rate. However, the statistical significance of this difference diminishes upon controlling for state-specific pre- and post-trend variations. A more nuanced examination of these temporal patterns is undertaken through an event study analysis, whose results are illustrated in Figure 1 below. Furthermore, these results may be affected by the potential heterogeneity in the impact of these laws. We will revisit this aspect in Subsection 8.2, where we subsequently disaggregate the analysis by examining the laws' effects on planned and unplanned murder rates separately.

Table 14: Robustness Check for Long-term Impact

	(1)	(2)	(3)	(4)	(5)	(6)
Law	0.091**	0.084**	0.088***	0.080**	0.070	0.075*
	(0.045)	(0.031)	(0.032)	(0.038)	(0.044)	(0.041)
State and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-Year Fixed Effects		Yes	Yes	Yes	Yes	Yes
Time-Varying Controls			Yes	Yes	Yes	Yes
Three Years Around Law Year				Yes	Yes	Yes
State-Specific Linear Time Pre-trends					Yes	Yes
State-Specific Linear Time Post-trends						Yes
N	850	850	845	845	845	845

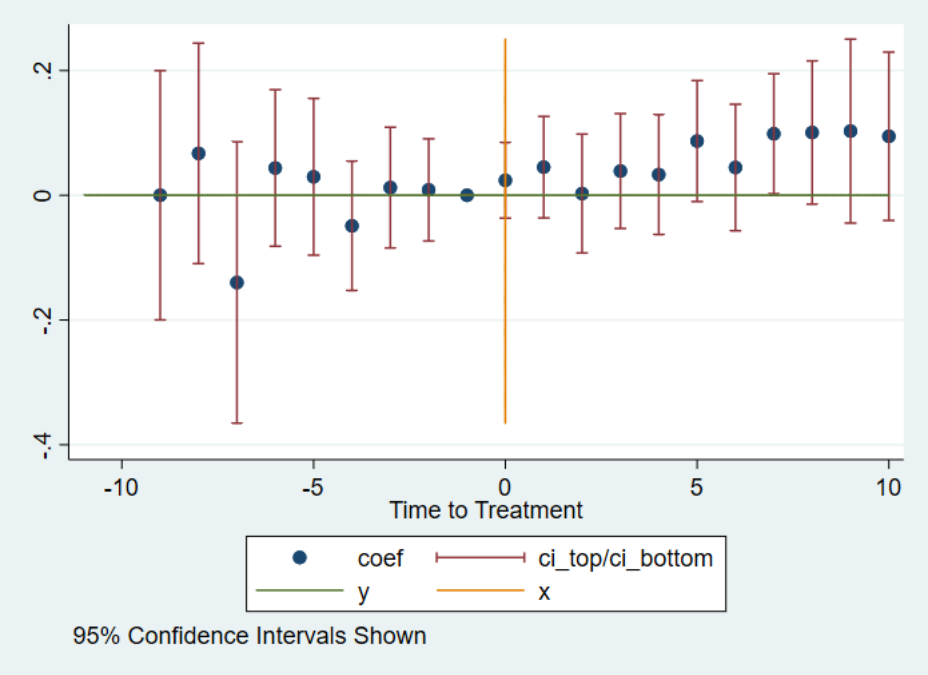
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Heteroskedasticity-robust standard errors in parentheses.

Notes: Results are large and statistically significant until time trends are added, when they become smaller and less statistically significant than in the two tables above. We revisit these results in the event study analysis below.

Figure 1 presents an event study analysis, indicating a gradual increase in murder rate following the enactment of the laws. The horizontal axis captures the time to treatment by the year. 0 on the horizontal axis represents the year when the SYG laws passed in the respective states. The vertical axis represents the difference in murder rates between states with the laws and states without the laws. The number on the vertical axis that corresponds with the number 5 on the horizontal axis is approximately 0.1. It means that 6 years after the passage of the SYG laws, murder rates increase by approximately 10% more in states with the laws, compared with states without the laws. If we remove the two years before law passage and the two years after law passage, the DiD effects could be slightly less pronounced.

Figure 1: Effect of Law on Murder Over Time



Notes: This figure reports the results from event study analysis of the SYG laws on murder. It plots both the point estimates and their 95 percent confidence intervals. Standard errors are clustered by the state. The years after the laws pass witness an increase in murder, and the effects are larger and persistent.

8.2 Planned Murder v.s. Unplanned Murder

Beyond analyzing the effect of SYG laws on the aggregate murder rate, this section disaggregates the impact by distinguishing between planned and unplanned murder rates. Our theoretical models (Section 3) posits that any increase in murder is driven by individuals overestimating the legal protection afforded by SYG laws and underestimating the risks of an armed confrontation. Because the victims of unplanned attacks are less prepared, they are more likely to make these poor risk assessments. Consequently, we hypothesize that unplanned murders will increase significantly more than planned murders. We test this prediction using a methodology similar to Section 8.1, incorporating a dummy variable interaction term to compare the law's estimated effect across the two murder types.

Table 15 reports the coefficient β_1 in Equations 70 to 75 for the logarithm form of planned and unplanned murder rate. In Panel A, Column (1), the regression on planned murders shows that SYG laws increase these rates by an estimated 8.9%. This estimate decreases to 8.6% when we

include region-by-year fixed effects, as seen in Column (2). However, when we include time-varying controls and a law year dummy, as seen in Columns (3) and (4), the estimate decreases to around 7.5%. When we add linear time trends, as seen in Columns (5) and (6), the coefficient estimates go up to 9.8% and 9.5%, respectively.

Panel B reports the impact of SYG laws on unplanned murder rates, consistently showing larger and more statistically significant coefficient estimates than planned murders. For instance, in Column (6), SYG laws are associated with a 11.5% increase in unplanned murder rates. The average difference between coefficients across specifications is 2.3 percentage points.

Table 15: The Effect of SYG Law on Planned and Unplanned Murder - with Law Year Dummy

Panel A: Planned Murder Rate	(1)	(2)	(3)	(4)	(5)	(6)
Law	0.089	0.086	0.076	0.075	0.098	0.095
	(0.089)	(0.056)	(0.057)	(0.057)	(0.060)	(0.058)
Panel B: Unplanned Murder Rate						
Law	0.107*	0.108**	0.107**	0.105**	0.114***	0.115***
	(0.058)	(0.051)	(0.047)	(0.047)	(0.042)	(0.041)
State and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-Year Fixed Effects		Yes	Yes	Yes	Yes	Yes
Time-Varying Controls			Yes	Yes	Yes	Yes
Law Year Dummy				Yes	Yes	Yes
State-Specific Linear Time Pre-trends					Yes	Yes
State-Specific Linear Time Post-trends						Yes
N	838	838	833	833	833	833

Notes. Heteroskedasticity-robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16 serves as a robustness check, focusing on the comparison of murder rates post-law enactment with those three or more years before. Notably, while planned murder rate results remain inconclusive, Panel B consistently confirms a statistically significant impact on unplanned murder rates, reinforcing the enduring behavioral shifts that drive unplanned violence. The average difference between the percentage increases across specifications is 2.7 percentage points, larger than

that in Table 15.

