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

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Abstract

This paper provides a theoretical model of what happens when self-defense regulations are relaxed, and tests it with an empirical analysis of the Stand Your Ground (SYG) laws. We build a game theoretical model based on Becker (1968), showing that a relaxation of self-defense regulations can increase arming of both victims and perpetrators, which deters some violent crimes but encourages others. In particular, the model suggests that the relaxation of self-defense regulations may increase murder success rates, because it encourages criminals to prepare for a stronger offense. It is also likely to increase unplanned murders more than planned murders by increasing the frequency with which lesser crimes escalate into more violent ones. We then use a difference-in-difference (DiD) model to test these implications. We find that, consistent with the model, SYG laws in the US increased the planned murder rate by 7.6% and unplanned murders by 10.4%, on average. Also, the effect size increases over time.

Keywords: Stand your ground law, self-defense, murder.

JEL Classification: I18, K14.

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1 Introduction

Based on the English common-law "duty to retreat," individuals in the US were required by law to back away when they felt endangered in public. They were allowed to defend themselves with force only when they were cornered (Kaplan, Weisberg and Binder, 2014).

In 2005, however, Florida became the first state to pass a Stand Your Ground (SYG) law, which allows individuals to take defensive actions when they reasonably believe that they are facing great bodily harm or death, even when they have the option to retreat. Ever since then, 29 other states have passed similar versions of the same law (Table 23).

One of the arguments for passing the law was to offer individuals the right to protect themselves (Bush, 2016). The hope was that giving individuals the opportunity to defend themselves would decrease the probability of success for perpetrators and in turn discourage crime, making neighborhoods safer. However, studies have mostly found that SYG laws didn't reduce violent crime (Chamlin, 2014; Chamlin and Krajewski, 2016; Gius, 2016; Yakubovich et al., 2021). On the contrary, multiple studies have found that the laws have increased murder rates (Cheng and Hoekstra, 2013; Humphreys, Gasparrini and Wiebe, 2017*a*,*b*; Levy et al., 2020; McClellan and Tekin, 2017). These studies attribute the increase in murder rates to the escalation of violence.

Escalation of violence may happen more often in unplanned murders than in planned murders because victims are more prepared. However, the current literature does not distinguish the impact of SYG laws on the two types of murder, even though they have different characteristics. If the increase in murder rates is primarily driven by planned murders, then the laws have made offenders more successful. This could happen because, after the law passes, offenders know that victims may be more prepared, and so they also have an incentive to prepare better. Since planned murder offenders are generally more experienced than victims, their increased preparations would be more effective.

Alternatively, if increases in murder rates are primarily driven by unplanned murders, then it provides evidence of violence escalation. When a victim's violent defense triggers perpetrators to become more aggressive, less serious crimes can escalate, some of which into murder. In this case, we may want to increase social interventions such as directed patrol policing strategies (Weisburd et al., 2017; Makarios and Pratt, 2012) to prevent crimes from becoming more serious.

Our theoretical model encompasses the two drivers of murder discussed above. Our model assumes that, after the initial threat, decisions of the offender and victim are made sequentially in the planned (first-degree) murders but simultaneously in the unplanned (second-degree) murders. Sequential decision making starts from the victim, when they decide on their level of self-defense. Victims are able to select a best course of action based on their predictions of the offender's response. When the SYG law passes, the victim expect to face a lower punishment on violent defense, and thus will raise defense effort. The offender observes the increase in victim self-defense and adjusts their effort accordingly. If the offender and the victim make decisions simultaneously, the victim would not know the offender's type. Compared to the sequential game, the victim is more likely to provoke the offender in the simultaneous game. As a result, SYG laws have a more negative impact on unplanned murder.

Since SYG laws emphasize deadly force and possibly produce a focal point to the public, potential victims may increase their defense power, such as turning to lethal weapons. This leads to a higher chance of offender dying in both games. The violent defense may also provoke an offender (Smith and Bouffard, 2014), especially in unplanned murder circumstances. Negative emotions generated by these offenders may reduce their time discount factor, making them more impulsive and dismissive of future consequences (Liu et al., 2013). As a result, the increased defense may induce an escalation of violence, causing the offender to kill the victim.

Our datasets for murder rates are the Offenses Known and Clearances by Arrest (OKCA) and Supplementary Homicide Report (SHR) from the FBI's Uniform Crime Report (UCR). We distinguish between first-degree and second-degree murders through the Murder Cases in 33 Large Urban Counties in the United States, 1988 (MC) dataset.

Our empirical analyses show that the rates of both first-degree murder and second-degree murder increase after the laws pass. Second-degree murder increases more than first-degree murder, and the results for second-degree murder are more robust. These observed increases are likely lower bounds on the estimated true effects due to nuanced circumstances. Out of 100 SYG cases collected by the Tampa Bay Times, 46 have a police record that is unclear about who instigated the altercation. Out of these 46, 8 were pending, 5 were found guilty, and 7 were pleas. The rest of the 26 were either not charged, dismissed, acquitted, or granted immunity. When it is difficult to figure out who the aggressor is, it is difficult to charge them.

Our results also shed light on other aspects of these laws. We find that new SYG laws do not entail a significant change to self-defense rules in the majority of states, but instead are mostly a change from case law to stipulation. The increase in unplanned murder and planned murder rates after the enactment of these SYG laws could be due in part to a misunderstanding of the law. Victims and offenders may falsely believe that the stand-your-ground law eliminates the limitation on self defense against a charge of murder and grants victims the right to meet force with force (McAdams, 2015) without taking the possibility of over-defense into account. This misunderstanding could magnify the effects we model.

The outline of this paper is as follows: Section 2 gives a detailed introduction of the stand-your-ground law. Section 3 gives a review of the literature of related topics. Section 4 introduces the model. Section 5 covers data. Section 6 includes preliminary analysis. Section 7 talks about identification methods. Section 8 covers results. Section 9 discusses policy implications. Section 10 concludes.

2 Background on Stand-Your-Ground Law in the U.S.

What is the legal liability if a victim, in a public place, shoots an attempted robber that threatened her with bodily harm? Under the Stand Your Ground law, that action is justifiable by presuming rather than proving the reasonable fear of death or serious bodily harm.

Stand You Ground law exempts a person's duty to retreat from the situation before turning to a lethal weapon. It can be viewed as an extension to castle doctrine in terms of the place that the situation occurs — expanding the location from home, yard, in some states also workplace and occupied vehicle to public area that one is legally allowed to be. Under the Stand Your Ground law killing is justifiable when a person reasonably believes the use of deadly force is necessary for self-defense against death, great bodily injury, or forcible felony including kidnapping, sexual assault, robbery and so on. In Florida, it was even permitted for a person who was engaging in unlawful activity.

On one side, the Stand Your Ground law gives the victim permissions to immediately use lethal weapon against armed offenders or certain types of crime. On the other side, the same permission can also encourage the victim to fight back with deadly weapon even if he/she can retreat with perfect safety or stop the crime with other forces. In appearance, the law entitles the victim with excessive self-defense rights in public place. However, we shall not simply judge a law without referring to its historical roots.

The English Common law principles are the foundation to the United States legal system. It originally held the concept of "duty to retreat" which means the victim must make an attempt to avoid violence before using lethal forces[1]. However, in late nineteenth century the majority of states of America abandoned the duty to retreat in public places (Epps, 1992).[2]

For example, in 1876, a decision made by the Ohio Supreme Court became the leading American case on the right to stand one's ground. The ruling mentioned: " The question, then, is simply this: Does the law hold a man who is violently and feloniously assaulted responsible for having brought such necessity upon himself, on the sole ground that he failed to fly from his assailant when he might have safely done so? The law, out of tenderness for human life and the frailties of human nature, will not permit the taking of it to repel a mere trespass, or even to save life, where the assault is provoked; 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."

In 1877, the Supreme Court of Indiana asserted:"[t]he tendency of the American mind seems to be very strongly against the enforcement of any rule which requires a person to flee when assailed,to avoid chastisement or even to save human life, and that tendency is well illustrated by the recent decisions of our courts, bearing on the general subject of the right of self-defence. 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-defence, his assailant is

[1]https://criminal.findlaw.com/criminal-law-basics/self-defense-overview.html

[2]Before the spate of "stand your ground" laws, the Florida Supreme Court noted that, while it required 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) (citing Wayne R. LaFave and Austin W. Scott, Jr., Substantive Criminal Law § 5.7(f) (West, 2d ed.1986)). 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.", *Beard v United States*, 158 US550 (1985) and *Rowe v United States*, 164 US 546 (1896).

killed, he is justifiable."

Although enacting the stand-your-ground law does not entail a significant change to self defense rules for the majority of states, the law has had a profound impact on public opinion towards self-defense and victim behavior. We illustrate this impact in section 4.2.

3 Studies on the SYG Law

Multiple papers have illuminated the reasons why escalation of violence happened. First of all, studies have found that criminals are more impulsive than the general public (Åkerlund et al., 2016; Nagin and Pogarsky, 2004; Loeber et al., 2012). Anderson (2002) has found that 35% of offenders did not think about punishment when they committed the crime. Also, victims are likely to have an unclear understanding of self-defense. Robinson and Darley (2004) point out that people often mis-perceive law based on gossip that passes from one person to another. Therefore, victims might think that they are carrying out proper self-defense, while sometimes they are actually over defending. The line is blurry sometimes between these two cases.

Literature has uncovered many reasons why a person could be underestimating punishment. Nagin and Pogarsky (2004) and Loeber et al. (2012) found that poor impulse control predicts violent offending among respondents. This means that during the offense, the offender has become irrational, which, in turn, means that sometimes it is not beneficial to the victim to choose self-defense even if they are offered the opportunity to. Since they might over-estimate the situation, it is more beneficial to take a step back. Liu et al. (2013) and Lake (2016) have found that negative emotions prime individuals to have lower time discount factor for the future. Fields et al. (2014) has found that impulsivity is positively correlated with stress. Novaco (2016) has found that anger impels aggressive behavior. Anderson (2002) even found that violent criminals ignore punishment when they commit crimes. They found that the majority of criminals are not deterred by stricter sanctions. Anderson (2002) also pointed out that while some criminals are deterred by existing punishments, additional punishments aren't likely to deter those who are already determined to offend.

