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. These laws authorize individuals to use force in self-defense without attempting escape upon perceiving a threat (e.g., §776.012, Fla. Stat. (2005)[1]; A.R.S. §13-418[2]). Proponents argue that SYG laws empower victims, deter crime, and ultimately reduce violence (e.g., Jeb Bush's speech, 2016[3]). 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[4]. Increased murders also devastate families and raise serious ethical questions about society's responsibility to prevent the loss of life.

This paper presents a novel game-theoretical framework to analyze how changes in self-defense regulations can increase crime. It models interactions between criminals and two distinct victim types: those who retreat and those who fight back. The study further differentiate between planned and unplanned attacks, empirically testing each mechanism separately. Finally, it 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 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 choose easier targets and intensify their efforts rather than relent. In unplanned attacks, because both the offender and the victim make decisions simultaneously, they lack knowledge of each other's planned actions. Following the implementation of the self-defense law, the victim is more likely to be convinced that they can out-compete the

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

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

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

[4] See Appendix A for details.

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. We utilize murder rate data from the FBI's Uniform Crime Reporting (UCR) program, 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 and shows a growing trend over time. Moreover, these findings likely underestimate the true impact due to reporting challenges inherent in SYG cases. Specifically, ambiguities in determining the aggressor often hinder the filing of charges, resulting in a significant number of SYG-related incidents potentially being excluded from official crime statistics[5].

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.

[5] As documented by the Tampa Bay Times, 46 SYG cases lacked clear police records on who initiated the altercation. Of these, 8 were pending, 5 resulted in guilty verdicts, 7 in pleas, and the remaining 26 resulted in no charges, dismissals, acquittals, or grants of immunity.

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 Becker (1968), focusing 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; Lee and Pinto, 2009; 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 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 national and regional analyses. At the national level, Cheng and Hoekstra (2013) initiated this line of inquiry, employing the Uniform Crime Report (UCR) dataset and demonstrating that the enactment of SYG laws is associated with an increase in murder rates. Subsequent research by McClellan and Tekin (2017), leveraging health records data, corroborated these findings, further strengthening the evidence linking SYG laws to increased murders. Addressing concerns about endogeneity, Gius (2016) utilized 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 concluded that SYG laws contribute to elevated murder rates.

Guettabi and Munasib (2018) employed the synthetic control method to examine variations in the impact of SYG laws across various states. Their findings indicated that the implementation of SYG laws was associated with significant increases in gun death rates in Alabama, Florida, and Michigan. In addition, Ren, Zhang and Zhao (2015) analyzed 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 found a reduction in burglaries in nearby Houston but not in faraway 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 operates at the national level rather than comparing and contrasting different 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 Retreating 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

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

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.

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

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

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 successfully prevents the offense, they incur no loss.

3.2 Contest between Offender and Fighting Victim

If the victim fights rather than retreats, the offender risks injury or death if the attack fails, reducing their expected payoff by D. The offender's expected benefit is given by

$$O(x) = p(x, s)B - x - (1 - p(x, s))D \tag{3}$$

If the victim successfully prevents the offense, they may face punishment for over-defense, with an expected value of $\alpha \in [0, L)$. The victim's expected loss is given by

$$V(s) = p(x,s)L + s + (1 - p(x,s))\alpha \tag{4}$$

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.

3.3 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 retreating victim, as well as the probability that the crime succeeds:

$$x^* = \frac{B^2 L}{(B+L)^2} \tag{5}$$

$$s^* = \frac{BL^2}{(B+L)^2} \tag{6}$$

$$p^* = \frac{x^*}{x^* + s^*} = \frac{B}{B+L} \tag{7}$$

If the victim fights, the optimal efforts for the offender and victim, along with the offender's probability of success are:

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

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

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

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

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 mathematically evidenced by the positive sign of the partial derivative of p^{**} with respect to α in Equation (10): $\frac{\partial p^{**}}{\partial \alpha} > 0$. When α decreases after the SYG laws, p^{**} will also decrease. However, if victims misperceive the leniency of SYG laws, they may underestimate the true probability of an offender's success. This misperception can lead to excessive defensive effort. This counterintuitive outcome is supported by the negative sign of the partial derivative of s^{**} with respect to α: $\frac{\partial s^{**}}{\partial \alpha} < 0$. The more α decreases, the more s^{**} increases. Determining the optimal level of defensive effort, should a victim choose to engage, remains a complex challenge.