Table 16: Robustness Check for Ashenfelter's Dip (Planned and Unplanned Murder)

Panel A: Log Planned Murder Rate	(1)	(2)	(3)	(4)	(5)	(6)
Law	0.089	0.086	0.076	0.067	0.083	0.084
	(0.089)	(0.056)	(0.057)	(0.059)	(0.069)	(0.071)
Panel B: Log Unplanned Murder Rate						
Law	0.107*	0.108**	0.107**	0.105*	0.111**	0.111**
	(0.058)	(0.051)	(0.047)	(0.052)	(0.051)	(0.051)
State and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-Year Fixed Effects		Yes	Yes	Yes	Yes	Yes
Time-Varying Controls			Yes	Yes	Yes	Yes
Prelaw Dummy				Yes	Yes	Yes
State-Specific Linear Time Pre-trends					Yes	Yes
State-Specific Linear Time Post-trends						Yes
N	833	833	828	828	828	828

Notes. Heteroskedasticity-robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Furthermore, Table 17 examines the long-term effects of SYG laws. Specifically, we are comparing periods more than two years before and after the law. Here, while planned murder rates still do not exhibit statistically significant increases, Panel B consistently reveals substantial and sustained rises in unplanned murder rates. This persistence highlights how SYG laws contribute to escalating unplanned violence over time. The difference in the point estimates is 3.3 percentage points on average, which is larger than that in both Tables 15 and 16.

Table 17: Robustness check for Long-term Impact (Planned and Unplanned Murder)

Panel A: Log Planned Murder Rate	(1)	(2)	(3)	(4)	(5)	(6)
Law	0.089	0.086	0.076	0.060	0.076	0.075
	(0.089)	(0.056)	(0.057)	(0.065)	(0.080)	(0.077)
Panel B: Log Unplanned Murder Rate						
Law	0.107*	0.108**	0.107**	0.101*	0.105*	0.108*
	(0.058)	(0.051)	(0.047)	(0.055)	(0.058)	(0.055)
State and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-Year Fixed Effects		Yes	Yes	Yes	Yes	Yes
Time-Varying Controls			Yes	Yes	Yes	Yes
Before and After Law Year Dummy				Yes	Yes	Yes
State-Specific Linear Time Pre-trends					Yes	Yes
State-Specific Linear Time Post-trends						Yes
N	833	833	828	828	828	828

Notes. Heteroskedasticity-robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18 reinforces these findings by directly comparing coefficients between planned and unplanned murders. Although differences are not uniformly statistically significant across specifications, they consistently demonstrate a positive association between SYG laws and both types of murder, with unplanned murders showing a stronger response.

Table 18: Comparison of Coefficients Between Planned Murder and Unplanned Murder

	(1)	(2)	(3)	(4)	(5)	(6)
Law * Unplanned	0.093	0.107**	0.042	0.042	0.008	0.019
(w/ Law Year Dummy)	(0.072)	(0.050)	(0.038)	(0.038)	(0.031)	(0.031)
Law * Unplanned				0.049	0.027	0.026
(w/ Pre-law Dummy)				(0.041)	(0.036)	(0.037)
Law * Unplanned				0.052	0.016	0.028
(w/ Around Law Year Dummy)				(0.042)	(0.042)	(0.044)
State and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-Year Fixed Effects		Yes	Yes	Yes	Yes	Yes
Time-Varying Controls			Yes	Yes	Yes	Yes
Before and After Law Year Dummy				Yes	Yes	Yes
State-Specific Linear Time Pre-trends					Yes	Yes
State-Specific Linear Time Post-trends						Yes
N	1666	1666	1656	1656	1656	1656

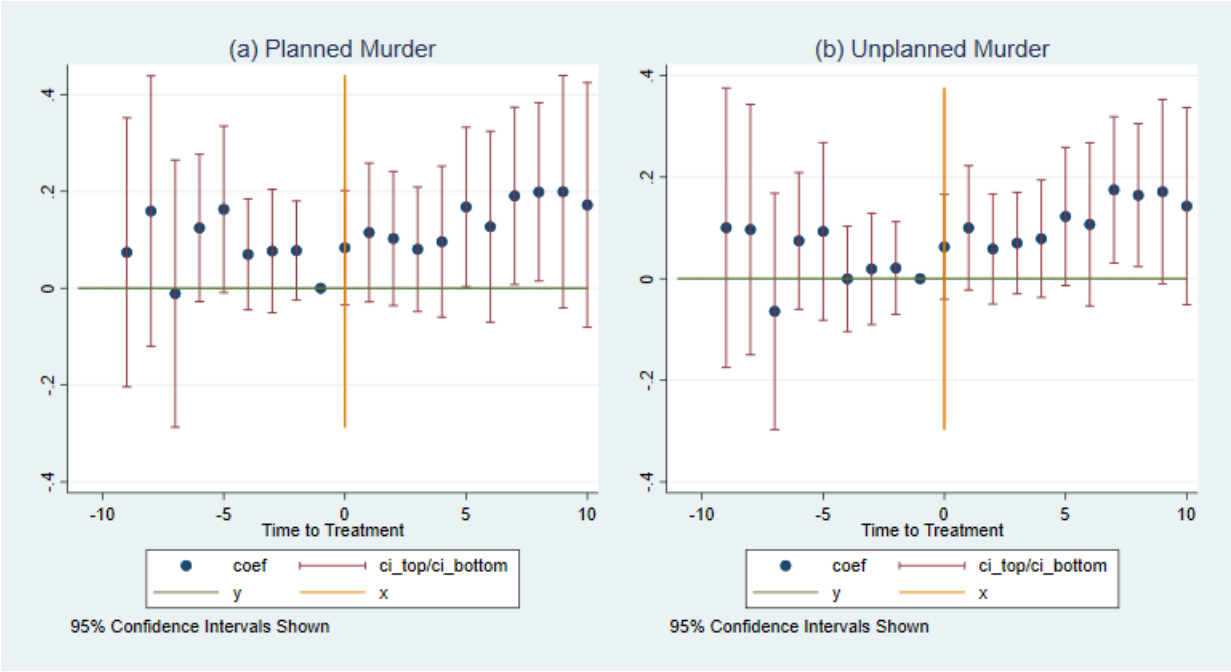
Heteroskedasticity-robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: We use an interaction term to examine the differences in coefficients between planned and unplanned murders. The differences in coefficients are not consistently statistically significant, but they are consistently positive.

Figure 2 visually supports these quantitative findings, illustrating larger jumps and smaller confidence intervals for planned murders compared to unplanned murders over time. There are no visible linear pre-trends for either planned murder or unplanned murders.

Figure 2: Effect of Laws on Planned and Unplanned Murder Over Time



Notes: The data reveals that planned murder exhibited higher short-term variation during the three-year period centered on the new legislation. However, the overall long-term change in unplanned murder was greater than that of planned murder, suggesting the influence of escalation and over-defense mechanisms. The overall upward trajectory for both types of murder indicates that the underlying effects are persistent and exacerbating over time.

In addition to the main coefficient of interest, the signs for the coefficients on control variables also agree with the predictions of the theoretical models. This information is presented in Table 19, where the signs for the partial derivatives in Column (3) match the signs for the coefficients from the empirical models in Column (4). The empirical results in Column (4) come from Panel B Column (6) in Table 15. The only disagreements between Columns (3) and (4) are for the following three variables: welfare, % 15-24 yo White male, and % 25-40 yo Black male. However, the impact of welfare at its mean value is 0.27*7.64, which is equal to 2.06, whereas the impact of assistance at its mean value is -0.66*4.73, which is equal to -3.12. The impacts on murder rate of welfare and assistance combined, therefore, is negative, which agrees with the theoretical predictions. The results are similar for % 15-24 yo White male and % 25-40 yo Black male. If we combine the impact of all four variables that affect victim's loss at the mean, it is equal to 2.06*0.06+(-13.61)*0.01+(-5.45)*0.11+17.04*0.01, which is equal to -0.44, and it agrees with the predictions of the theoretical model. The theoretical model points out the possibility of $\frac{\partial p}{\partial \alpha} < 0$, and it is negative indeed.