Another irrationality could come from people's tendency to be over-optimistic about themselves, which was noted in the findings of Weinstein (1980). Both the offenders could be over-optimistic about their punishments and the victims could be over-optimistic about their ability to defend themselves. Supporting evidence for offenders being over-optimistic comes from Kleck et al. (2005). They have found that even among those who are already in jail, it is difficult to correctly perceive the punishment for their crime. Anderson (2002) found that "83% of the criminals thought it was not very likely that they would be caught." Lerner and Keltner (2000) and Lerner and Keltner (2001) have found that anger can make people more optimistic towards risk.

3.1 Modeling Crime

Ever since Becker (1968), economists have started systematically analyzing crime. It illustrates how criminals weigh their gains and losses before they make a decision on committing a crime, which provides a foundation for both theoretical and empirical exploration of the issue. Like ours, studies have extended Becker's work by allowing victims to play a role in self-protection (Skogh, 1973; Shavell, 1991; Ben-Shahar and Harel, 1995, 1996; Lee and Pinto, 2009; Guha and Guha, 2012; Baumann, Denter and Friehe, 2019). But our paper is the first to focus on the the relaxation of the regulation on over-defense and to analyze the behavior change of perpetrators and victims in first- and second-degree murder.

We model the interaction between the offender and the victim as a contest, in which the potential victim can exert defense effort to prevent herself from the attack while the offender's effort increase the probability of a successful attack. Some studies in the Economics of Crime model the probability of a successful attack in the form of a Tullock contest, in which the offender can put effort to raise and the victim can reduce such probability. For example, Goyal and Vigier (2014) model a contest between attackers and a central planner and analyze the optimal resource allocation for the central planner to defend attackers in a network. Hong and Neilson (2020) treat the interaction between a cybercriminal and a victim as a contest and examine the optimal punishment for cybercrimes. Ours compares the offender and the victim's interaction in a unplanned murder (simultaneous game) with a planned murder (sequential game).

Our paper is also closely related to a group of paper compares the effort levels of the Cournot–Nash play (simultaneous game) with those of the Stackelberg plays (sequential game)(Dixit, 1987; Baik and Shogren, 1992; Leininger, 1993; Yildirim, 2005; Dixit, 1987). The seminal paper, Dixit (1987), constructs an asymmetric contest that contains a favorite player who is more likely to win in a one-shot Cournot–Nash game and a underdog player. Dixit finds that given the chance to move first, the favorite player overcommits to his effort with respect to his Cournot–Nash amount, while the underdog undercommits. Unlike this seminal work, our result does not depend on the fact that the favorite player has a higher marginal probability of success. Our model shows that the offender always has a higher chance to succeed in a one-shot Cournot-Nash play than in a Stackelberg play. The relaxation of over-defense punishment induces violent defense effort from the victim, which results in the offender's higher likelihood to die or to be provoked by the violent defense.

Related studies support the idea that the victim's defense effort can provoke the offender, making him discount the future punishment and become more violent. For example, Liu et al. (2013) and Lake (2016) have found that negative emotions prime individuals to have lower time discount factor for the future. Fields et al. (2014) has found that impulsivity is positively correlated with stress. Novaco (2016) has found that anger impels aggressive behavior. Lerner and Keltner (2000) and Lerner and Keltner (2001) have found that anger can make people more optimistic towards risk.

3.2 Empirical Studies

In order to test the model, we use the stand-your-ground law and crime data. Work has been done in this area both on the national level and on regional level.

Cheng and Hoekstra (2013) is the first work that touches upon this realm. They use the Uniform Crime Report (UCR) dataset for crime data. They found that murder has increased after the law passes. McClellan and Tekin (2017) uses a slightly different crime data set to arrive at the same conclusion. They claim that the UCR data only records crime that has been reported, but a large amount of crime is not reported. Their data set is from the health records, so they don't have missing data problem. Gius (2016) uses a two stage fixed effects model to address endogeneity issues and come to the same conclusion. The endogeneity issue that they address is that states with higher crime rates may be more likely to enact the SYG law, resulting in a reverse causality problem. The instrument they use is the percent of the population that voted Republican in the last presidential election.

On the state level, Guettabi and Munasib (2018) looks at heterogeneous effects between states using a synthetic control method. The found that Alabama, Florida and Michigan's gun death rate increased significantly after the law was passed. Ren, Zhang and Zhao (2015) evaluates the deterrent effect of the Texas castle doctrine law and the subsequent Horn shooting on burglary in the two largest cities in Texas, Houston and Dallas. Interrupted time-series designs (ARIMA) were employed in the study to analyze the intervention effects. Their finding is after a very publicized incident in Houston, burglaries were reduced in Houston but not in Dallas.

Our study differs to the existing studies in two ways. First, it considers the difference between planned and unplanned murder cases. Second, it considers the difference between different time periods before and after the law passes. Third, it uses more recent data. Since we are exploring the behavioral aspects of the response to the law, we are only doing the exploration on the aggregate level instead of on a state level.

4 Model

We build our model upon Becker (1968) and Hong and Neilson (2020). The major difference is that we model the planned murder as a sequential game and the unplanned murder as a simultaneous game between an offender and a victim. The victim moves first in the planned murder, choosing the costly defense effort s to exert. The offender in this type of murder observes the victim's defense effort before deciding whether to commit a crime and, if so, how much costly effort x to exert to improve the chances of success. However, in unplanned murder, the victim and the offender make decisions simultaneously — neither of them observes the other player's effort before making their own decision.

The probability that the murder is successful (the targeted victim is killed) is determined by the relative effort of the offender and the victim and governed by the function $p : \mathbb{R}^2_+ \to [0,1]$ given by $p(x,s)$ with $p_x > 0$ and $p_s < 0$. The probability of success is a function of the offender's and the victim's effort. Increases in the offender's effort x make success more likely while increases in the victim's defense effort s make it less likely. Also, the success function is concave in x and convex in s, with $p_{xx} < 0$, $p_{ss} > 0$, and $p_{xs} = p_{sx} < 0$.

4.1 Offender

The offender is risk neutral and chooses both whether to commit a murder and how much effort to provide if he does. His expected utility from attempting the murder is given by

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

where B is the benefit he receives and $\delta(s)F$ is the expected fine he pays conditional on the murder being successful. $\delta(s)$, the offender's discount factor, distinguishes offenders holding different time preferences. δ is a function of the victim's defense effort s and decreases in s for the reason that more violent defenses from the victim can provoke the offender and make him discount more heavily about the future. F captures the probability of prosecution and conviction together with the actual fine imposed by law and enforcement. The cost of effort is x/β in which the size of β determines the offender's marginal cost (relative to the victim) of attempting the murder. If the murder is not successful, the offender may be hurt or killed by the victim reducing his expected payoff by D.

The offender maximizes $O(x)$ subject to the constraint $x > 0$. Thus, B must be greater than $\delta(s)F - D$. The necessary and sufficient condition for an interior solution to this problem is simply

$$p_x(x^{br}(s), s)(B - \delta(s)F + D) = \frac{1}{\beta} \tag{2}$$

We use implicit function theorem to obtain the following

$$\frac{dx^{br}(s)}{ds} = -\frac{p_{xs}(B - \delta(s)F + D) - p_x\delta_s F}{p_{xx}(B - \delta(s)F + D)} = -\frac{p_{xs}}{p_{xx}} + \frac{p_x\delta_s F}{p_{xx}(B - \delta(s)F + D)} \tag{3}$$

Note that $\frac{dx^{br}(s)}{ds} > 0$ if $|\delta_s| > |\frac{p_{xs}[(B+D)/F - \delta(s)]}{p_x}|$. Which means if the offender can be easily provoked by the victim's self-defense (δ being very responsive to s), the inequality $\frac{dx^{br}(s)}{ds} > 0$ is likely to hold, so the offender exerts more effort as the victim fights harder in defense. In addition, the magnitude of the right hand side of the inequality $|\frac{p_{xs}[(B+D)/F - \delta(s)]}{p_x}|$ tends to be small because the punishment F for murder is large, partial effect p_x is usually greater than the magnitude of the cross effect p_{xs}, and $0 \leq \delta(s) \leq 1$.

4.2 Victim

The victim suffers a loss L if the murder succeeds, but she can reduce the probability of death by taking a certain amount of costly defense effort, s. If the victim stops the murder, she may be fined for over-defense. The victim's expected loss is given by

$$V(s) = p(x,s)L + s + (1 - p(x,s))\gamma K(s)$$

The victim must pay for the cost of defense effort, s, but doing so reduces the probability of suffering the loss, L. The marginal cost of the victim's defense effort is normalized to 1. If the victim stops the murder, she is subject to a expected fine $K(s) \in [0, L)$ which is determined by the degree of over defense. Thus, K is a function of the victim's defense effort s with $K_s > 0$ and $K_{ss} = 0$.

$\gamma \in [0, 1]$ reflects the SYG law's impact on K. The SYG law can reduce the expected fine the victim perceives through γ for the following reasons. First, the law allows the victim to defend herself without retreat. There is a reduced burden of proof for the victim and the victim is less likely to be penalized by over-defense law. Second, the SYG law's information effects change the public view on over-defense (McAdams (2015)). Audience may falsely believe that the SYG statute eliminates the limitation on the self-defense defense against a charge of murder and grants the right to meet force with force. The legislature also reinforced such belief by stating "[T]he Legislature finds that it is proper for law-abiding people to protect themselves, their families, and others from intruders and attackers . . . and . . . [that] no person or victim of crime should . . . be required to needlessly retreat in the face of intrusion or attack." in the preamble to the SYG bill. Additionally, jury verdicts of acquittal on murder cases like "Zimmerman and Martin" may lead to a greater willingness to use deadly defensive force in cases where there is an alternative.

The other conditions for an expressive influence are satisfied. Media attention to the passage of the new law and then to various killings, prosecutions, and acquittals, most prominently the Zimmerman trial, gave intense publicity to these legal expressions. The legislature has expertise over public attitudes and jury verdicts of acquittal may be thought to aggregate evidence of those attitudes.