Another consequence of reduced penalties for over-defense is a decrease in the victim's overall costs. The model demonstrates this through the positive relationship between α and V^{**}: $\frac{\partial V^{**}}{\partial \alpha} > 0$. As the cost of over-defense diminishes, victims are more likely to opt for confrontation rather than retreat. This shift in defensive strategy, however, inadvertently increases the probability of offender success. This can be observed by comparing the offender's probability of success under retreat (p^*) in Equation (7) to the probability under confrontation (p^{**}) in Equation (10), where $p^{**} > p^*$. This is resulted from the offender taking potential risks into account. When the offender increases their effort in order to avoid injury, they will improve their probability of success.

This analysis reveals some unintended consequences of SYG laws. Examining the impact on the aggregated probability of offender success (p), we observe opposing forces. While the partial derivative of p with respect to α is positive on the intensive margin, it is negative on the extensive margin. Consequently, the overall effect of α on p is indeterminate, represented by $\frac{\partial p}{\partial \alpha}?0$.

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.

3.4 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. In a Stackelburg game where the victim retreats, the optimal efforts of the offender and victim, and the offender's probability of success are given by:

$$x^{\dagger} = \frac{B^2}{4L} \tag{11}$$

$$s^{\dagger} = \frac{B}{2} - \frac{B^2}{4L} \tag{12}$$

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

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

$$x^{\dagger\dagger} = \frac{(B+D)^2}{4(L-\alpha)} \tag{14}$$

$$s^{\dagger\dagger} = \frac{B+D}{2} - \frac{(B+D)^2}{4(L-\alpha)} \tag{15}$$

$$p^{\dagger\dagger} = \frac{B+D}{2(L-\alpha)} \tag{16}$$

Analogous to the scenario of an unplanned attack, reducing the penalty for over-defense by the fighting victim decreases the probability of success for the aggressor. This is mathematically demonstrated by the positive partial derivative of $p^{\dagger\dagger}$ in Equation (16) with respect to α: $\frac{p^{\dagger\dagger}}{\alpha} > 0$. However, a reduction in the victim's overall cost only occurs when the potential loss to the victim exceeds the damage inflicted upon the aggressor. This is because, in a planned attack, the aggressor can anticipate and adjust to the victim's level of preparation. In this model, the effect of changes in the over-defense penalty on the victim's outcome is given by $\frac{\partial V^{\dagger\dagger}}{\partial \alpha} = \frac{(2(L-\alpha)-(B+D))(2(L-\alpha)+(B+D))}{4(L-\alpha)^2}$. This expression is positive when the potential loss to the victim (L) is high and the combined cost

of fighting for the aggressor $(B + D)$ is low. Consequently, victims who would otherwise retreat will choose to fight if they believe their potential losses are high, and if they perceive the aggressor as not highly motivated to succeed.

When comparing planned attacks (sequential game) with unplanned attacks (simultaneous game), we see that victims are less likely to switch from retreating to fighting under planned attacks. This results in a lower risk on the extensive margin (fewer victims engaging in fighting effort) while the benefits on the intensive margin (fighting victims exerting more effort) remain similar. Consequently, the overall negative impact on victims is less severe in planned attacks than in unplanned attacks.

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

We use the SYG laws as a motivating example, but what exactly are they? Consider this: if a victim in a public place shoots an attacker who they think is threatening them with bodily harm, even if the victim has the opportunity to run away, what are the legal implications? Under SYG laws, such an action could be considered justifiable either based on the victim proving a reasonable fear of death or serious bodily harm, or a presumption of self-defense unless prosecutors could prove otherwise.

The foundation of the U.S. legal system is rooted in English common law principles, which traditionally imposed a "duty to retreat" before resorting to lethal force (Wolf, 2014). However, by the late nineteenth century, many American states had abandoned this duty in public places (Epps, 1992).[7] The landmark 1876 Ohio Supreme Court decision in *Erwin v. State* became pivotal in 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." Similarly, the 1877 Indiana Supreme Court decision

[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

in *Runyan v. State* asserted[9]: "The weight of modern authority, in our judgment, establishes the doctrine, that, when a person, being without fault and in a place where he has a right to be, is violently assaulted, he may, without retreating, repel force by force, and if, in the reasonable exercise of his right of self-defense, his assailant is killed, he is justifiable."

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 (the traditional "castle doctrine," which, in some states extends to one's vehicle and workplace). Instead, they apply this principle to any public space where an individual has a right to be. Under SYG provisions, lethal force becomes legally 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[10].

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

We use various datasets for our project. First, we sourced crime data from the Uniform Crime Report's Offenses Known and Clearances by Arrest (OKCA) files[11] and the Supplementary Homicide Reports (SHR) files[12]. Additionally, we incorporated data from the Murder Cases in 33 Large Urban Counties in the United States, 1988 (MC) dataset[13] as an auxillary source. We gathered information

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

[10] § 776.012, Fla. Stat. (2005).