Table 19: Agreement Between Theory and Empirical Models

(1) Theoretical Model Result	(2) Theoretical & Empirical Model Connection	(3) Combine Columns (1) and (2)	(4) Empirical Model Result
$\frac{\partial p}{\partial B} > 0$	$\frac{\partial B}{\partial poverty} > 0$	$\frac{\partial p}{\partial poverty} > 0$	$\frac{\partial p}{\partial poverty} = 1.28$
	$\frac{\partial B}{\partial welfare} < 0$	$\frac{\partial p}{\partial welfare} < 0$	$\frac{\partial p}{\partial welfare} = 0.27$
	$\frac{\partial B}{\partial assistance} < 0$	$\frac{\partial p}{\partial assistance} < 0$	$\frac{\partial p}{\partial assistance} = -0.66$
	$\frac{\partial B}{\partial unemployment} > 0$	$\frac{\partial p}{\partial unemployment} > 0$	$\frac{\partial p}{\partial unemployment} = 0.003$
	$\frac{\partial B}{\partial income} > 0$	$\frac{\partial p}{\partial income} > 0$	$\frac{\partial p}{\partial income} = 0.33$
	$\frac{\partial B}{\partial prisoner} < 0$	$\frac{\partial p}{\partial prisoner} < 0$	$\frac{\partial p}{\partial prisoner} = -0.04$
	$\frac{\partial \alpha}{\partial police} < 0$	$\frac{\partial p}{\partial police} < 0$	$\frac{\partial p}{\partial police} = -0.2$
$\frac{\partial p}{\partial L} < 0$	$\frac{\partial L}{\partial 15-24Wmale} > 0$	$\frac{\partial p}{\partial 15-24Wmale} < 0$	$\frac{\partial p}{\partial 15-24Wmale} = 2.06$
	$\frac{\partial L}{\partial 15-24Bmale} > 0$	$\frac{\partial p}{\partial 15-24Bmale} < 0$	$\frac{\partial p}{\partial 15-24Bmale} = -13.61$
	$\frac{\partial L}{\partial 25-40Wmale} > 0$	$\frac{\partial p}{\partial 25-40Wmale} < 0$	$\frac{\partial p}{\partial 25-40Wmale} = -5.45$
	$\frac{\partial L}{\partial 25-40Bmale} > 0$	$\frac{\partial p}{\partial 25-40Bmale} < 0$	$\frac{\partial p}{\partial 25-40Bmale} = 17.04$
$\frac{\partial p}{\partial \alpha}?0$	$\frac{\partial \alpha}{\partial SYG} < 0$	$\frac{\partial p}{\partial SYG}?0$	$\frac{\partial p}{\partial SYG} = 0.12$

Notes: This table presents a comparison between theoretical predictions and empirical coefficients from Panel B Column (6) in Table 15. The theoretical model results match the empirical model results except for welfare, % 15-24 yo White male, and % 25-40 yo Black male. However, after taking into account the average effect of the other variables in their category, the total effect sign matches with the model results. The theoretical model points out the possibility of $\frac{\partial p}{\partial \alpha} < 0$, and it is negative indeed.

In summary, our analysis underscores that while planned murder rates also rise following the implementation of SYG laws, unplanned murders contribute more significantly to the overall increase in murder rates. These empirical findings are consistent with the theoretical predictions derived from our game-theoretic framework, which anticipates the potential for individuals to shift from retreat to confrontation and to over-defend.

8.3 Robustness Checks

To enhance the robustness of our findings, we conduct additional analysis employing the event study approach by Callaway and Sant'Anna (2020), specifically designed for panel data with staggered

adoption. Leveraging their accompanying R package, we replicate Figure 1 using their approach, resulting in Figure 3. The findings from this alternative estimation strategy are consistent with the results obtained from our initial analysis.

Figure 3: Effect of Law on Murder Over Time (Callaway and Sant'Anna, 2020)

Notes: In the pre-legislation periods, the majority of observed murder rates fall below the overall mean. Conversely, in the post-legislation periods, most rates exceed the mean. This shift indicates a higher average murder rate following the new laws. Furthermore, the precision of the estimates (indicated by the confidence intervals) decreases the further the observation is from the treatment period (the year the laws were passed). This reduction in precision is attributed to the decreasing number of available data points in the more distant time periods.

Furthermore, Figure 4 illustrates the effect of SYG laws on planned and unplanned murders using the same methodology, showing narrower confidence intervals compared to Figure 2. Even though the results are slightly less statistically significant, the overall magnitudes are consistent between the two figures.

Figure 4: Effect of Law on Planned and Unplanned Murder Over Time (Callaway and Sant'Anna, 2020)

Notes: The estimated treatment effects for planned murders are slightly smaller in magnitude compared to those for unplanned murders. Additionally, the estimates for planned murder are less precise (indicated by wider confidence intervals). These findings are consistent with the observed patterns illustrated in Figure 2, which also highlights differences in the behavior and volatility of the two murder types.

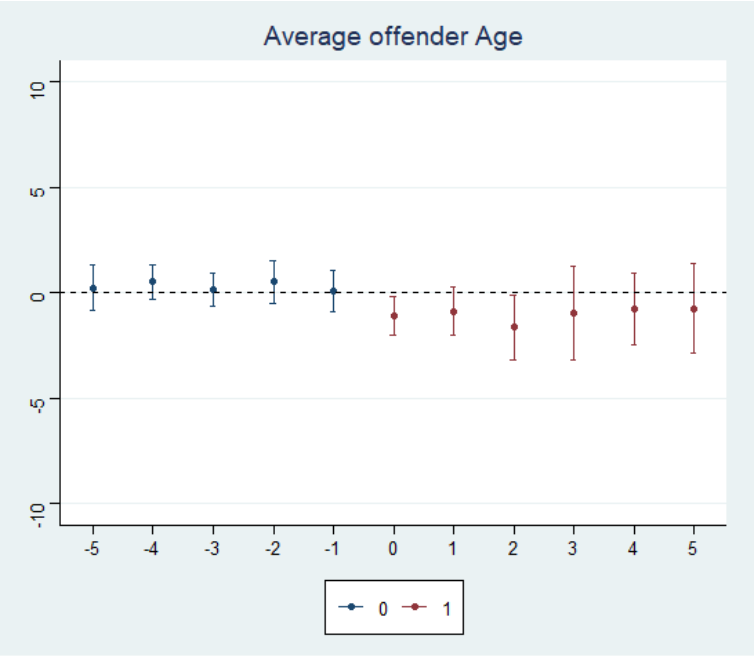
8.4 Additional Results

To examine the consequences of SYG laws in greater detail, we conduct additional event study analysis utilizing SHR data spanning the period from 2000 to 2016. These analysis are on the SYG law's effect on the average offender age, average victim age, percent cases with white offenders, percent cases with black offenders, and percent cases with non-white and non-black offenders. The results of these analysis are presented in Figures 5 to 9. For this set of five graphs, the horizontal axis represents time relative to the law's enactment: negative values denote years prior to the law's passage, zero marks the year of enactment, and positive values indicate subsequent years.

Figure 5 shows that the average offender age in SYG states decreased by approximately one year more than in control states following the law's passage. This effect persists for at least the next five years. This shift towards younger offenders is noteworthy, as younger individuals are generally more likely to engage in social mingling, potentially increasing opportunities for conflict escalation.