4.2.1 Unplanned Murder

An unplanned murder is an intentional killing done without advance planning. We model this type of murder with a simultaneous game in which neither the offender and the victim observes the opposition's effort choice.

The victim chooses s to minimize $V(s)$. Letting $s^{br}(x)$ denote the victim's best-response function, the first order condition is

$$p_s(x, s^{br}(x))(L - \gamma K) + 1 + (1 - p(x, s^{br}(x)))\gamma K_s = 0 \tag{4}$$

Differentiating (4) we obtain the comparative static derivatives

$$\frac{ds^{br}(x)}{dx} = -\frac{p_{sx}(L-\gamma K) - p_x \gamma K_s}{p_{ss}(L-\gamma K) - p_s \gamma K_s} > 0 \tag{5}$$

$$\frac{\partial s^{br}(x)}{\partial \gamma} = -\frac{(1-p)K_s}{p_{ss}(L-\gamma K) - p_s \gamma K_s} < 0 \tag{6}$$

The victim's best response to an increase in the offender's effort is to also increase her defense effort. The pass of the SYG law reduces γ and therefore lower the victim perceived punishment for over defense. As a result, the victim responds with more defense effort.

Using $x^{br}(s)$ from the expression (2) and $s^{br}(x)$ from the expression (4) to solve for x^* and s^*. We denote the equilibria x^* and s^* in the simultaneous game as x_u and s_u for the next section.

4.2.2 Planned Murder

For planned murder, the offender plans it in advance, so we assume he observes the victim's defense effort before attempting the murder. The victim takes account the offender's best response when choosing s. The timing of the game prescribes that the victim moves before the offender in planned murder. The necessary and sufficient condition for an interior solution to this problem is

$$[p_x(x^{br}(s^*), s^*)\frac{\partial x^{br}(s^*)}{\partial s} + p_s(x^{br}(s^*), s^*)](L - \gamma K(s^*)) + 1 + (1 - p(x^{br}(s^*), s^*))\gamma K_s(s^*) = 0 \tag{7}$$

To guarantee an interior solution for equation (7), we assume the victim's expect loss funtion V is strictly convex in s and $p_s(x, 0) = -\infty$. Differentiating (7) we obtain the comparative static derivatives[3]

$$\frac{\partial s^*}{\partial \gamma} = -\frac{-[p_x(x^{br}(s^*),s^*)\frac{\partial x^{br}(s^*)}{\partial s} + p_s(x^{br}(s^*),s^*)]K + (1-p)K_s}{[p_{xx}(\frac{\partial x^*}{\partial s})^2 + p_x\frac{\partial^2 x^*}{\partial s^2} + (p_{xs}+p_{sx})\frac{\partial x^*}{\partial s} + p_{ss}](L-\gamma K) - [(p_x\frac{\partial x^*}{\partial s} + p_s) - \frac{1}{2}(1-p)]\gamma(2K_s)} < 0 \tag{8}$$

From expression (7) we know that $p_x(x^{br}(s^*),s^*)\frac{\partial x^{br}(s^*)}{\partial s} + p_s(x^{br}(s^*),s^*)$ must be less than 0. The SYG law reduces γ, which incentivizes the victim to increase her defense effort. From expression (6) and (8), we find that the victim in both the planned and unplanned murder spend more defense effort when facing less punishment for self defense.

Proposition 1. *Assuming V is strictly convex in s. If $\frac{dx^{br}(s)}{ds} > 0$, then $s_u > s_p$ and $x_u > x_p$. If $\frac{dx^{br}(s)}{ds} < 0$, then $s_u < s_p$ and $x_u > x_p$. In either case, the offender puts more effort in an unplanned murder than in a planned murder.*

Proof. We denote the offender's and the victim's equilibrium effort for an unplanned murder as x_u, s_u and for a planned murder as x_p, s_p.

$$\begin{aligned}
\frac{dV(x^{br}(s),s)}{ds}\Big|_{s=s_u} &= \frac{\partial V(x^{br}(s_u),s_u)}{\partial s} + \frac{\partial V(x^{br}(s_u),s_u)}{\partial x}\frac{dx^{br}(s_u)}{ds} \\
&= 0 + \frac{\partial V(x^{br}(s_u),s_u)}{\partial x}\frac{dx^{br}(s_u)}{ds} \\
&> 0 = \frac{dV(x^{br}(s_p),s_p)}{ds} \qquad , \text{if } \frac{dx^{br}(s)}{ds} > 0 \qquad (9) \\
&< 0 = \frac{dV(x^{br}(s_p),s_p)}{ds} \qquad , \text{if } \frac{dx^{br}(s)}{ds} < 0 \qquad (10)
\end{aligned}$$

where we also make use of the fact that $\frac{\partial V(x,s)}{\partial x} > 0$.

From the expression (9), we have $s_u > s_p$. $\frac{dx^{br}(s)}{ds} > 0$ implies $x_u > x_p$.

From the expression (10), we have $s_u < s_p$. $\frac{dx^{br}(s)}{ds} < 0$ implies $x_u > x_p$. □

Proposition 1 compares the offender and the victim's equilibrium effort in a simultaneous game and in a sequential game. The offender always puts more effort in an unplanned than in a planned

[3] Assuming the victim's expected loss function is strictly convex in s, the second order condition of equation (7) is,

$$[p_{xx}(\frac{\partial x^*}{\partial s})^2 + p_x\frac{\partial^2 x^*}{\partial s^2} + (p_{xs}+p_{sx})\frac{\partial x^*}{\partial s} + p_{ss}](L-\gamma K) - [(p_x\frac{\partial x^*}{\partial s} + p_s) - \frac{1}{2}(1-p)]\gamma(2K_s) > 0$$

murder. From expressions (3), (9), and (10) we know that the victim's defense effort depends on whether the offender can be easily provoked or not. In the following, we discuss the proposition 1 under two main conditions and relate it to the influence of the SYG law.

Condition 1: The offender is easily provoked

When $|\delta_s| > |\frac{p_{xs}[(B+D)/F-\delta(s)]}{p_x}|$, the marginal impact of s on δ is high. Not knowing that the offender can be easily provoked, the victim in unplanned murder will put more defense effort rather than withdraw from the situation. In planned murder, the offender observes the victim's defense effort before committing the crime, thus, greater defense effort than s_u prompts the offender to work harder ($\frac{dx^{br}(s)}{ds} > 0$) and make the crime more likely to succeed. Anticipating this, the victim will put in less defense effort and run away instead.

According to expressions (6) and (8) , enacting the SYG law reduces the perceived punishment of the victim for over defense. Therefore, whether it is a planned murder or an unplanned murder, the victim exerts more efforts for defense than before. If $\delta_{ss} < 0$, conditon $|\delta_s| > |\frac{p_{xs}[(B+D)/F-\delta(s)]}{p_x}|$ still holds, the offender in either planned or unplanned murder exerts more effort when committing the crime. The unplanned murder becomes more violent under the law because both the offender and the victim put in greater effort. If $\delta_{ss} \geq 0$, conditon $|\delta_s| > |\frac{p_{xs}[(B+D)/F-\delta(s)]}{p_x}|$ may no longer be true. The increased defense effort discourage the offender's effort, which will elicit more defense effort from the victim in planned murder than in unplanned murder. Because the victim of an unplanned murder is less prepared $s_u < s_p$ and the offender is more aggressive $x_u > x_p$, the offender's probability of success in unplanned murder becomes larger than in planned murder, $p(x_u, s_u) > p(x_p, s_p)$

Condition 2: The offender is not easily provoked

When $|\delta_s| < |\frac{p_{xs}[(B+D)/F-\delta(s)]}{p_x}|$, the marginal impact of s on δ is low. Knowing that the offender cannot be easily provoked, the victim in planned murder chooses better preparations to discourage the offender's effort ($\frac{dx^{br}(s)}{ds} < 0$). Greater defense effort than s_u reduce the likelihood of a successful crime. There is more reduction in planned murder than unplanned murder.

Meanwhile, enacting the SYG law discourages the offender, because the increased defense effort reduces the offender's effort in planned or unplanned murder. If $\delta_{ss} \geq 0$, the condition $|\delta_s| < |\frac{p_{xs}[(B+D)/F-\delta(s)]}{p_x}|$ still holds. Passing the law discourages the offender's effort making both planned and unplanned murder less likely to happen. If $\delta_{ss} < 0$, the condition $|\delta_s| < |\frac{p_{xs}[(B+D)/F-\delta(s)]}{p_x}|$ may not hold after passing the law. The victim's defense effort may eventually lead to more effort from the offender. Although both s_u and s_p increase due to the law, s_u will increase further and surpasses s_p. After the law was passed, the unplanned murder becomes more violent since both the offender and the victim commit to a higher level of effort.

We find that the SYG law makes unplanned murder either more violent or more likely to occur compared to planned murder under condition 1. In condition 2, the unplanned murder also becomes more violent when $\delta_{ss} < 0$ and the victim's defense effort and the offender's effort in unplanned murder has a more significant increase than in other cases.

The offender is less likely to succeed and the crime is less violent only when $\delta_{ss} \geq 0$ and condition 2 is satisfied.

5 Data

We obtained three types of data for the project. Crime data comes from the Uniform Crime Report's Offenses Known and Clearances by Arrest (OKCA) files (Bureau of Justice Statistics (BJS), 2000-2015) and the Supplementary Homicide Reports (SHR) files (Federal Bureau of Investigation (FBI), 2000-2015*b*). We also used the Murder Cases in 33 Large Urban Counties in the United States, 1988 (MC) (Bureau of Justice Statistics, 1988) as a reference. Law passing date data comes from various sources such as Wallace v. State (2015). Control variables include the size of the police force, unemployment rate, poverty rate, number of prisoners, and demographic data. They also come from various sources such as the UCR Police Employee Data (LEOKA) files (Federal Bureau of Investigation (FBI), 2000-2015*a*). The time period we work with is 2000-2015, because the first state to pass the law is Florida, which passed it in 2005, and the latest year with available data is 2015.

5.1 Crime Data

We obtained the OKCA files from the UCR Data Tools website (Bureau of Justice Statistics (BJS), 2000-2015) [4]. We downloaded the data by the state for the years 2000 to 2015, and combined them into a panel. The OKCA contains data on crime that has been reported to police, including the

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

charge for the crime. What we are most interested in in the OKCA data is the category of Murders and Non-negligent Manslaughters.