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

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

[13] Bureau of Justice Statistics (1988).

on the dates of law passage from various sources including Wallace v. State (2015). Our control variables encompass metrics such as the size of the police force, unemployment rate, poverty rate, number of prisoners, and demographic data, sourced from diverse outlets such as the UCR Police Employee Data (LEOKA) files[14]. We chose the study period of 2000 to 2014 because Florida was the first state to pass the law in 2005, and 2014 represents the latest year for which comprehensive data was available.

5.1 Crime Data

The OKCA files come from the UCR Data Tools website (Bureau of Justice Statistics (BJS), 2000-2015)[15]. 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[16]. 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). Notably, Florida's SHR data was sourced separately from Florida's own SHR database[17] and processed in a similar fashion as the national data.

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

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

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

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

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 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 25 of Appendix C. 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.

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. 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[18]. 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[19].

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[20], 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[21]. 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[22].

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 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.

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

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

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 model and the empirical model 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.

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 contains analysis results that motivate the implementation of the panel regressions. First, we group the state-years into those without the law and those with the law. For instance, Massachusetts, which never adopted the law, would be a state-year without the law in 2000 and 2014. Florida, on the other hand, enacted the law in 2005. Therefore, Florida in 2000 would count as a state-year without the law, and Florida in 2014 would be a state-year with the law. As a result, Florida-2000 would be in the same group as Massachusetts-2000 and Massachusetts-2014, where as Florida-2014 would be in the other group. We compared the murder rates between these two groups, and the results are presented in Table 8. Between 2000 and 2014, there were 551 state-years without the law and 174 state-years with the law. State-years with the law exhibit notably higher murder rates (5.46 per 100,000) compared to those without (4.19 per 100,000).

Given potential differences in characteristics between states with and without the law, we focus next on states that have enacted the law and compare murder rates before and after its imple-

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.

Table 8: Comparison between States With Law and States Without Law (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. The average murder rates for state-years without law and with law are statistically significantly different. The average murder rate for state-years without the law is 4.22 and for state-years with the law is 5.35.

mentation. Table 9 reveals that states with the law have an average murder rate of 5.03 before implementation and 5.50 after. The difference is not as large as in Table 8, but it is still statistically significant at the 5% level.

Table 9: Comparison between 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. The average murder rates for states before and after the law are statistically significantly different at the 5% level. The mean murder rate for state-years without the law is 5.03, and it is 5.50 for state-years with the law.

The underlying principle of this legislation posits that arming victims will empower them to deter offenders. However, Table 10 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 escalate confrontations in response to armed victims. This escalation could ultimately result in increased violence and potentially greater harm to the victim.

Table 10: Percent of Offenders and Victims with Previous 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 5% level. Data come 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 11, demonstrates substantial heterogeneity in the likelihood of fictim 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 11: 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 12 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 12: 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).

Furthermore, as illustrated in Table 13, second-degree murder victims exhibit a higher likelihood of possessing a weapon compared to victims of first-degree murder. This disparity in victim armament implies that for first-degree murder victims, who are less likely to be armed, the potential effectiveness of SYG laws may be diminished. Conversely, for second-degree murder victims, the presence of weapons on both sides of the encounter can increase the risk of escalated violence. These findings align with our theoretical expectation that offenders in first-degree murder cases are more likely to possess a greater degree of planning and preparation.

Table 13: 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%	.35	2662	1.85*
Second Degree	648	18%	.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 a two sample t test is .06, which is significant at the 10% level.

Moreover, differences extend to the offenders: Table 14 indicates that second-degree murder of-

fenders are more likely to be under the influence of drugs compared to first-degree murder offenders, potentially heightening their propensity for violence (Goldstein, 1985).

Table 14: 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%	.43	867	2.10**
Second Degree	206	33%	.47		

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

Notes: 25% of the first degree murder perpetrators are under the influence of drugs compared to 33% of the second degree murder perpetrators. The percentage for second degree murder perpetrators is statistically significantly higher.

In summary, initial findings from two-sample t tests indicate higher murder rates in state-years with the law. For states that have enacted the law, there is a significantly higher murder rate. Therefore, we use the Difference-in-Difference (DiD) design to further explore the issue and to obtain causal inference. Note that a much higher percentage of offenders had committed an offense than victims, and we need to take this into account when considering the effect of victim self-defense.

When we compare first- and second-degree murder, it becomes evident that second-degree murder victims are more likely to have prior criminal records and are more likely to be armed. Second-degree murder perpetrators are more likely to be under the influence of substances. These factors collectively provide a foundation for our in-depth comparative analysis of the two murder types, which will be further elaborated upon below.