Figure 6 similarly shows a decrease in the average victim age compared with non-SYG states

Figure 5



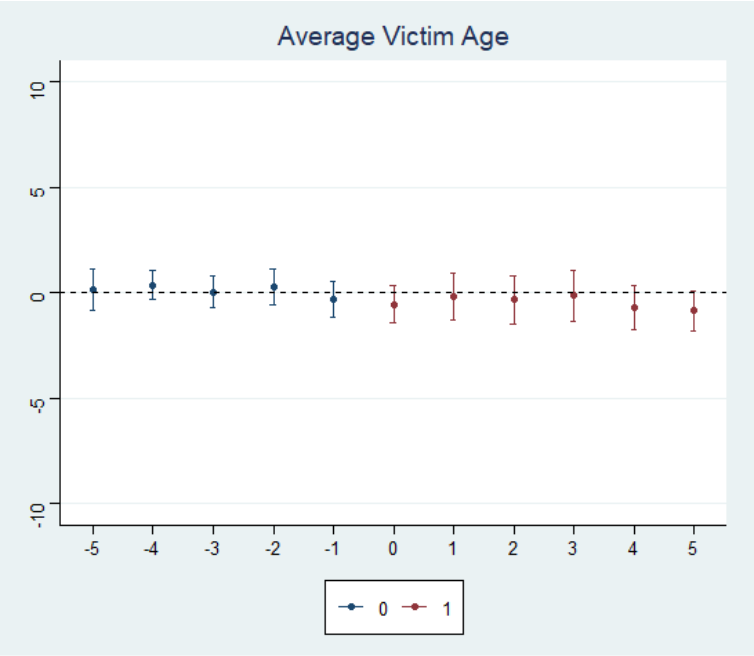
Notes: Average offender age has decreased more in states with the laws than those without.

following the enactment of SYG laws. This decline is less than that in the average offender age, but it is exacerbated over time. This comparable, though slower, shift in victim age suggests that the instigation of conflicts leading to homicide is not attributable solely to one party. Instead, it indicates that both younger offenders and younger victims are increasingly involved, making it difficult to definitively identify which side is the primary initiator of the fatal confrontations.

Figures 7, 8, and 9 present the event study results, focusing on the change in the proportion of White, Black, and other racial/ethnic groups among murder offenders following the enactment of SYG laws. The analysis reveals distinct and varying trends across groups.

Specifically, the proportion of White offenders remains relatively stable between with-law and without-law states post-legislation, even as overall murder rates increased. In contrast, this proportion decreased for Black offenders. On the contrary, the proportion increased for other racial/ethnic groups. These findings suggest that the increase in murder rates after SYG laws is driven most by other racial/ethnic groups, then White offenders, and least by Black offenders.

Figure 6



Notes: Compared with states without the laws, average victim age has decreased more in states with the laws.

9 Discussions

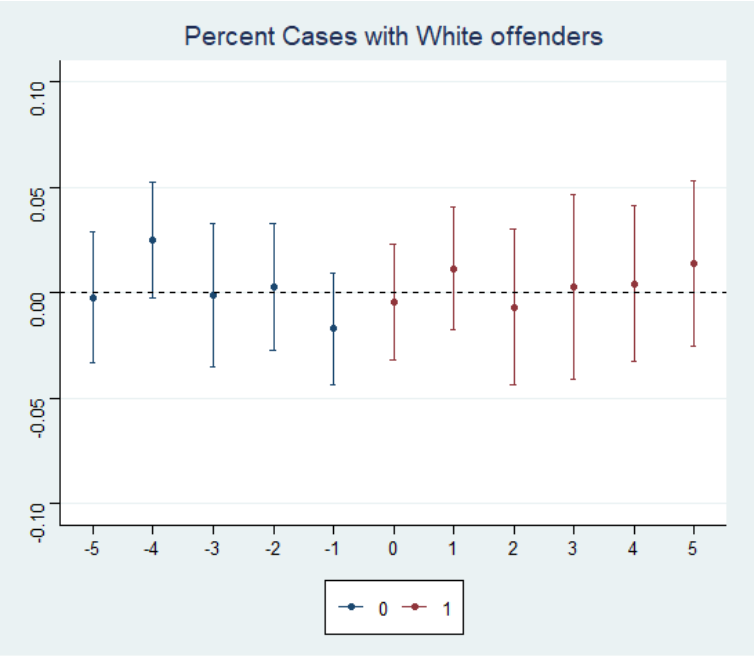
Legislative actions frequently result in unintended consequences (Podkopacz and Feld, 2001; Chesney-Lind, 2002), and the implementation of SYG laws is no exception. This study contributes to the literature by theoretically and empirically illustrating how the relaxation of punishment for self-defense can inadvertently and systematically contribute to escalated conflict and a resultant increase in homicide.

In 2017, Florida shifted the burden of proof in pre-trial hearings[24], requiring prosecutors to demonstrate that a person was not acting in self-defense, rather than placing the onus on the accused to prove innocence. This change can further encourage individuals to prepare for and engage in more violent encounters, resulting in more murders.

The language of SYG statutes itself may contribute to the observed homicide increase. Nearly 90% of states with SYG laws explicitly mention the use of deadly force or lethal weapons in their provisions, often utilizing phrases such as "can use a lethal weapon against," "can use deadly force to," "killing is necessary," or "can meet force with force, including deadly force." This strong focus may inadvertently promote the use of lethal force as the default self-defense option, rather than

[24] Act effective June 9, 2017, ch. 2017-72, 2007 Fla. Laws

Figure 7



Notes: Compared with states without the SYG laws, states with the laws have a similar average proportions of white offenders over time after the laws, suggesting that as murder rates increase over time, the number of White offenders increase proportionally.

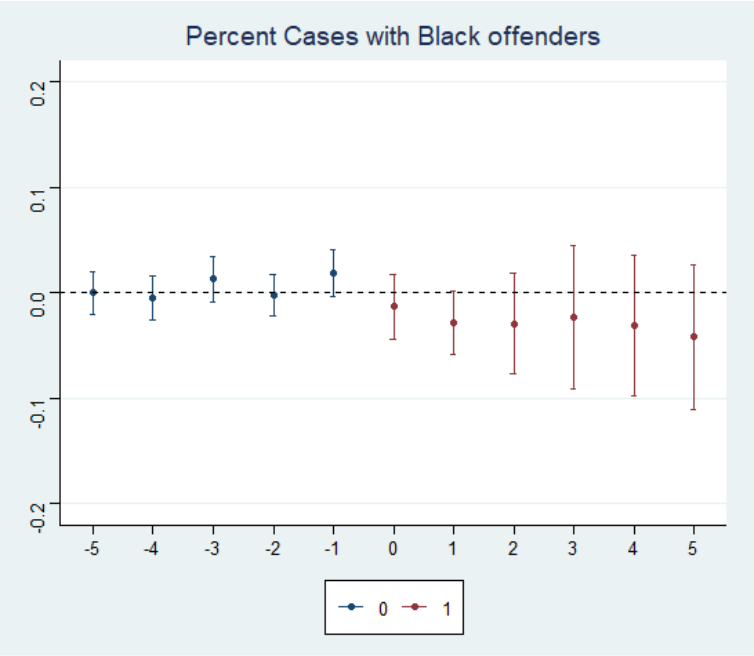
encouraging de-escalation or less-harmful methods, thereby contributing to the observed escalation in violent crime. Furthermore, evidence suggests that laws can significantly influence social norms (Lane, Nosenzo and Sonderegger, 2023), potentially shifting public perceptions and behaviors toward more aggressive, lethal responses in conflict and self-defense scenarios.

This legal emphasis on lethal force is then compounded by how public perception often diverges from the legal nuances of the law. While SYG statutes legally hinge on the individual's "reasonable belief" of imminent danger of death or serious injury, there is a pervasive concern that public interpretation simplifies this standard to a "shoot first, ask questions later" mentality[25]. This misalignment between the precise legal text and generalized public understanding creates a dangerous environment where individuals may feel protected when escalating minor conflicts into lethal confrontations, operating under an oversimplified, aggressive interpretation of the law.

Given that fighting violence with violence has demonstrated clear and unintended consequences, as illustrated by this study, policy attention should shift beyond the reactive measure of SYG laws

[25]The Norgard case, for example: https://www.naplesnews.com/story/news/crime/2020/01/12/road-rage-shooting-david-norgard-golden-gates-estates-justifiable-stand-your-ground-law-florida/4418769002/.