We obtained the SHR data from the National Archive of Criminal Justice Data (NACJD) hosted at the University of Michigan (Federal Bureau of Investigation (FBI), 2000-2015*b*). The SHR contains more detailed data on homicide, including the circumstances under which the homicide occurs. Compared to the OKCA data, SHR data is presented by incidents. We aggregated the number of cases by state, year, and circumstances, and merged them to generate a panel. The top five circumstances are listed in Table 1. Data from states and years with very small numbers of observations are dropped from the SHR based on findings by Office of Juvenile Justice and Delinquency Prevention (2000-2015). Florida data is missing from the national SHR database, but we were able to obtain it from Florida's own SHR database (Florida Department of Law Enforcement, 2000-2015), and process the data in the same fashion as for the national data.

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

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.

Murder rate is defined as the number of murders per 100,000 people. Summary statistics for the murder rate is in Table 2. The highest murder rate (14.6) is in Louisiana in 2007; the lowest (.6) is in North Dakota in 2000.

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

	Count	Max	Min	Mean	Std. Dev.
Murder Rate	850	14.6	.6	4.5	2.3
Planned Murder Rate	838	10.3	.3	3.2	1.7
Unplanned Murder Rate	838	2.3	.1	.7	.4

The highest murder rate in the OKCA data is 14.6, the lowest is .6. The highest planned murder rate in the SHR data after adjustments is 10.3, and the lowest is .3. The highest unplanned murder rate is 2.3, and the lowest is .1.

5.2 Planned and Unplanned Murder Data

The UCR's various data files do not categorize murders as planned and unplanned. However, Murder Cases in 33 Large Urban Counties in the United States, 1988 (MC) has information on whether a murder is a first degree murder or a second degree murder. First-degree murder is defined to be an unlawful killing that is both willful and premeditated (FindLaw, n.d.*a*). Second-degree murder is defined to be an intentional killing that is not premeditated (FindLaw, n.d.*b*). We will use first-degree murder data as planned murder data, and second-degree murder data as unplanned murder data.

Although the data is only available for 1988, we recognize the proportion of first-degree murder under each circumstance should be constant. The list of the top five circumstances can be found in Table 3.

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

Top five circumstances in MC is very similar to top five circumstances in SHR. See Table 1 for detailed comparison.

Table 4 shows that most first degree murder offenders know their victims, which helps explain why it is possible for them to successfully plan ahead.

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	

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.

Crucially, we use this dataset to elicit the proportion of murders that are planned and the proportion that is unplanned. Table 5 shows the most serious charge faced by the defendants.

Table 5: Murder Cases in 33 Large Urban Counties in the United States, 1988

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

The majority of the cases recorded are either first degree murders or second degree murders.

These first degree and second degree murders are conducted under the circumstances listed in Table 6 and Table 7.

Table 6: 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
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				
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

Table 7: Murder Circumstances (continued)

Code	Circumstance	Total	First degree	Second degree
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
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/insurance scam	50	40	7
g14	Suicide pact	2	1	1
g19	Other	15	10	5
g20	"Thrill Kill"	7	5	2

From Table 6 and Table 7, we know the percentage of first degree murder under each circumstance. By merging this information to the SHR, we are able to obtain the percentage of first degree murder for each state in each year.

5.3 Controls

The controls used in this paper are based on previous research that documented the link between these factors with crime. They include the size of the police force, the number of individuals that are incarcerated, and socioeconomic factors.

Levitt (2002) found that the size of the police force significantly affects crime. Therefore, we included data on the number of police officers per 100,000 population. Data is obtained from the Uniform Crime Report Police Employee Data 2000-2014 (Federal Bureau of Investigation (FBI), 2000-2015*a*).

Levitt (1996) found that the number of prisoners significantly affects crime through incapacitation effect. This data is obtained from the Bureau of Justice Statistics Bulletin 1999-2014 (U.S. Bureau of Justice Statistics, 2000-2014).

Papers such as Raphael and Winter-Ebmer (2001) have documented the relationship between unemployment rate and crime. Therefore, we have included unemployment rate data that comes from the America FactFinder (Bureau of Labor Statistics, 2000-2014*a*), which has since been deprecated, but the same data could be found in Bureau of Labor Statistics (2000-2014*b*).

Poverty rate has been found to be related to crime (Ludwig, Duncan and Hirschfield, 2001; Hipp and Yates, 2011), as well as household income (Alba, Logan and Bellair, 1994) and demographic data (Piquero and Brame, 2008; Farrington, 1986). Poverty rate, median household income and demographic data are obtained from the American Community Survey 2000-2014 through the IPUMS data builder (the U.S. Census Bureau, 2000-2014).

Since income is correlated with crime, alleviation measures through public assistance (Hannon and DeFronzo (1998)) and welfare spending (Fishback, Johnson and Kantor (2010)) are effective. Public assistance and welfare spending data are obtained from the Annual Survey of State Government Finances (United States Census Bureau, 2000-2014).

In addition, Duggan (2001) has documented the association between gun ownership and crime. They used proprietary data of gun magazine subscription as a proxy for gun ownership. Absent private data, we used percent of suicides committed with guns (PSG) mentioned in Kleck (2015) as proxy for this paper. This data is obtained from the Underlying Cause of Death database from Centers for Disease Control and Prevention (2000-2014).

Summary statistics for controls are in Table 8. They are provided at the national level. We did not include the percentage of the population that is outside of the workforce, because it has a similar effect as the unemployment rate.

Table 8: 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) per capita	120	107
	(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

There are around four times as many planned murders than unplanned murders. There are six times as many white male as black male in the age group of 15-24, around ten times as many white male as black male in the age group of 25-44.

6 Preliminary Data Analysis

This section contains analysis results that motivate the application of the panel regressions. First, we group the state-years into those without the law and those with the law. For example, Massachusetts never had the law, so Massachusetts in 2000 would be a state-year without the law, as well as Massachusetts in 2014. Florida enacted the law in 2005, so Florida in 2004 would count as a state-year without the law, whereas Florida in 2006 would count as a state-year with the law. We compared the murder rates between these two groups, and the results are in Table 9. Between years 2000 and 2014, there are 551 state-years without the law and 174 state-years with the law. The state-years with the law have significantly higher murder rate than the state-years without the law.

Table 9: Comparison between States With Law and States Without Law (2000-2014)

State and Year	Summary Statistics					Comparison	
	Count	Min	Max	Mean	SD	Degrees of Freedom	t
Without Law	551	.62	13.25	4.22	2.30	723	5.76***
With Law	174	.90	14.56	5.35	2.10		

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

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 that for state-years with the law is 5.35.

Since states without the law could have different characteristics than states with the law, we zoom in to looking specifically at states which have passed the law and compare murder rates before and after the law is passed for these states. Table 10 shows that states who have implemented the law has an average murder rate of 5.03 before the law, and 5.50 after the law.

Table 10: 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		

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

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 intention of the law is for victims to deter offenders. However, according to Table 11, victims are significantly less likely to have a prior record than offenders. Therefore, they are less experienced with handling criminal confrontations than offenders are. By encouraging an increase in arming by victims, the law encourages offenders to increase their preparations as a response. Compounding the fact that both the victims and the offenders increase their efforts with the fact that offenders are more experienced in crime, the implication is that offenders' probability of success may increase.

Table 11: Percent of Offenders and Victims with Previous Criminal Records

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

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

Of the offenders who committed murder, 69% had previously committed an offense. Of the victims who were subjects of murder, 37% had previously committed an offense. The difference is statistically significant at the 5% level.

The law may also impact different types of offenses differently. Self-defense data from the National Crime Victimization Survey (1992-2016) shows that 33% of those who were subjected to abusive language took self-defense action, whereas 11% of those whose homes were forcibly entered defended themselves (Table 12). Therefore, escalation of violence is more likely to happen in what we consider to be less serious crimes.

Table 12: 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

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.

Specifically, the law's potential impact on first-degree and second-degree murder may differ due to victim characteristic. Victims in first-degree and second-degree murder have different prior exposure to the criminal justice system. According to Table 13, 35% of the victims in a first degree murder had previously committed an offense. 43% of the victims in a second degree murder had previously committed an offense. The difference is statistically significant at the 5% level. Since first degree murder victims have significantly less experience than second degree murder victims, they are less likely to have effective self-defense (Kurlychek, Brame and Bushway, 2006; National Collaborating Centre for Mental Health - UK, 2015). Therefore, on the one hand, first degree murder offenders are more likely to succeed. On the other hand, second degree murder situations are more likely to trigger an escalation of violence.

Table 13: Percent of Victims with Previous Criminal Records in First Degree Murder 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		

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

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).

Not only are second-degree murder victims more likely to have a prior criminal record, they are also more likely to have a weapon (Table 14). This is another factor that contributes to the potential of an escalation of violence.

Table 14: 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		

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

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.

Along with the differences between first-degree second-degree murder victims, there are also differences between first-degree and second-degree murder offenders. Table 15 shows that second-degree murder offenders have higher percentage of using drugs than first-degree murder offenders, consistent with our theory that first-degree murder offenders are more deliberate and second-degree murder offenders are more likely to be provoked (Goldstein, 1985).

Table 15: 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		

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

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.

From the two-sample t-test results, we could see that state-years with the law, on average, have more murders. States that have implemented the law have significantly higher murder rates after the law than before. Therefore, we would like to use the Difference-in-Difference (DiD) design to further explore the issue and obtain causal inference. Note that a much higher percentage of offenders have committed an offense than victims, and we need to take this into account when we consider the effect of victim self-defense.

When we compare first-degree and second-degree murder, we can see that second degree murder victims are more likely to have previous criminal records and more likely to have weapons on them. Second degree murder perpetrators are more likely to be under the influence of substances. All these factors build the foundation for our more rigorous comparison between the two types of murder that we would elaborate below.

7 Empirical Strategy

The DiD framework is the most fitting for evaluating the effect of the law separately on planned and unplanned murders. The control group is the states that have never passed the law, and the treatment group is the states that have passed the law. Since the states that have passed the law passed them in different years, we will implement a staggered DiD model. Since the first states that passed the law passed them in 2005, we start our analysis from the year 2000 to give them a few years of data for comparison. Data is available from 2000 to 2014.