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 17 is the general specification, where i stands for the state and t stands for the year.

$$murder_{it} = \beta_0 + \beta_1 law_{it} + \beta_2 states_i + \beta_3 year_t + \beta_4 \boldsymbol{x_{it}} + \beta_5 law_{it} * year_t + \epsilon_{it} \tag{17}$$

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 D. 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. This subsection includes robustness checked aimed at confirming the causal interpretation of the estimated effects.

8 Results

8.1 DiD Effects on Murder Rate

Tables 15 through 17 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).

Table 15, 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 15: 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 deviations in parentheses.

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

To assess if the laws were introduced in response to prior increases in murder rates, Table 16 adds a pre-law dummy variable. Across specifications, murder rates show no significant increase two years before law passage compared to three or more years earlier. The coefficients on the law variable are comparable to those in Table 15.

Table 16: 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 deviations in parentheses.

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

Table 17 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 17: 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

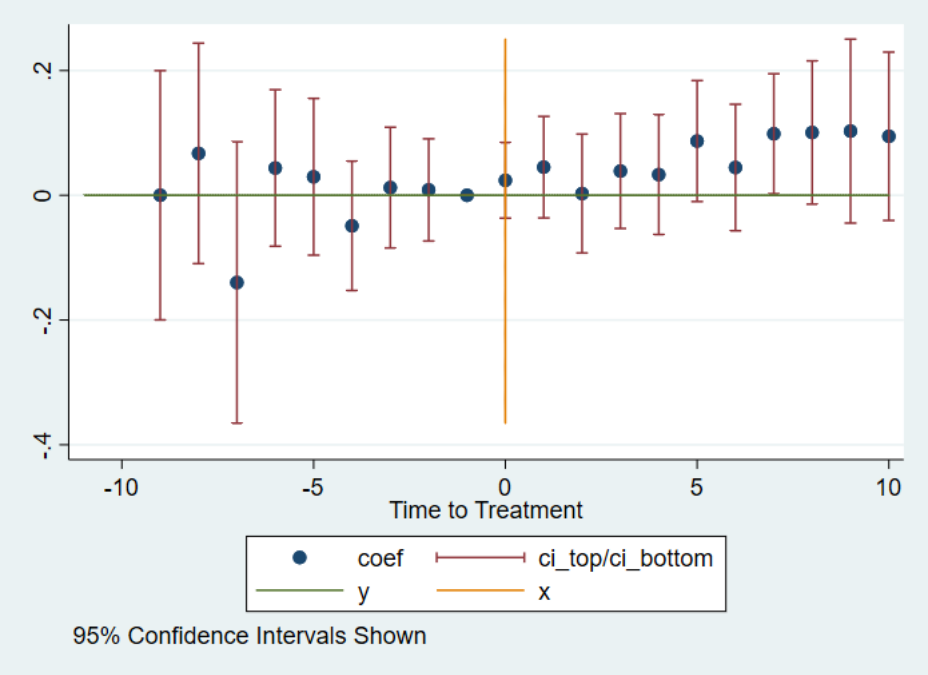
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Heteroskedasticity-robust standard deviations 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

In addition to examining the effect of the SYG laws on aggregate murder rate, we distinguish between their effects on planned and unplanned murder rates. According to our game-theoretical models detailed in Section 3, increases in murder rates can be attributed to individuals over-estimating the degree to which SYG laws decrease the punishment to over-defense and overlooking the risks for themselves. Victims in unplanned attacks are more likely to make the above judgments because they are more prepared than victims in planned attacks. Therefore, we predict unplanned murders to increase more than planned murders. We analyze this by employing a method similar to Section 8.1 and introduce a dummy variable interaction term to compare coefficients between the impact of SYG laws on planned and unplanned murders.

Table 18 reports the coefficient β_1 in Equations 18 to 23 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 18: 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 deviations in parentheses.

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

Table 19 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 18.

Table 19: 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 deviations in parentheses.

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

Furthermore, Table 20 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 18 and 19.

Table 20: 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 deviations in parentheses.

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

Table 21 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 21: 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