Figure 8



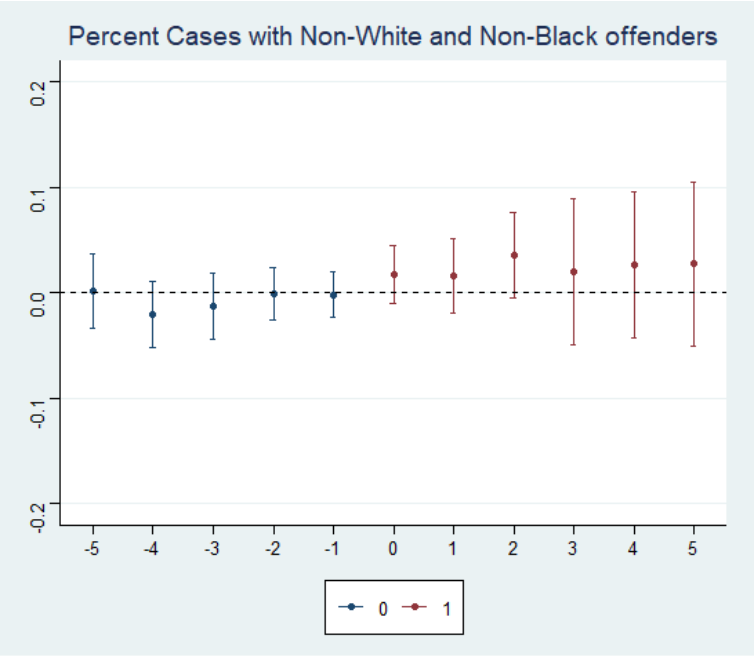
Notes: Compared with states without the SYG laws, states with the laws have a smaller average proportion of black offenders over time after the law, suggesting that as murder rates increase over time, the number of Black offenders increases less.

toward societal factors that deter crime at its root. More sustainable and effective reductions in violence can be achieved by expanding educational, health and economic opportunities for vulnerable populations. Investing in comprehensive programs–such as high-quality educational initiatives, drug rehabilitation initiatives, and youth development programs–can directly address the fundamental causes of crime and conflict(Anderson, 2002). This proactive approach promotes long-term community safety and well-being without incurring the exacerbating effects and unintended homicides associated with the relaxation of self-defense standards, possibly at a reduced cost.

10 Conclusion

This study provides a comprehensive analysis of the impact of self-defense regulations on both planned and unplanned crime through the lens of both theoretical frameworks and empirical models. We find that changes in self-defense laws alter offenders' perceptions of risk, influencing their decisions and behaviors in criminal scenarios. Specifically, offenders escalate their efforts when they perceived potential injury to themselves. Victims are more likely to exert fighting efforts as opposed

Figure 9



Notes: Compared with states without the laws, states with the laws have a larger average proportion of other offenders over time after the legislation, suggesting that as murder rates increase over time, the number of other offenders increases more (proportionally).

to retreating efforts due to perceived decrease in overall cost, downplaying the increased probability that the offender is more likely to succeed. This increased engagement by victims can also lead to their over-defense, particularly when victims misperceive the true leniency of the law. The propensity for this shift from retreat to active self-defense is hypothesized to be more pronounced in unplanned murders, as offenders in these scenarios have limited opportunity to assess the victim's level of preparedness.

Empirical testing of this theoretical framework reveals significant increases in both second-degree (unplanned) and first-degree (planned) murders following the enactment of SYG laws. Notably, the rate of second-degree murder increases by an estimated 1.7 to 3.2 percentage points more than first-degree murder rates post-SYG law implementation, highlighting distinct impacts across different types of murders. The empirical results match the theoretical predictions.

Our study also introduces novel evidence suggesting that the escalation in murder rates intensifies over time. As illustrated in Figure 3, average murder rate increases by 10% more one year after SYG laws are passed, with this difference rising to 15% a decade later, when comparing states that have the law with states that don't. This temporal trend suggests a cumulative effect as

societal perceptions and responses to SYG laws evolve, potentially exacerbating their impact on crime dynamics.

One limitation of this study is that it primarily examines the average effect of SYG laws across states, overlooking potential variations in impact among different jurisdictions. Future research can delve deeper into these state-specific differences to provide a more nuanced understanding of SYG law effects. Moreover, variations in prosecutorial decisions and charging practices could potentially present discrepancies between police-reports (used in this study) and murder rates calculated from convictions. To address this concern, ongoing efforts are needed to incorporate court-processing data, which will offer a more comprehensive assessment of how SYG laws influence murder rates.

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Appendix A Cost of Crime

McCollister, French and Fang (2010) estimates the cost to society for all index crimes in the United States. According to Table 20, the cost of homicide/murder is approximately 30 times more than that of rape, which is the second most costly type of crime among the index crimes. This emphasizes the societal costs of murders and the societal benefits of reducing them, from an economic standpoint alone.

Table 20: Cost of Index Crimes

Type of Crime	Cost Per-Offense
Homicide/Murder	8,982,907
Rape	240,776
Assault	107,020
Robbery	42,310
Burglary	6,462
Theft/larceny	3,532
Motor vehicle theft	10,772
Arson	21,103

Note: all unit costs are expressed in 2008 dollars.

Appendix B SYG Law Dates

The expansion of the "Castle Doctrine" to public places began with Florida passing its SYG law in 2005. Arizona followed in 2006, with 28 additional states gradually enacting various forms of the law thereafter. The most recent state to pass an SYG law so far is Wyoming (2018). It is important to note that among these thirty states, North Dakota, Ohio, and Wisconsin have limited versions that restrict "stand-your-ground" provisions primarily to cars and places of business, rather than to all public locations. Table 21 provides a complete list of states and the dates when they passed laws expanding the traditional Castle Doctrine(NUL, 2013).

In Florida, the SYG law now includes a provision that places the burden of proof on prosecutors to disprove a defendant's self-defense claim before trial. This provision can lead to situations where no arrest is made or charges are dropped early, even if the offender cannot conclusively prove they had a "reasonable belief of bodily harm." Consequently, these uncharged incidents do not contribute to either the murder or the justifiable homicide statistics used in this analysis. Therefore, the findings presented in this paper, which rely on official homicide data, should be interpreted as representing the lower bound of the true effect of SYG laws on fatal violence.

Table 21: States that Passed the Stand Your Ground Law

States	**Law Signed**	**Law Stipulations**
Florida	4/26/2005	
Arizona	4/24/2006	
Kansas	5/25/2006	
Alabama	6/1/2006	
South Carolina	6/9/2006	
Georgia	7/1/2006	
Indiana	7/1/2006	
Mississippi	7/1/2006	
South Dakota	7/1/2006	
Kentucky	7/21/2006	
Louisiana	8/15/2006	
Alaska	9/13/2006	
Michigan	10/1/2006	
Oklahoma	11/1/2006	
Tennessee	5/22/2007	
North Dakota	8/1/2007	SYG from one's vehicle
Missouri	8/28/2007	House & Vehicle
Texas	9/1/2007	
West Virginia	3/12/2008	
Ohio	9/9/2008	SB184: car, home, temporary residence
Montana	4/27/2009	

continued...

... Table 21 continued

States	Law Signed	Law Stipulations
Nevada	5/19/2011	
North Carolina	6/23/2011	
Pennsylvania	6/28/2011	
New Hampshire	9/14/2011	
Wisconsin	12/21/2011	car, business, and home ((n.d.))
Iowa	7/1/2017	
Utah	5/8/2018	
Idaho	7/1/2018	
Wyoming	7/1/2018	

Notes: This table presents the dates of SYG law passage for each of the thirty states that have it, listed in chronological order.