Our outcomes of interest are natural log of planned and unplanned murder per 100,000 population. If unprepared offenders are more likely to cause an escalation of conflict, second-degree murder will increase more than first-degree murder.

Our specification is similar to that in Cheng and Hoekstra (2013). The specification controls for the differential trends of murder rate by the states. Equation 11 is the general specification, where i stands for the state and t stands for the year.

$$murder_{it} = \beta_0 + \beta_1 law_{it} + \beta_2 states_i + \beta_3 year_t + \beta_4 \boldsymbol{x}_{it} + \beta_5 law_{it} * year_t + \varepsilon_{it} \tag{11}$$

The main variable of interest, law_{it}, takes a value between 0 and 1. For a state that has never passed the law, the variable is equal to 0. For a state that has passed the law, during the year when the law is passed, the value depends on the exact date the governor signed the bill. For example, Gov. Jeb Bush signed the bill on April 26, 2005 for the state of Florida, so the law variable is equal to .68 for Florida in 2005, since there are 249/365 days left in the year after April 26. The years after the law is passed, the variable law_{it} would take on the value of 1.

The $states_i$ variables are the state fixed effects that capture factors such as the prevailing cultural attitude toward self-defense that differ between states but are fixed over time. The $year_t$ variables are the year fixed effects that capture factors such as improvements in police technology that vary through time but are constant between states. Inside $\boldsymbol{x}_{it}$ we have the size of the police force, the unemployment rate, poverty rate, income, prisoner count, last year's prisoner count, demographic variables (percentage of black males 15-24 and 25-44 years old, percentage of white males 15-24 and 25-44 years old), and government's spending on welfare (subsidy and public welfare spendings). All of the controls have been proven to be correlated with murder rate in existing literature. See details in Section 5.

We have evidence that changes in murder rate don't affect the decision to pass the law. In other words, we have evidence that there is no reverse causality. Figure 5 in the Appendix shows that out of the 30 states that passed the law, 9 had an increase of murder rate before the law, and 19 had a decrease. β_1 is the parameter of interest here.

Our specific specifications are covered in Equations 12 to 17. Equation 12 controls for state fixed effect and year fixed effect.

$$murder_{it} = \beta_0 + \beta_1 law_{it} + \boldsymbol{\beta_2 states}_i + \boldsymbol{\beta_3 year}_t + \varepsilon_{it} \tag{12}$$

Equation 13 controls for region-by-year fixed effects as well. Due to cultural reasons, each region of the United States is likely to share a similar murder rate trend over time, but the trends of different regions are likely to be different.

$$murder_{it} = \beta_0 + \beta_1 law_{it} + \beta_2 states_i + \beta_3 year_t + \boldsymbol{\beta_4 region_i * year_t} + \varepsilon_{it} \tag{13}$$

Equation 14 also controls for time varying factors, which are listed above in Subsection 5.3.

$$murder_{it} = \beta_0 + \beta_1 law_{it} + \beta_2 states_i + \beta_3 year_t + \beta_4 region_j * year_t + \boldsymbol{\beta_5 x_{it}} + \varepsilon_{it} \tag{14}$$

Equation 15 controls for Ashenfelter's dip (Ashenfelter, 1978). Including the prelaw dummy will allow us to check if, in anticipation of the law passing, people are committing more murder. We would also be able to check if the law is a response to an uptick in crime rate, and address the problem of endogeneity (Besley and Case, 2000).

$$\begin{aligned} murder_{it} = {} & \beta_0 + \beta_1 law_{it} + \beta_2 states_i + \beta_3 year_t + \beta_4 region_j * year_t + \beta_5 x_{it} \\ & + \boldsymbol{\beta_6 prelaw_{it}} + \varepsilon_{it}, \end{aligned} \tag{15}$$

Equation 16 controls for crime's time trend for each state. ***Year*** is a group of 50 variables that each take on the values of 1-15 that correspond with each state.

$$\begin{aligned} murder_{it} = {} & \beta_0 + \beta_1 law_{it} + \beta_2 states_i + \beta_3 year_t + \beta_4 region_j * year_t + \beta_5 x_{it} \\ & + \boldsymbol{\beta_7 states_i * year} + \varepsilon_{it} \end{aligned} \tag{16}$$

Equation 17 controls for crime's post law time trend for each state.

$$\begin{aligned} murder_{it} = {} & \beta_0 + \beta_1 law_{it} + \beta_2 states_i + \beta_3 year_t + \beta_4 region_j * year_t + \beta_5 x_{it} \\ & + \beta_7 states_i * year + \boldsymbol{\beta_8 law_{it} * states_i * year} + \varepsilon_{it} \end{aligned} \tag{17}$$

The results with murder rate on the left hand side are presented in 8.1. Results with first-degree and second-degree murder rate on the left hand side are presented in 8.2. Both sections include robustness checks that strengthen our causal interpretation of the estimated effects.

8 Results

8.1 DiD effect on Murder Rate

Tables 16 through 18 estimate the DiD equations 12 to 17. They report the effect of the law on murder rate together with heteroskedasticity-robust standard errors clustered by time and by state. Results show that, on average, the years after law passes have a higher murder rate than the years before. The point estimates are between 8.4% and 9.3%, which are consistent with those in Cheng and Hoekstra (2013).

In Table 16, Column (1) shows that after controlling for state and year fixed effects, SYG law increases murder rate by 9.1% more for state-years with the law than for those without it. Results are statistically significant at the fiver percent level. The significance level remains at the five percent level when we control for region-by-year fixed effects, as shown in Column (2).

Column (3) includes time-varying controls as detailed in Section 5.3. The point estimate decreases to 8.8% while the level of significance increases to one percent. Column (4) adds a dummy variable for the year when the law was passed. The concern is that there may be other events happening during the year of the law that cause the murder rate to change. However, including this variable does not affect the magnitude or significant level of the coefficient on law. When this variable is introduced, the coefficient decreases by a small amount to 8.6%. After adding time trends in Columns (5) and (6), the coefficients increases to 9% and 9.3%, while maintaining the same level of significance.

Table 16: 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

Heteroskedasticity-robust standard deviations in parentheses

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

To test whether laws pass in response to increases in the murder rate, we include robustness checks by adding a variable that is equal to 1 for the two years prior to the law passing year, and 0 for all other years. The results from the regression are reported in Table 17. They show that, across six specifications, murder rate has increased between 8.4% and 9.9% compared to three or more years before the laws pass.

Columns (1) - (3) in Table 16 are the same as those in Table 17. Column (4) adds a prelaw dummy, which equals one two years before the laws pass, and equals zero for all other years. For example, Florida passed the law in 2015. Therefore, this variable is equal to one in Florida for 2013 and 2014, and zero for all other years. Compared to the average crime rate three or more years before the law passes, the two years before the law passes don't witness an increase of crime, meaning that the laws aren't passed in response to a rise in crime.

Table 17: 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

Heteroskedasticity-robust standard deviations in parentheses

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

Table 18 shows that compared to two years or more before the law passes, two years or more after the law passes may not see a much higher murder rate. Column (4) shows us that compared to two years or more before the law passed, the murder rate increases by 8% at the 5% level of significance. However, when we add state-specific time pre-trend, as shown in Column (5), the coefficient decreases to 7% and it is no longer significant. When we add state-specific post-trend, as shown in Column (6), the coefficient increases back to 7.5%, and it becomes significant at the 5% level. This signals to us that most of the changes happen in the year prior to the law, the year when the law is passed, and the year after the law is passed.

Table 18: 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

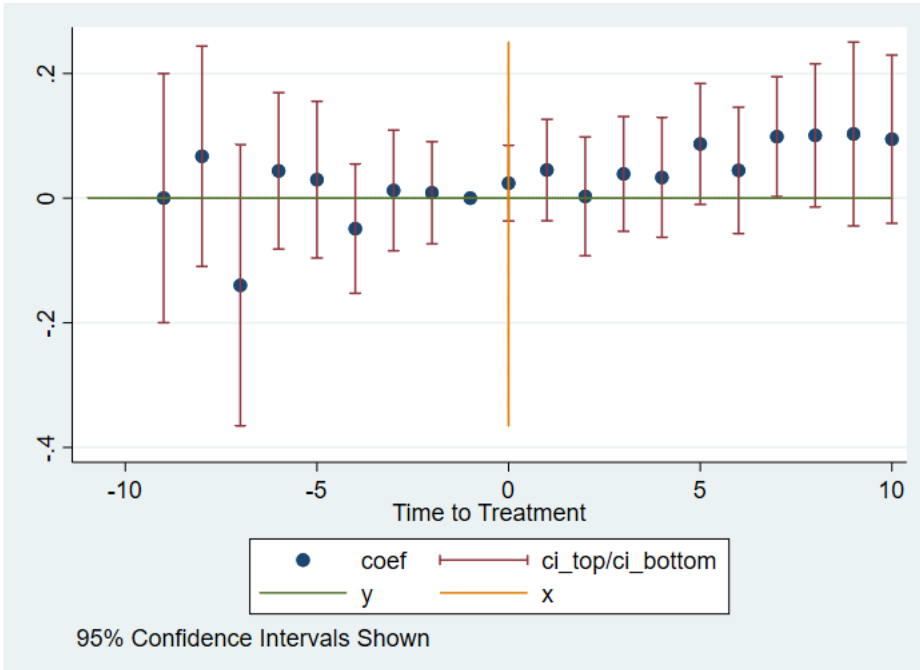
Heteroskedasticity-robust standard deviations in parentheses

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

Notes. Results are large and statistically significant until time trends are added.

Figure 1 shows the effects separately by year, revealing a reversal in murder trend over the years. Compared to state-years without the laws, state-years with the laws had a decrease in murder rates before the laws were passed. However, after the laws were passed, they see a gradual increase in murder rate. This could be due to the gradual adoption of practices in response to the passing of the SYG laws by both the offenders and the victims.