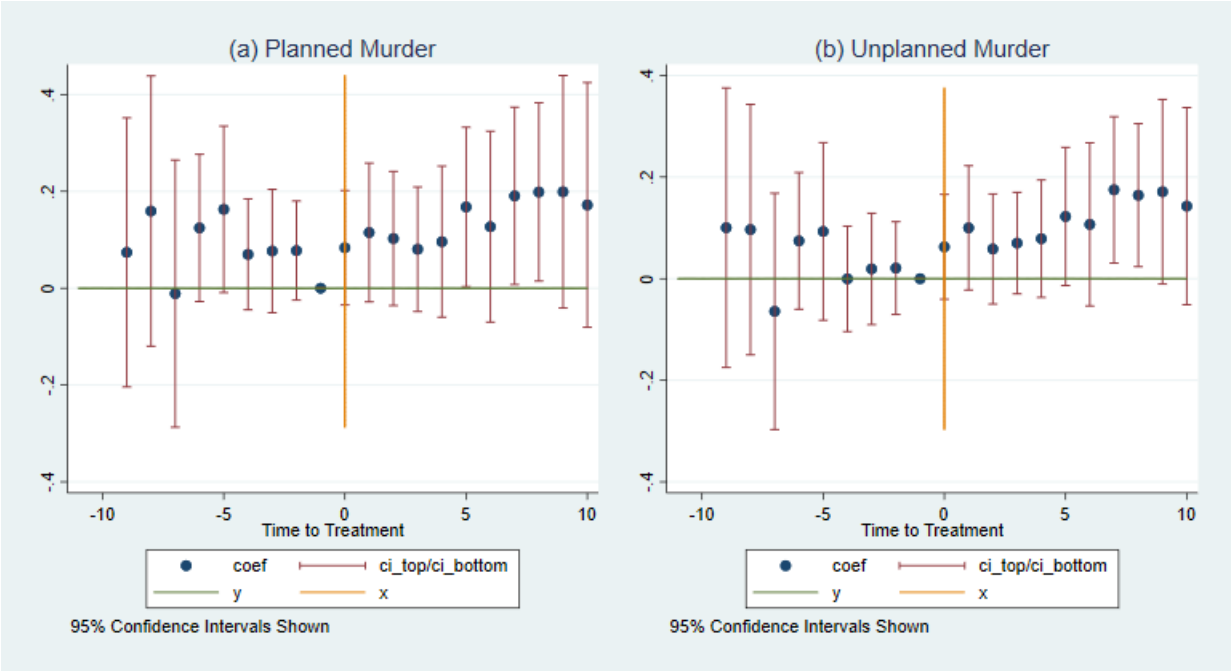
Heteroskedasticity-robust standard deviations in parentheses.

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

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: There are more variations in planned murder during the three year period around the year when laws are passed. Disregarding those variations, there are larger changes for unplanned murder than for planned murder, indicating the existence of escalation and over-defense. Both types of murder had an upward trajectory, indicating the persistence and exacerbate of the effects.

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 22, 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 18. 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 22: 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 the empirical coefficients from Panel B Column (6) in Table 18. 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-periods, most murder rates are below the mean, while in the post periods, they exceed the mean. Precision of estimates decreases with time from treatment due to reduced number of observations in those 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 effects for unplanned murders are slightly smaller than those for unplanned murders. Also, they are less precise.

9 Discussions

Legislative actions often yield unintended consequences (Podkopacz and Feld, 2001; Chesney-Lind, 2002), and SYG laws are no exception. This study illustrates how the relaxation of self-defense standards can inadvertently contribute to escalated crime and increased homicides.

In 2017, Florida shifted the burden of proof in pre-trial hearings[23], 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. Currently enacted in 30 states, SYG laws have sparked legislative proposals at both state and federal levels to expand their implementation[24].

Nearly 90% of states with SYG laws emphasize the use of deadly force or lethal weapons in their statutes. For example, they use the words "can use a lethal weapon against", "can use deadly

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

[24] 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.

force to," "killing is necessary," and "can meet force with force, including deadly force." This focus may inadvertently promote the use of lethal force over less harmful self-defense methods, thereby contributing to an escalation in violent crime. Evidence also suggests that laws can influence social norms (Lane, Nosenzo and Sonderegger, 2023), potentially shifting public perceptions and behaviors toward more aggressive responses in self-defense scenarios.

Public perception of SYG laws often diverges from their legal nuances. While these laws hinge on the individual's "reasonable belief" of imminent danger of death or serious injury, there is a concern that public interpretation might simplify them to "shoot first, ask questions later[25]." This misalignment could potentially lead to a perception that it's acceptable to escalate minor conflicts into lethal confrontations under the protection of these laws.

To delve into more details of the consequences of the SYG laws, we conduct event study with SHR data from 2000 to 2016, whose results are presented in Figure 5. The horizontal axis shows the number of years before and after the law. Negative represent years before the law passing year, zero representing the law passing year, and positive represents years after the law passing year. The average offender age after the SYG laws has decreased by roughly one year more than other states. This decrease is persistent over the next five years. Compared with older individuals, younger ones are more likely to mingle, which creates more opportunities to escalate conflicts.