Appendix C Theoretical Model Derivations

The offender's profit function is:

$$O(x) = \frac{x}{x+s}B - x - \frac{s}{x+s}D \tag{24}$$

The victim's loss function is:

$$V(s) = \frac{x}{x+s}L + s + \frac{s}{x+s}\alpha \tag{25}$$

In the simultaneous game, the two parties act at the same time, resulting in the economist solving the following first order conditions:

$$\frac{\partial O}{\partial x} = 0 \tag{26}$$

$$\frac{\partial V}{\partial s} = 0 \tag{27}$$

The optimal results for the interaction between the offender and the fighting victim are therefore:

$$x^{**} = \frac{(B+D)^2(L-\alpha)}{(B+D+L-\alpha)^2} \tag{28}$$

$$s^{**} = \frac{(B+D)(L-\alpha)^2}{(B+D+L-\alpha)^2} \tag{29}$$

$$p^{**} = \frac{B+D}{B+D+L-\alpha} \tag{30}$$

$$V^{**} = \frac{L(B+D)^2 + 2L(B+D)(L-\alpha) + \alpha(L-\alpha)^2}{(B+D+L-\alpha)^2} \tag{31}$$

$$O^{**} = \frac{B(B+D)^2 - 2D(B+D)(L-\alpha) - D(L-\alpha)^2}{(B+D+L-\alpha)^2} \tag{32}$$

The response of the above variables to the severity of punishment for over-defense are:

$$\frac{\partial x^{**}}{\partial \alpha} = \frac{-(B+D)^3}{(B+D+L-\alpha)^3} < 0 \tag{33}$$

$$\frac{\partial s^{**}}{\partial \alpha} = \frac{-2(B+D)^2(L-\alpha)}{(B+D+L-\alpha)^3} < 0 \tag{34}$$

$$\frac{\partial p^{**}}{\partial \alpha} = -\frac{B+D}{B+D+L-\alpha} < 0 \tag{35}$$

$$\frac{\partial V^{**}}{\partial \alpha} = \frac{[3(B+D)+(L-\alpha)](L-\alpha)^2}{(B+D+L-\alpha)^3} > 0 \tag{36}$$

$$\frac{\partial O^{**}}{\partial \alpha} = \frac{2(B+D)^3}{(B+D+L-\alpha)^3} > 0 \tag{37}$$

For the analysis involving an interaction between the offender and a retreating victim, the results are presented below. Equations 38 - 42 are the direct counterparts to Equations 28 - 32. The key distinction for the retreating victim scenario is that the parameters α and D are set to zero in these equations.

$$x^{*} = \frac{B^2 L}{(B+L)^2} \tag{38}$$

$$s^{*} = \frac{BL^2}{(B+L)^2} \tag{39}$$

$$p^{*} = \frac{B}{B+L} \tag{40}$$

$$V^{*} = \frac{BL(B+2L)}{(B+L)^2} \tag{41}$$

$$O^{*} = \frac{B^3}{(B+L)^2} \tag{42}$$

The comparison between V^{**} and V^{*} is done through setting α to zero in V^{**} to model zero punishment for over-defense, and keeping D as non-zero because there could still be damage to the offender. If $\frac{\partial V^{**}}{\partial D} > 0$, we know that $V^{**} > V^{*}$ because $\frac{\partial V^{**}}{\partial \alpha} > 0$ (See Equation 36).

After setting α to zero, the fighting victim's loss function is:

$$V^{**} = \frac{L(B+D)(B+D+2L)}{(B+D+L)^2} \tag{43}$$

The victim's loss increases as the damage to the offender increases, meaning that $V^{**} > V^{*}$.

$$\frac{\partial V^{**}}{\partial D} = \frac{2L^3}{(B+D+L)^3} > 0 \tag{44}$$

The comparison between O^{**} and O^{*} is also conducted through setting α to zero to model zero punishment for over-defense, and keeping D as non-zero because there could still be damage to the offender. If $\frac{\partial O^{**}}{\partial D} > 0$, we know that $O^{**} > O^{*}$ because $\frac{\partial O^{**}}{\partial \alpha} > 0$ (see Equation 37). After setting α to zero, the optimal benefit function for the offender that encounters the fighting victim is:

$$O^{**} = \frac{B(B+D)^2 - 2DL(B+D) - DL^2}{(B+D+L)^2} \tag{45}$$

As the damage to the offender increases, the offender's optimal benefit decreases:

$$\frac{\partial O^{**}}{\partial D} = -\frac{3L^2(B+D) + L^3}{(B+D+L)^3} < 0 \tag{46}$$

Therefore, when $\alpha = 0$, $O^{**} < O^{*}$. As α increases, O^{**} also increases.

For the planned murders, the victim moves first in preparing their defensive efforts.

$$\frac{\partial V}{\partial s} = 0 \tag{47}$$

After taking into account the victim's optimal response to their actions, the offender prepares their offensive efforts.

$$\frac{\partial O}{\partial x} = 0 \tag{48}$$

The optimal results for the interaction between the offender and the fighting victim in the Stackleburg game above are:

$$x^{\dagger\dagger} = \frac{(B+D)^2}{4(L-\alpha)} \tag{49}$$

$$s^{\dagger\dagger} = \frac{(B+D)}{2} - \frac{(B+D)^2}{4(L-\alpha)} \tag{50}$$

$$p^{\dagger\dagger} = \frac{(B+D)}{2(L-\alpha)} \tag{51}$$

$$V^{\dagger\dagger} = (B+D) - \frac{(B+D)^2}{4(L-\alpha)} + \alpha \tag{52}$$

$$O^{\dagger\dagger} = \frac{(B+D)^2)}{4(L-\alpha)} - D \tag{53}$$

The response of the above variables to the level of punishment for over-defense are:

$$\frac{\partial x^{\dagger\dagger}}{\partial \alpha} = \frac{(B+D)^2}{4(L-\alpha)^2} > 0 \tag{54}$$

$$\frac{\partial s^{\dagger\dagger}}{\partial \alpha} = -\frac{(B+D)^2}{4(L-\alpha)^2} < 0 \tag{55}$$

$$\frac{\partial p^{\dagger\dagger}}{\partial \alpha} = \frac{(B+D)}{(L-\alpha)^2} > 0 \tag{56}$$

$$\frac{\partial V^{\dagger\dagger}}{\partial \alpha} = 1 - \frac{(B+D)^2}{4(L-\alpha)^2} \tag{57}$$

$$\frac{\partial O^{\dagger\dagger}}{\partial \alpha} = \frac{(B+D)^2}{4(L-\alpha)^2} > 0 \tag{58}$$

For the interaction between the offender and the retreating victim in the Stackleburg game, the results are below. Equations 59 - 63 are the counterparts of Equations 49 - 53. The difference is that α and D are zero for the retreating victim.

$$x^{\dagger} = \frac{B^2}{4L} \tag{59}$$

$$s^{\dagger} = \frac{B}{2} - \frac{B^2}{4L} \tag{60}$$

$$p^{\dagger} = \frac{B}{2L} \tag{61}$$

$$V^{\dagger} = B - \frac{B^2}{4L} \tag{62}$$

$$O^{\dagger} = \frac{B^2}{4L} \tag{63}$$

The comparison between $p^{\dagger\dagger}$ and $p^{\dagger}$ is done through setting α to zero to model zero punishment for over-defense, and keeping D as non-zero because there could still be damage to the offender if the victim defends themselves. $p^{\dagger\dagger} > p^{\dagger}$ if $\frac{\partial p^{\dagger\dagger}}{\partial D} > 0$ because $\frac{\partial p^{\dagger\dagger}}{\partial \alpha} > 0$ (see Equation 56). If $\alpha = 0$, the offender's probability of success is then:

$$p^{\dagger\dagger} = \frac{B+D}{2L} \tag{64}$$

As the damage to the offender increase, their probability of success also increases:

$$\frac{\partial p^{\dagger\dagger}}{\partial D} = \frac{1}{2L} > 0 \tag{65}$$

Therefore, when $\alpha = 0$, $p^{\dagger\dagger} > p^{\dagger}$, and as α increases, the difference between $p^{\dagger\dagger}$ and $p^{\dagger}$ also increases.