Figure 1: Effect of Law on Murder Over Time



Notes. This figure reports the results from DiD regression of the SYG laws on murder. It plots both the point estimates and their 95 percent confidence intervals. All specifications include the time-varying covariates detailed in Section 5.3, as well as state by year fixed effects. Standard errors are clustered by state. The year when the laws pass witness an increase in murder, and the effects are larger and persistent. However, there may be a pre-trend coupled with low crime rate in the three years surrounding the law year.

8.2 Planned Murder v.s. Unplanned Murder

In addition to examining the aggregate murder rate, we examine planned murder rate and unplanned murder rate separately. Based on our behavioral models in Section 4, the increase in murders can happen for two reasons: arms race and victim over-defense. Since there is a higher chance that victims will have a weapon in unplanned murders, we hypothesized that unplanned murder cases will increase more. We analyze this by doing a similar exercise as in Section 8.1, and use a dummy variable interaction term to compare the coefficients between planned murders and unplanned murders.

Table 19 reports the coefficient β_1 in Equations 12 to 17 for the logarithm form of planned and unplanned murder rate. According to the planned murder regression in Panel A, Column (1), SYG law increases planned murder by 8.9% on average. 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 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 the SYG law on unplanned murder rate. The coefficient estimates are relatively stable across specifications, larger than those of planned murder rate, and more statistically significant. The difference between the percentage increases is 2 percentage points in Column (6). The average difference between the percentage increases across specifications is 2.3 percentage points.

Table 19: 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

Heteroskedasticity-robust standard deviations in parentheses

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

Table 20 shows the result comparing the murder rates after the law passed to three or more years before the law passed. The first three columns are the same as Table 19. However, coefficient estimates in Column (4) of Panel A is still not significant. Columns (4) - (6) in Panel B are statistically significant and consistent with the results of the main specification. This stability of estimation confirms the significant impact of SYG law on unplanned murder. Also, the difference in the point estimates for Column (6) is 2.7 percentage points, which is larger than that in Table 19.

Table 20: 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

Heteroskedasticity-robust standard deviations in parentheses

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

Table 21 shows that compared to two years or more before the law, two years or more after the law don't observe a significant increase in planned murder rate. However, we do observe a significant increase in unplanned murder rate. Therefore, the law has a persistent influence on people's behavior that induces unplanned murder. These results contrasts with the unstable results of total murder, as seen in Table 18. Also, the difference in the point estimates is 3.3 percentage point, which is larger than that in both Tables 19 and 20.

Table 21: 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

Heteroskedasticity-robust standard deviations in parentheses

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

Table 22 shows the difference between coefficients on the law variable for planned and unplanned murder. Across specifications, the differences are not consistently statistically significant, but they are consistently positive.

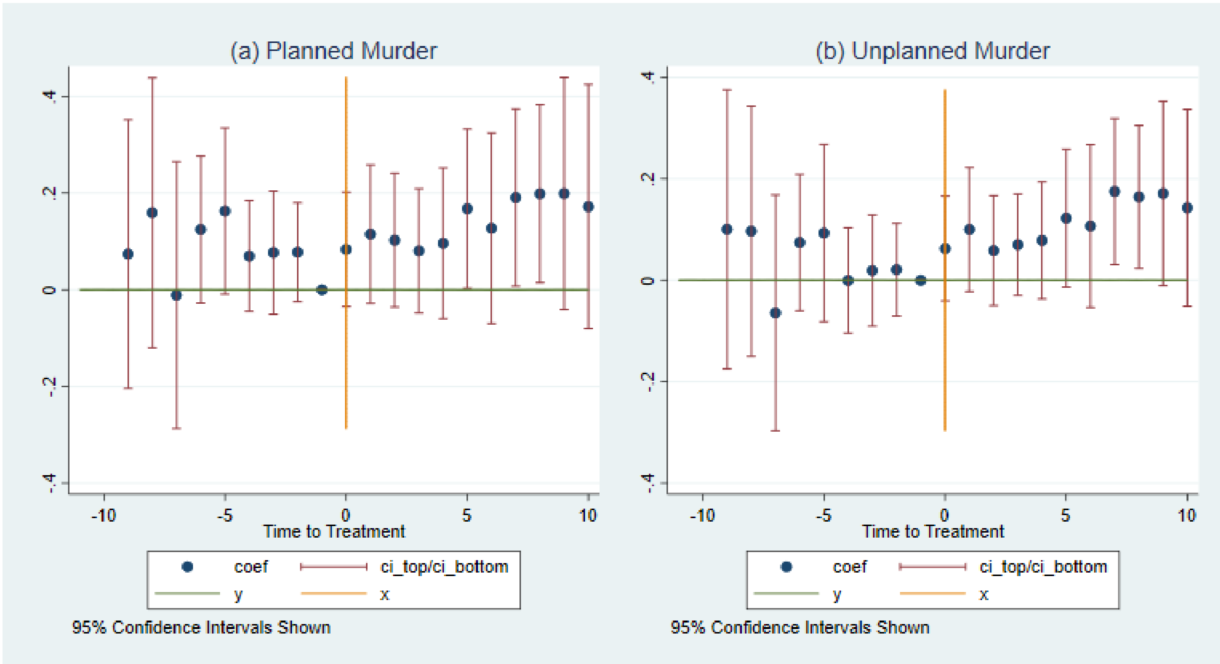
Table 22: Comparison of Coefficients Between Planned Murder and Unplanned Murder

	(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

Notes. When we add an interaction term to check the difference in coefficients between planned and unplanned murders, the differences are not consistently statistically significant, but they are consistently positive.

Consistent with Table 22, Figure 2 also shows evidence of more change in unplanned murder than planned murder. Panel (b) has lower values for the pre-period, higher values for the post-period, and smaller confidence intervals.

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



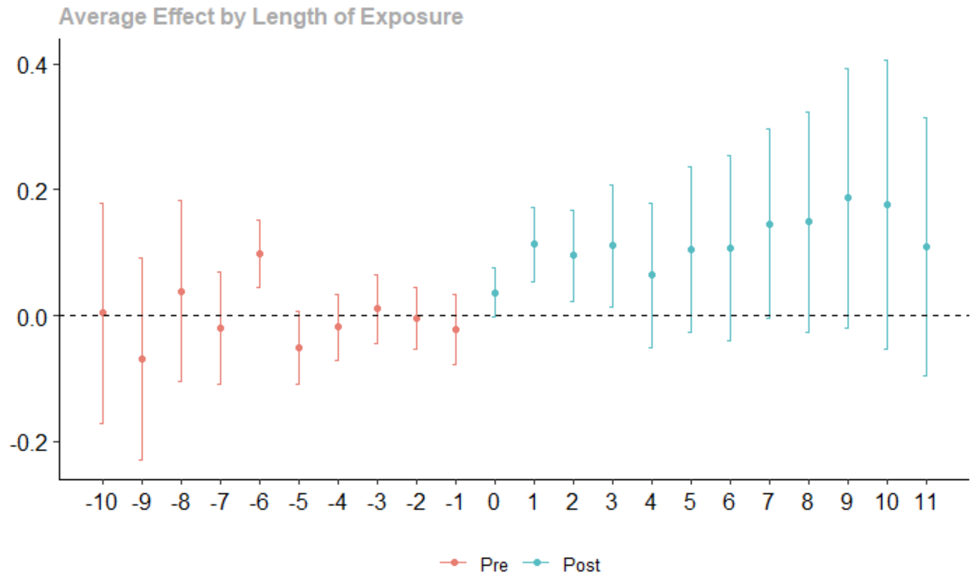
Notes. There are more variations in planned murder during the three year period around the year when laws are passed. Disregarding those variations, there are larger changes for unplanned murder than for planned murder, indicating the existence of over defense issues. Both types of murder had an upward trajectory, indicating the existence of the “arms race.”

Overall, we have presented clear evidence that although planned murder rose after the SYG law, unplanned murder rates contributed to the increase in the total murder rate more than planned murder rates did. Therefore, both the ”arms race” effects and the over-defense effects exist, which is consistent with findings from our game theoretical model.

8.3 Robustness Checks

Callaway and Sant’Anna (2020) introduced a DiD procedure that focuses on staggered adoption for panel data. Using their accompanied R package, we replotted Figure 1. The results are in Figure 3, which are consistent with Figure 1.

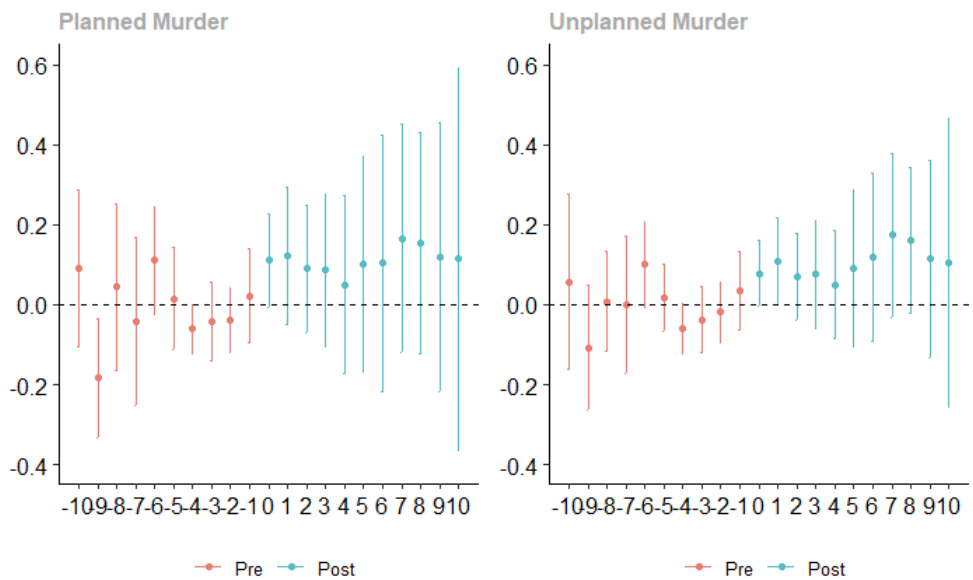
Figure 3: Effect of Law on Murder Over Time (Callaway and Sant'Anna, 2020)



Notes. In the pre periods, most of the murder rates are below the mean. In the post periods, most of them are above the mean. The further away the time period is from the treatment date, the less precise the estimate. This is because we have fewer observations for those dates.