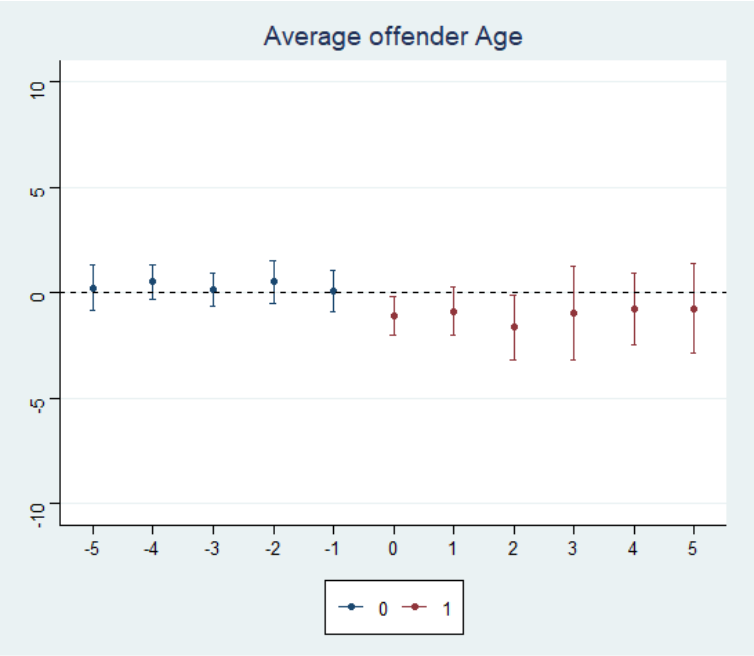
Similarly, average victim age decreases, though at a slower rate than that for offenders, suggesting that either side of conflicts can be identified as the side that has initiated the conflict. The results are presented in figure 6.

Figures 7, 8, and 9 present the event study results for proportion of White, Black, and other racial/ethnic groups among offenders in murders. The analysis reveals varying trends. While the DiD effect of the proportion of White offenders remain relatively stable as overall crime rates increase, the DiD effect of proportion of Black offenders appears to decrease. In contrast, the DiD effect of proportion of offenders from other racial or ethnic groups exhibits a pronounced increase compared to the other groups. These findings suggest that the relative involvement of different racial/ethnic groups in the escalation of conflicts varies.

Beyond SYG laws, focusing on societal factors that deter crime, such as expanding educational and economic opportunities, may yield more sustainable reductions in violence. Investing in educational programs, drug rehabilitation intiatives, and youth development programs can address root

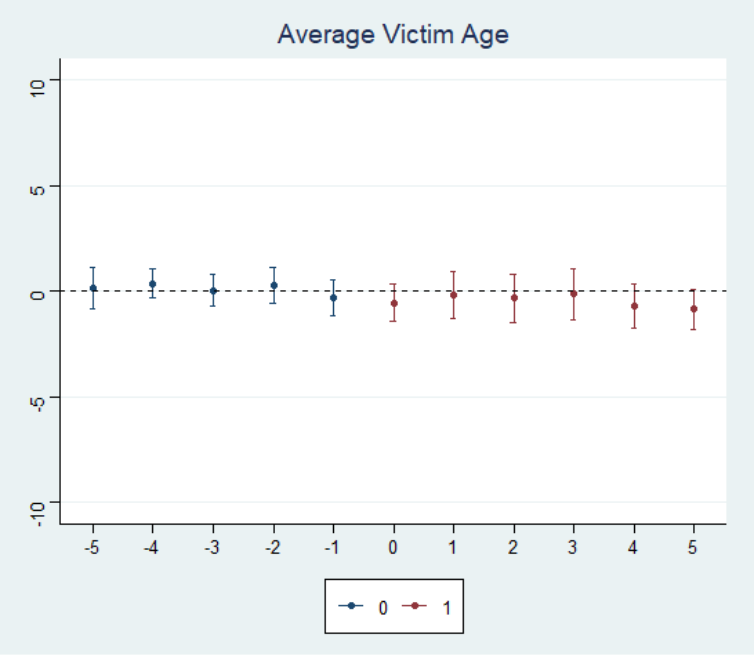
[25]The Norgard case, for example: https://www.naplesnews.com/story/news/crime/2020/01/12/road-rage-shooting-david-norgard-golden-gates-estates-justifiable-stand-your-ground-law-florida/4418769002/.