The comparison between $V^{\dagger\dagger}$ and $V^{\dagger}$ is carried out through setting α to zero in $V^{\dagger\dagger}$ to model zero punishment for over-defense, and keeping D as non-zero because there could still be damage to the

offender if the victim defends themselves. If $\frac{\partial V^{\dagger\dagger}}{\partial D} > 0$, we know that $V^{**} > V^{*}$ if the victim's loss is disproportionally large, because $\frac{\partial V^{\dagger\dagger}}{\partial \alpha} > 0$ under that condition (see Equation 57). The fighting victim's loss function after setting $\alpha = 0$ is:

$$V^{\dagger\dagger} = (B + D) - \frac{(B + D)^2}{4L} \tag{66}$$

As the damage to the offender increases, the fighting victim's loss decreases:

$$\frac{\partial V^{\dagger\dagger}}{\partial D} = -\frac{B + D}{2L} < 0 \tag{67}$$

Equation 67 tells us that $V^{\dagger\dagger} < V^{\dagger}$ when $\alpha = 0$. As α increases, $V^{\dagger\dagger}$ increases if the victim's loss is disproportionally large, according to Equation 57.

The comparison between $O^{\dagger\dagger}$ and $O^{\dagger}$ is conducted through setting α to zero in $O^{\dagger\dagger}$ and keeping D as non-zero because there could still be damage to the offender. If $\frac{\partial O^{\dagger\dagger}}{\partial D} > 0$, we know that $O^{\dagger\dagger} > O^{\dagger}$ because $\frac{\partial O^{\dagger\dagger}}{\partial \alpha} > 0$ (see Equation 58). After setting $\alpha = 0$, the offender's optimal net benefit function is:

$$O^{\dagger\dagger} = \frac{(B + D)^2}{4L} - D \tag{68}$$

As the damage to the offender increases, their optimal net benefit decreases:

$$\frac{\partial O^{\dagger\dagger}}{\partial D} = -\frac{3L^2(B + D) + L^3}{(B + D + L)^3} < 0 \tag{69}$$

Equation 69 tells us that $O^{\dagger\dagger} < O^{\dagger}$ when $\alpha = 0$. As α increases, $O^{\dagger\dagger}$ increases.

Appendix D Dropped Observations

The panel dataset used in this study comprises annual observations from all 50 U.S. states spanning the period 2000 - 2014, resulting in a potential maximum of 750 state-year observations. The primary source for these data is the SHR, as compiled by the Office of Juvenile Justice and Delinquency Prevention (2000-2015).

A known issue with the SHR data is the occurrence of missing observations and significant discrepancies between the FBI's official murder estimates and the SHR-recorded figures for certain state-years. To ensure data quality, we implement a data cleaning rule: any state-year observation is excluded if the FBI-estimated murder rate exceeds the SHR-recorded rate by a factor of five or more.

Applying this criterion results in the removal of 13 observations (representing 1.73% of the total dataset). These excluded state-year observations are fully documented in Table 22. This table also

summarizes the number of remaining pre- and post-intervention periods for each state used in the DiD and event study analyses. For instance, while Alabama, which enacted its SYG law on June 1, 2006, has missing data for 2010-2014, it retains six pre-law and three post-law observations. A similar pattern of limited data attrition holds for other states with missing values. Consequently, the relatively small proportion and non-systematic nature of the excluded data suggest that they are unlikely to introduce substantial bias or compromise the validity of the subsequent statistical analyses.

Table 22: Years Dropped from Data

State	Years Dropped	Law Signing	# Pre-Periods	# Post-Periods
Alabama	2010, 2011, 2012, 2013, 2014	6/1/2006	6	3
Florida	2014	4/26/2005	5	8
Kansas	2000	5/25/2006	5	8
Kentucky	2000, 2001, 2002, 2003	7/21/2006	3	8
North Dakota	2008	8/1/2007	7	6
South Dakota	2006	7/1/2006	6	8

Notes: Of the 750 potential state-year observations in the initial dataset (2000-2014), 13 were excluded due to significant discrepancies between the FBI estimates and the recorded data in the SHR. These excluded observations, detailed above, represent 1.73% of the total and were removed based on a pre-defined criterion (FBI-estimated murder rate exceeding the SHR-recorded rate by a factor of five or more). The pattern of these exclusions is largely consistent with data quality control measures carried out by the Office of Juvenile Justice and Delinquency Prevention (OJJDP) in their compilation of the SHR data (2000-2015).

Appendix E Additional Preliminary Analysis

This section supplements the preliminary analysis presented in Section 6. This section starts with Table 23. The underlying principle of this legislation posits that arming victims will empower them to deter offenders. However, Table 23 highlights a significant disparity: offenders possess significantly higher rates of prior criminal records compared to victims. This discrepancy suggests a potential risk. Offenders, often more experienced in criminal situations, may be adept in escalating confrontations in response to armed victims to avoid injury to themselves. This escalation could ultimately result in increased violence and potentially greater harm to the victim.

Table 23: Percent of Offenders and Victims with Prior Criminal Records

	Summary Statistics			Comparison	
	Count	Mean	SD	Degrees of Freedom	t
Offenders	1987	69%	.46	2726	16.07***
Victims	741	37%	.48		

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: 69% of the murder offenders had previously committed an offense. 37% of the murder victims had previously committed an offense. The difference is statistically significant at the 1% level. Data comes from the MC dataset.

Moreover, the differential impact of this legislation may vary depending on the specific type of offense. An analysis of National Crime Victimization Survey (NCVS) data (1992-2016), presented in Table 24, demonstrates substantial heterogeneity in the likelihood of victim self-defense across different offense categories. Victims are more likely to employ self-defense measures in response to abusive language (33%) compared to home invasions (11%).

This disparity suggests that individuals may be more likely to perceive self-defense as a viable option in less severe, rather than more severe, criminal incidents. This reluctance in more severe incidents may stem from concerns about over-defense, or alternatively, from apprehension regarding potential threats to their own safety if they choose to resist. Mitigating the legal consequences of justifiable self-defense may encourage individuals to prioritize their personal safety less during a confrontation.

Table 24: Percent of Individuals Taking Defense Action

	Count	Mean	SD
Abusive Language	190	33%	.47
Attempted Theft	790	28%	.45
Forcible Entry of Car	205	19%	.39
Property Damage	357	13%	.34
Forcible Entry of Home	1561	11%	.31

Notes: According to the NCVS, the percentage of cases where a victim took self-defense actions differ between types of crime. The highest percentage is in the category of abusive language, and the lowest is in forcible entry of home.

Additionally, differences between first- and second-degree murder victims further delineate the law's potential impacts. Table 25 reveals that 35% of first-degree murder victims and 43% of second-degree murder victims had previous offenses. This distinction is statistically significant, suggesting that first-degree murder victims may be less prepared to defend themselves effectively due to lack of experience (Kurlychek, Brame and Bushway, 2006; National Collaborating Centre for Mental Health - UK, 2015).

Table 25: Percent of Victims with Criminal Records in First- and Second-Degree Murder

Murder Type	Summary Statistics			Comparison	
	Count	Mean	SD	Degrees of Freedom	t
First Degree	631	35%	.48	841	2.25**
Second Degree	210	43%	.50		

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: 35% of first degree murder victims had previously committed an offense compared to 43% of second degree murder victims. The difference is statistically significant at the 5% level (data come from the victim file of MC).

Appendix F First- and Second-degree Identification

The paper assumes that the shares of first- and second-degree murders for each circumstance are constant across geographic locations and over time. The discussion related to this assumption can be found in Subsection 5.2. Table 26 lists the number of first- and second-degree murder cases under each circumstance in the MC dataset.