Figure 4 shows that the confidence intervals for unplanned murder is much smaller than for planned murder, although the magnitude difference is less pronounced than in Figure 2.

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



Notes. The effects for planned murder are slightly smaller than those for unplanned murder. Also, they are less precise.

9 Policy Implications

It is not uncommon for laws to have unintended consequences (Podkopacz and Feld, 2001; Chesney-Lind, 2002). Same is true with the SYG law. This study has offered further evidence of the negative effects of the law. Coupled with the existing studies, we take a stance against the law. Currently 30 states have passed the law. Law makers in the other 20 states should pay attention to this fact when they make decisions about passing it. Law makers in the 30 states with the law should consider rolling it back. In 2017, Florida shifted the burden of proof in pre-trial hearings[5]. The prosecutor now has to prove that a person is not conducting self-defense rather than the offender having to prove their innocence. This could be even more inducive for criminals and other states should not follow suit.

When examining the SYG law's detail by state, we find that among states that has passed the SYG law, nearly 90% of them emphasized the deadly force or lethal weapon in SYG statute or

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

legislature statement. For example, they use the words “can use lethal weapon against”, “can use deadly force to”, “killing is necessary”, and “can meet force with force, including deadly force.” Such information may create a focal point that encourages public to choose lethal weapons among all sorts of defense methods in self-defense, which contributes to the escalation of crime. Consistent with our empirical analysis, the SYG law’s impact on unplanned murder is persistent. To mitigate such impact, states may consider rephrase the sentence and eliminate the focus on deadly force in self-defense regulations in general.

Meanwhile, the administration needs to educate the public about the law. First, they need to explain the law. For example, the SYG law applies to the situation where the person has a “reasonable belief” that there is an imminent danger of death or serious bodily injury. Although “reasonable believe” is objective in SYG or self-defense law, people may form subjective believes towards death threat or great bodily harm without proper education of the law. Second, they should mention the unintended consequences. They should inform the public that the SYG law has increased murder success rates for offenders and converted other types of crime to murder. These can be conducted by bringing prosecutors into the community and the schools for a talk, or even editing relevant information into the textbooks. During these talks/textbook edits, examples should be added so children and the general public can get a intuitive idea about what the law entails and have an opportunity to interact with prosecutors.

If such laws need to be passed as they are, however, relevant training needs to be conducted. In order to be able to protect oneself, people need to be able to use the gun correctly and effectively. If people are unfamiliar with the use of the gun, they are likely to face retaliation and even more serious consequences than if they choose to walk away from a situation.

Compared to passing controversial laws such as the SYG law, a better way to deter crime is to increase education opportunities and economic opportunities in society. Anderson (2002) mentioned that educational programs, drug rehabilitation programs and youth programs could help reduce crime. Fighting violence with violence seem to have unintended consequences, as illustrated by this study.

10 Conclusion

This paper examines at how the SYG law affects murder rate differently for first-degree and second-degree murder. We present evidence that second degree murder increases more after the SYG law than first degree murder after the SYG law is passed. The results extend the finding that SYG law increases murder rate as a whole (Cheng and Hoekstra, 2013; Humphreys, Gasparrini and Wiebe, 2017*a*). Our central estimate is that the rate of second degree murder increases by between 1.7 and 3.2 percentage points more than the rate of first degree murder.

One limitation of this study is that it looks at the average effect of the law on all states. It is possible that different states face differential effects from the law. Further research is needed to address the differential impact of the law on individual states.

The murder data we use come from police reports. However, when the prosecuting attorney determines the charges, they don't always follow those that are filed in the police reports. It is possible that the police report is biased towards a lighter crime, as evident in the Michael Drejka case, when the police did not initially arrest the gunman, but later he was charged with manslaughter by the prosecution (Fields, 2018). It is also possible that the police decide to report the case as a more serious offense, but later prosecution decides the case to be less serious than the police report suggests. Further research could be conducted with prosecution data, or even court decisions data.

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11 Appendix

In 2005, Florida passed the stand-your-ground law; Arizona followed suit in 2006, then 28 other states gradually passed variations of this law, the last one being the state of Wyoming that passed it in 2018. Within these thirty states, North Dakota, Ohio, and Wisconsin have limited versions that restrict stand-your-ground to cars and business.

Table 23 is a list of states and dates of the passing of some law that expands the castle doctrine (NUL, 2013). In Florida, some arrests are not made because of a provision of the law. In this case the offender won't even be charged, so won't contribute to either murder or justifiable homicide.

Table 23: 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	
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	

Figure 5 provides an intuitive view of how the murder rate has evolved over time. The orange dot denotes the year when the law was passed.

Figure 5: Time Series Graphs of State Murder Rate

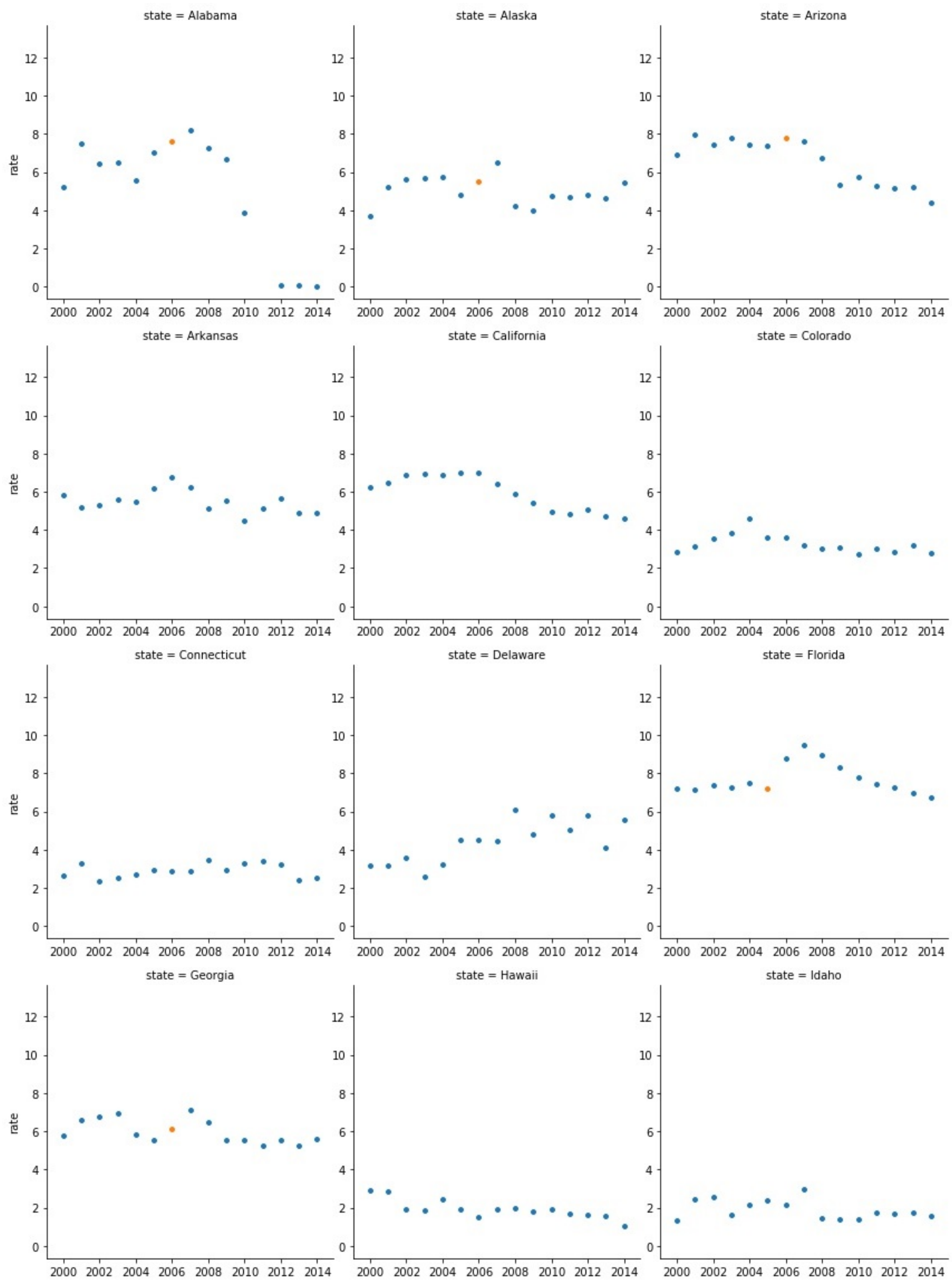

Figure 5: Time Series Graphs of State Murder Rate (cont.)