Figure 5



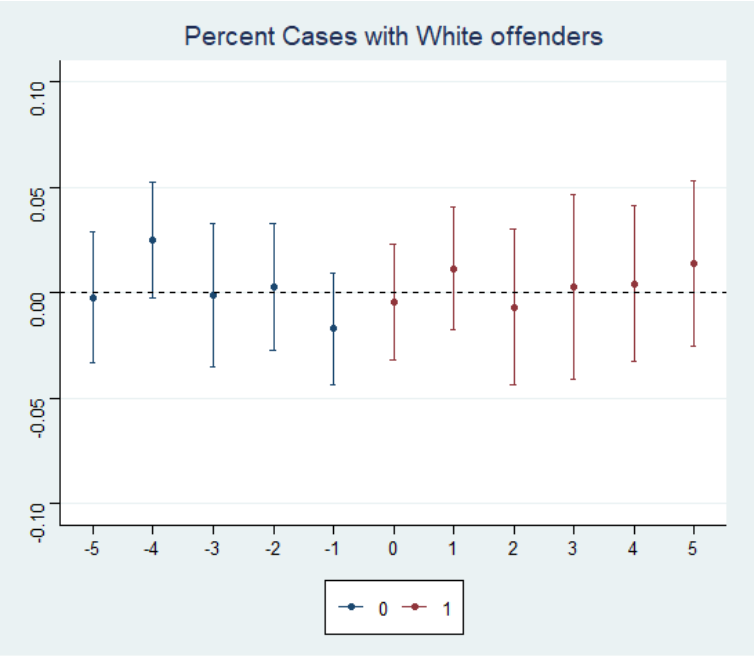
Notes: Average offender age has decreased more in states with the laws than those without.

Figure 6



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

Figure 7



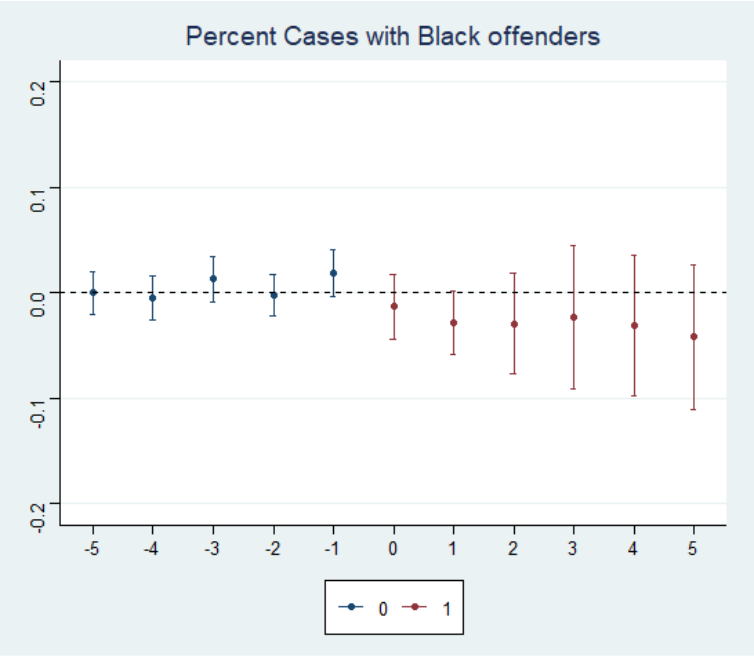
Notes: Compared with states without the laws, states with the laws have a similar average proportions of White offenders over time, suggesting that as murder rates increase over time, the number of White offenders increase proportionally.

causes of crime and violence (Anderson, 2002), promoting long-term community safety without the unintended consequences associated with reactive legislative measures. Fighting violence with violence has unintended consequences, as illustrated by this study.

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 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 can also lead to 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

Figure 8



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

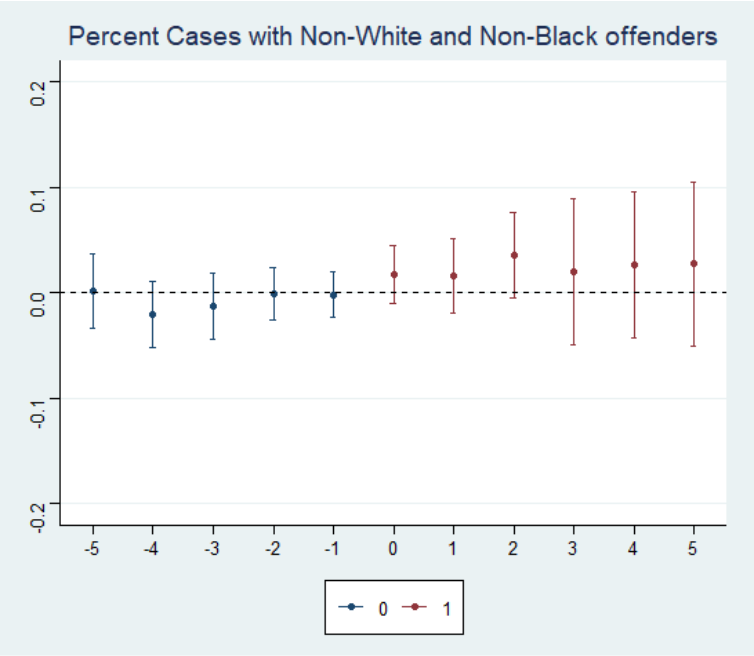
offenders in these scenarios have limited opportunity to assess the victim's level of preparedness.