Table 26: Murder Circumstances

Code	Circumstance	Total	First degree	Second degree
Felony-murder				
a01	Robbery	392	274	53
a02	Burglary	37	25	3
a03	Sexual assault	32	28	1
a04	Arson	9	9	0
a05	Kidnapping	3	3	0

continued...

... Table 26 continued

Code	Circumstance	Total	First degree	Second degree
a06	Escape	2	1	0
Other felony				
a07	Larceny	7	5	0
a08	Auto theft	26	24	2
a09	Other sex offense	0	0	0
a10	Homosexual prostitution (PRETEXT FOR ROBBERY)	3	3	0
a11	Heterosexual prostitution (PRETEXT FOR ROBBERY)	1	1	0
a12	Other	9	8	1
a13	Suspected felony	2	1	1
Issue Oriented Dispute				
b01	Romantic triangle	54	34	19
b02	Property/money	251	153	70
b03	Drugs (users dispute over drugs or paraphernalia)	18	11	6
b04	Business transaction;grievance	20	12	7
b05	Redress of insult;personal honor	236	173	54
b06	Matters of opinion	129	89	34
b07	Racial;ethnic clash	23	16	6
b08	Jealousy	41	33	8
b09	Traffic dispute	25	18	4
b10	Issue unknown	110	70	34
b11	Rebuff of sexual advance	32	22	8
b19	Other	8	7	1
Domestic/Personal Dispute				

continued...

... Table 26 continued

Code	Circumstance	Total	First degree	Second degree
c20	Lover/spouse quarrel	284	192	75
c21	Domestic quarrel (other family)	104	76	22
c22	Other	1	1	0
Situational Disputes				
d30	Barroom dispute/brawl	62	39	20
d31	Legitimate recreation	37	27	8
d32	Illegitimate recreation (gambling, cock fighting, etc.)	15	12	3
d33	Illegitimate recreation (drugs)	3	3	0
d34	"Street" fight	28	17	11
d35	Random "street" encounter	0	0	0
d39	Other	0	0	0
Homicide by-product of criminal business activity				
e01	Turf battle	34	11	22
e02	Bad deal/bad drugs	38	25	11
e03	Money owed	62	40	19
e04	Revenge for acting as police informant	6	4	1
e05	Punishment for skimming drugs/money	15	12	3
e06	Stealing drugs/drug money	111	77	29
e07	Dispute over drugs	24	18	5
e08	Drug manufacture	3	1	2
e09	Drug purchase/sale scam	52	45	5
e10	One of the above but can't distinguish	17	15	2
e11	Punishment for stealing drugs/money	28	10	14
e12	$ owed for crack house rent	0	0	0
e13	Sex for drugs	3	1	2
e14	Argument re drug house ops	5	1	4

continued...

... Table 26 continued

Code	Circumstance	Total	First degree	Second degree
e19	Other-, drug business	23	9	14
e20	Suspected drug business	9	6	3
e30	Prostitution	17	15	2
e39	Other	11	6	3
e40	Suspected other criminal business	1	0	1
Homicide involved "juvenile" organized gangs				
f01	Turf battle between rival gangs	7	7	0
f02	Other gang fight between rival gang members	24	23	0
f03	Gang fight between members of same gang	0	0	0
f04	Drive-by shooting	12	12	0
f05	One of the above but can't distinguish	1	1	0
f19	Other gang-related	27	23	4
f20	Suspected gang activities	1	1	0
Miscellaneous				
g01	Child abuse	92	55	16
g02	Psychopath	8	8	0
g03	Gun/weapon accident	47	18	14
g04	Other accident	33	12	16
g05	Assist in self-murder	3	2	0
g06	Mercy killing	1	1	0
g07	Justifiable homicide by police officer	1	0	0
g08	Justifiable homicide by civilian	0	0	0
g09	Sniper	0	0	0
g10	Reverse felony	10	1	5
g11	Unknown circumstance	73	58	12
g12	Bizarre/unprovoked behavior	60	46	13
g13	"Contract" killing/Hit for money/	50	40	7

continued...

... Table 26 continued

Code	Circumstance	Total	First degree	Second degree
	insurance scam			
g14	Suicide pact	2	1	1
g19	Other	15	10	5
g20	"Thrill Kill"	7	5	2

Notes: This table lists the first- and second-degree murder cases under each circumstance in the MC data set.

Appendix G Detailed Empirical Specifications

Our detailed specifications are covered in Equations 70 to 75. β_1 is the parameter of interest in all six specifications. Equation 70 controls for state and year fixed effects.

$$murder_{it} = \beta_0 + \beta_1 law_{it} + \boldsymbol{\beta_2 states_i} + \boldsymbol{\beta_3 year_t} + \epsilon_{it} \tag{70}$$

Equation 71 controls for region-by-year fixed effects as well. Regional cultural factors may lead to some degree of homogeneity in murder rate trends within each region of the United States. Inter-regional variations in these trends are also expected.

$$murder_{it} = \beta_0 + \beta_1 law_{it} + \boldsymbol{\beta_2 states_i} + \boldsymbol{\beta_3 year_t} + \boldsymbol{\beta_4 region_j * year_t} + \epsilon_{it} \tag{71}$$

Equation 72 further controls for time varying factors listed in Subsection 5.3.

$$murder_{it} = \beta_0 + \beta_1 law_{it} + \boldsymbol{\beta_2 states_i} + \boldsymbol{\beta_3 year_t} + \boldsymbol{\beta_4 region_j * year_t} + \boldsymbol{\beta_5 x_{it}} + \epsilon_{it} \tag{72}$$

Equation 73 controls for "Ashenfelter's dip" (Ashenfelter, 1978). The inclusion of a pre-law dummy variable enables us to investigate whether, in anticipation of heightened victim resistance due to the impending passage of the SYG law, a discernible increase in murder rates occurs prior to its passage. Furthermore, it enables us to assess whether the passage of the SYG law is a reactive response to a pre-existing upward trend in murder rates, thereby mitigating concerns of endogeneity (Besley and Case, 2000).

$$\begin{aligned} murder_{it} = \beta_0 + \beta_1 law_{it} + \boldsymbol{\beta_2 states_i} + \boldsymbol{\beta_3 year_t} + \boldsymbol{\beta_4 region_j * year_t} + \boldsymbol{\beta_5 x_{it}} \\ + \beta_6 prelaw_{it} + \epsilon_{it}, \end{aligned} \tag{73}$$

Equation 74 incorporates state-specific linear time trends to control for the temporal variation in crime rates within each state. This is achieved by including an interaction term between a state-specific dummy variable ($states_i$) and the *year* variable. As the dataset encompasses 15 years of data, the year variable takes on values from 0 to 14, resulting in a set of 50 state-specific time trends.

$$\begin{aligned} murder_{it} = \beta_0 + \beta_1 law_{it} + \boldsymbol{\beta_2 states_i} + \boldsymbol{\beta_3 year_t} + \boldsymbol{\beta_4 region_j} * \boldsymbol{year_t} + \boldsymbol{\beta_5 x_{it}} \\ + \boldsymbol{\beta_7 states_i} * year + \epsilon_{it} \end{aligned} \tag{74}$$

Finally, Equation 75 also controls for crime's post-law time trend for each state to account for state-specific heterogeneity.

$$\begin{aligned} murder_{it} = \beta_0 + \beta_1 law_{it} + \boldsymbol{\beta_2 states_i} + \boldsymbol{\beta_3 year_t} + \boldsymbol{\beta_4 region_j} * \boldsymbol{year_t} + \boldsymbol{\beta_5 x_{it}} \\ + \boldsymbol{\beta_7 states_i} * year + \boldsymbol{\beta_8} law_{it} * \boldsymbol{states_i} * year + \epsilon_{it} \end{aligned} \tag{75}$$