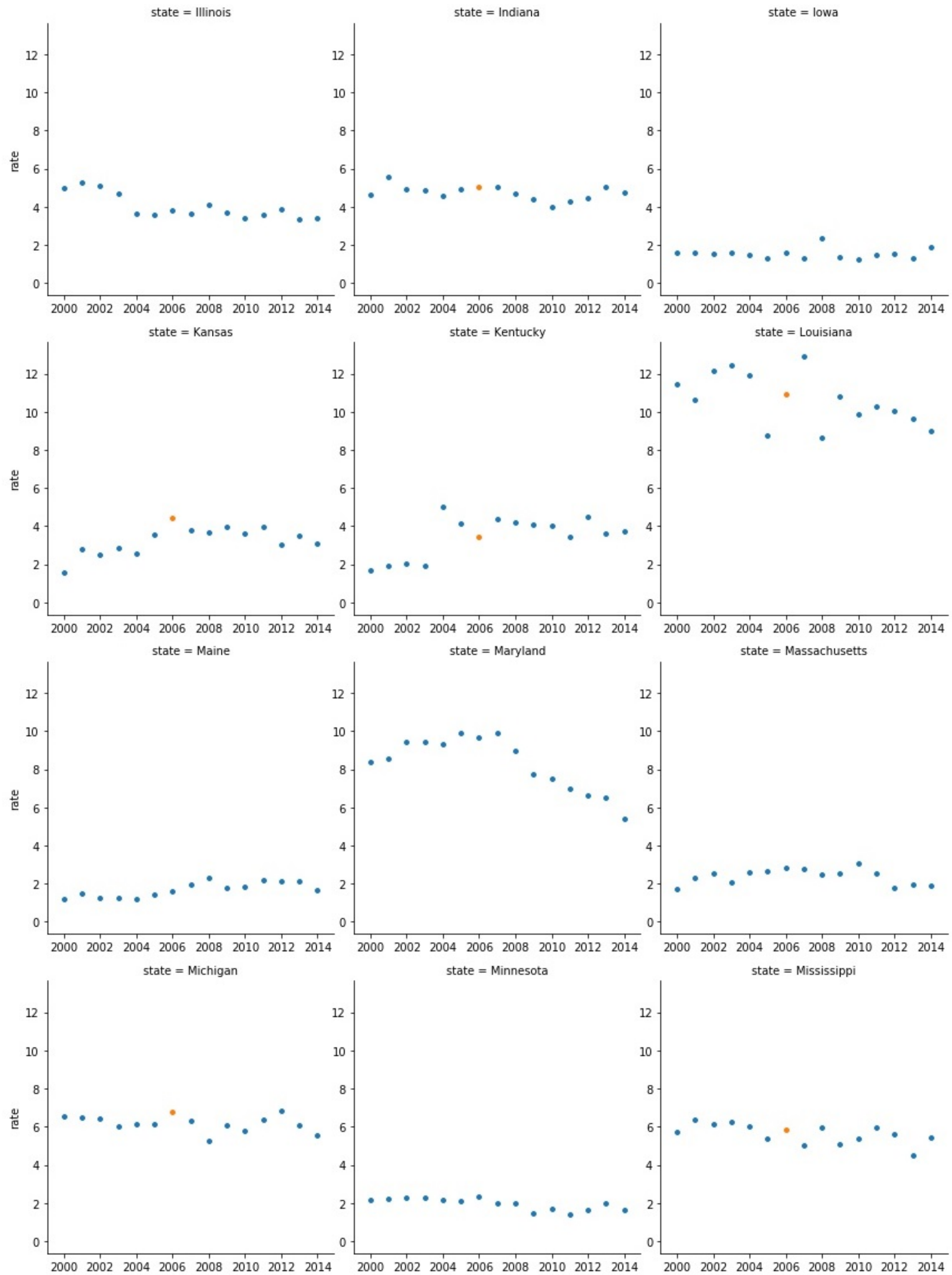

Figure 5: Time Series Graphs of State Murder Rate (cont.)

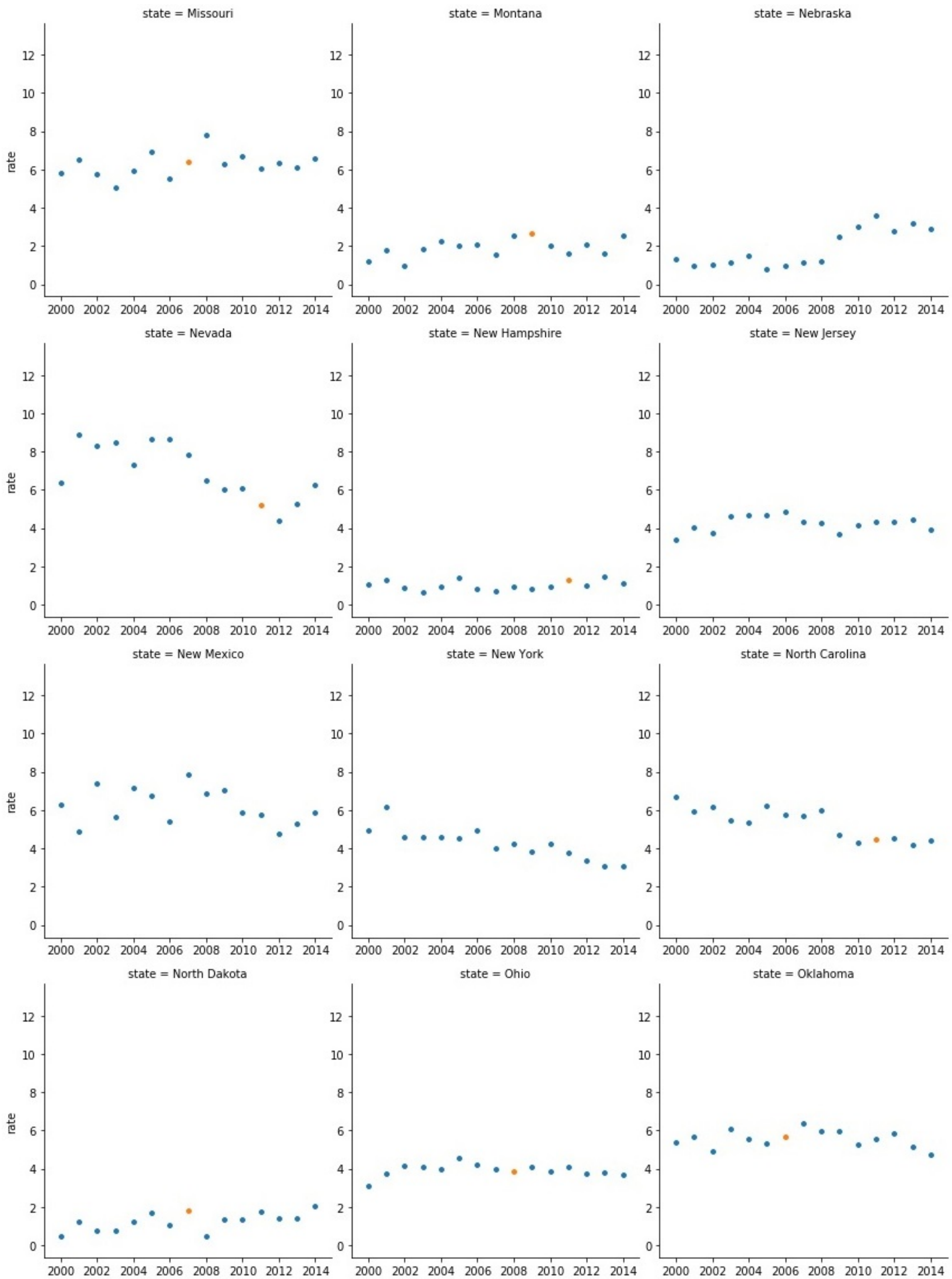

Figure 5: Time Series Graphs of State Murder Rate (cont.)

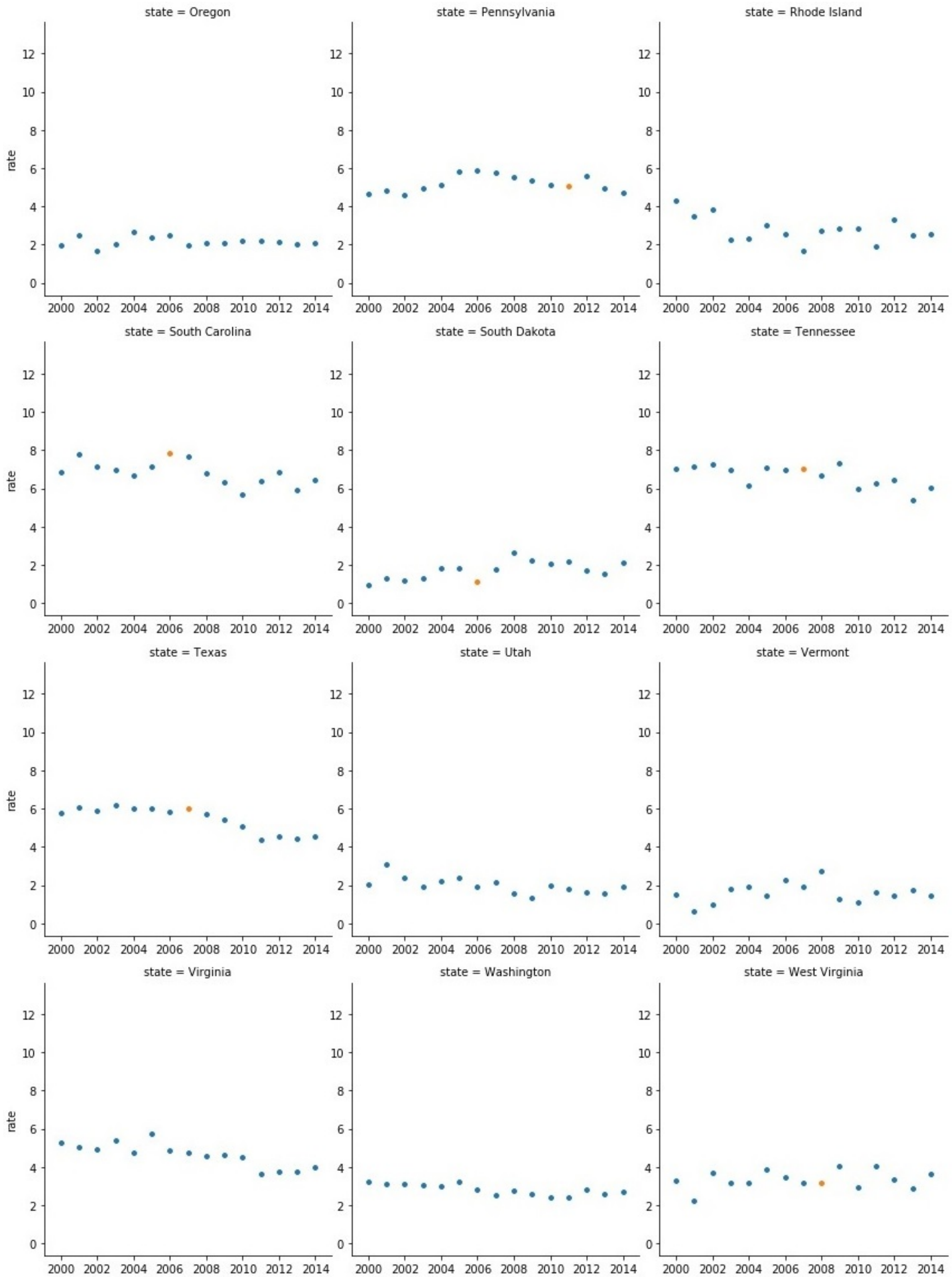

Figure 5: Time Series Graphs of State Murder Rate (cont.)