Empirical testing of these theoretical frameworks 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

Figure 9



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

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 23, 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 23: 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

In 2005, Florida passed the SYG law; Arizona followed suit in 2006, and then 28 other states gradually passed variations of this law. The last one on the record is the state of Wyoming, which passed it in 2018. Among these thirty states, North Dakota, Ohio, and Wisconsin have limited versions that restrict stand-your-ground to cars and businesses. Table 24 is a list of states and dates of the passing of laws that expand the castle doctrine (NUL, 2013). In Florida, some arrests are not made because of the provision that puts the burden of proof on prosecutors. This ensures that some offenders won't be charged, even if they cannot prove that they have "reasonable belief of bodily harm". These cases, in turn, won't contribute to either murder or justifiable homicide statistics. Therefore, the results presented in this paper are the lower bound.

Table 24: 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	

continued...

... Table 24 continued

States	Law Signed	Law Stipulations
West Virginia	3/12/2008	
Ohio	9/9/2008	SB184: car, home, temporary residence
Montana	4/27/2009	
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 alphabetical order.

Appendix C 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 assumptions can be found in Subsection 5.2. Table 25 lists the number of first- and second-degree murder cases under each circumstance in the MC dataset.

Table 25: 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

continued...

... Table 25 continued

Code	Circumstance	Total	First degree	Second degree
a05	Kidnapping	3	3	0
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	3	3	0
	(PRETEXT FOR ROBBERY)			
a11	Heterosexual prostitution	1	1	0
	(PRETEXT FOR ROBBERY)			
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	18	11	6
	(users dispute over drugs or paraphernalia)			
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

continued...

... Table 25 continued

Code	Circumstance	Total	First degree	Second degree
Domestic/Personal Dispute				
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

continued...

... Table 25 continued

Code	Circumstance	Total	First degree	Second degree
e14	Argument re drug house ops	5	1	4
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

continued...

... Table 25 continued

Code	Circumstance	Total	First degree	Second degree
g13	"Contract" killing/Hit for money/ insurance scam	50	40	7
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 D Detailed Empirical Specifications

Our detailed specifications are covered in Equations 18 to 23. β_1 is the parameter of interest in all six specifications. Equation 18 controls for state and year fixed effects.

$$murder_{it} = \beta_0 + \beta_1 law_{it} + \boldsymbol{\beta_2 states_i} + \boldsymbol{\beta_3 year_t} + \epsilon_{it} \tag{18}$$

Equation 19 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.

$$murder_{it} = \beta_0 + \beta_1 law_{it} + \boldsymbol{\beta_2 states_i} + \boldsymbol{\beta_3 year_t} + \boldsymbol{\beta_4 region_j * year_t} + \epsilon_{it} \tag{19}$$

Equation 20 further controls for time varying factors listed in Subsection 5.3.

$$murder_{it} = \beta_0 + \beta_1 law_{it} + \boldsymbol{\beta_2 states_i} + \boldsymbol{\beta_3 year_t} + \boldsymbol{\beta_4 region_j * year_t} + \boldsymbol{\beta_5 x_{it}} + \epsilon_{it} \tag{20}$$

Equation 21 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).

$$\begin{aligned} murder_{it} = \beta_0 + \beta_1 law_{it} + \boldsymbol{\beta_2 states_i} + \boldsymbol{\beta_3 year_t} + \boldsymbol{\beta_4 region_j * year_t} + \boldsymbol{\beta_5 x_{it}} \\ + \beta_6 prelaw_{it} + \epsilon_{it}, \end{aligned} \tag{21}$$

Equation 22 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.

$$\begin{aligned} murder_{it} = \beta_0 + \beta_1 law_{it} + \boldsymbol{\beta_2 states_i} + \boldsymbol{\beta_3 year_t} + \boldsymbol{\beta_4 region_j} * \boldsymbol{year_t} + \boldsymbol{\beta_5 x_{it}} \\ + \boldsymbol{\beta_7 states_i} * year + \epsilon_{it} \end{aligned} \tag{22}$$

Finally, Equation 23 also controls for crime's post-law time trend for each state to account for state-specific heterogeneity.

$$\begin{aligned} murder_{it} = \beta_0 + \beta_1 law_{it} + \boldsymbol{\beta_2 states_i} + \boldsymbol{\beta_3 year_t} + \boldsymbol{\beta_4 region_j} * \boldsymbol{year_t} + \boldsymbol{\beta_5 x_{it}} \\ + \boldsymbol{\beta_7 states_i} * year + \boldsymbol{\beta_8} law_{it} * \boldsymbol{states_i} * year + \epsilon_{it} \end{aligned} \tag{23}$$