The right of self-defense: Who is a threat?*

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Abstract

This paper investigates the impact of Stand Your Ground laws, which extend self-defense rights beyond private property, on various crime-related outcomes. Initiated by Florida in 2005, these laws now exist in twenty-five U.S. states, allowing individuals to use reasonable force, including deadly force, in self-defense in any location legally occupied. Our analysis uncovers significant consequences by utilizing a generalized difference-in-differences methodology to assess the staggered enactment of SYG laws across counties. We find that the adoption of SYG laws increases racial and justifiable homicide rates, as well as hate crime incidents. These results challenge the idea that broadening the scope of self-defense laws will increase public safety by deterring crime. Instead, it might increase discriminatory violence and societal divisions.

Keywords: Stand Your Ground, Crime, Homicide, Difference-in-Differences.
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1 Introduction

The Stand Your Ground (SYG) law, also known as the "Shoot First" law, is rooted in the Castle Doctrine. It gives individuals the right to use self-defense, including deadly force, in public spaces when they believe there is a threat, eliminating the requirement to retreat. The SYG law has sparked considerable debate due to its potential negative outcomes. Supporters argue it deters crime, while critics contend it encourages unnecessary violence by allowing individuals to act on perceived threats without attempting to de-escalate the situation safely.

The concept behind SYG laws is based on a long-standing principle that individuals have the right to defend themselves against imminent threats using necessary force. This principle has evolved. Initially, the right to self-defense was primarily recognized within one's home as part of the "no duty to retreat" principle adopted in the United States. The principle asserts that people can use reasonable force, including deadly force, to protect themselves from an intruder in their home. Contrastingly, the "duty to retreat" law requires individuals to avoid conflict by retreating outside their home, if safely possible, representing an alternative approach. This law mandates retreat to a safe location when faced with a threat, provided the individual can do so without engaging in violence, except when the individual is in their home, where the Castle Doctrine supports the right to stand one's ground.

The debate around SYG laws intensified following high-profile incidents, such as the deaths of Miguel Antonio DeJesus and Diego Ortiz in 2007 and Trayvon Martin in 2012, which raised questions about the necessity and justification of using deadly force in self-defense situations. These laws have led to increased scrutiny over what constitutes justifiable homicide, sparking discussions on whether deadly force is applied equitably and without bias. Moreover, SYG laws have faced criticism for their potential racial bias, with evidence suggesting that they may disproportionately affect people of color. This has fueled concerns that SYG laws not only perpetuate racial discrimination but also result in uneven application, with majority group members often receiving more lenient treatment compared to marginalized communities.

Supporters of SYG laws argue for their necessity in protecting individual rights and enhancing public safety, while detractors warn they may lead to an escalation in violence. The empirical investigation into the impact of SYG laws on homicide rates and firearm-related fatalities yields mixed results. McClellan and Tekin [2017] observed an increase in homicides among white males without similar findings across other demographics. Research has identified a rise in firearm deaths associated with SYG laws, with specific effects noted in Florida [Guettabi and Munasib, 2018]. Cheng and Hoekstra [2013] and Ukert et al. [2018] reported increases in homicides, particularly in suburban areas following the Castle Doctrine's extension, but found no evidence of reductions in other violent crimes such as burglary, robbery, and aggravated assault.

Further analysis reveals a correlation between SYG laws and an increase in firearms homicides and overall homicide rates ([Humphreys et al., 2017, Crifasi et al., 2018, Levy et al., 2020, Degli Esposti et al., 2022]). In contrast, Alexander Adams [2022] reported no definitive link between SYG laws and crime trends. The literature also discusses the increase in gun use among offenders following the enactment of self-defense laws, with varied impacts on gun deaths across different urban settings ([Munasib et al., 2018, D'Alessio et al., 2022]). Chakraborty et al. [2022] expanded this examination to include the impact of SYG alongside right-to-carry and background check laws, showing significant legislative effects on state homicide rates. These studies underscore the complex and regionally specific effects of SYG laws on general crime.

The SYG law was introduced relatively recently, with Florida being the first state to implement it in 2005, followed by 24 additional states, with the latest one adopting it in 2018. Figure A.1 shows a map of the US states that have adopted the SYG law, organized by adoption year. To provide a clear picture of the staggered implementation of the SYG, Figure A.2, Panels A and B, respectively, show the frequency distribution of states and counties involved in SYG adoption by year.

The motivation for this research emerges from Figure A.3, which shows the evolution of homicide and justifiable homicide rates in the U.S. from 2000 to 2015 by states that implemented or did not implement the SYG law. Plot (a) shows that for homicide rates, the gap across the years is constant. However, the gap for justifiable homicide rates, presented in plot (b), shows a clear increase after 2006 for states implementing the SYG law.

It is difficult to assess the general effects of the SYG law implementation on justifiable homicide rates by observing average trends. For this reason, this paper aims to evaluate the impact of strengthening the right of self-defense on several outcome variables. Specifically, we investigate the implications of SYG on justifiable homicide rates and place a specific emphasis on racially driven justifiable homicides. We test an initial hypothesis suggesting that if SYG laws are introduced to deter crime, states that adopt these laws will see a decline in general crime rates following implementation. However, our initial analysis does not show any statistically significant evidence supporting this hypothesis with similar results obtained by Alexander Adams [2023]. Once we show that there is no evidence for a deterrence effect generated by the SYG law, we delve deeper into more nuanced crime-related variables such as justifiable homicide and hate crime rates.

We argue that the implementation of SYG laws will not lead to a decrease in justifiable homicide rates. Instead, states adopting SYG laws may experience an increase in justifiable homicides, contrary to the laws' intended crime deterrence effect. Furthermore, based on the emerging research indicating a concerning overlap of hate crimes, racial bias, and SYG laws [Grimes, 2018], we argue that SYG laws will lead to an increase in hate crime incidents. The broadened legal justification for using deadly force provided by SYG laws may encourage individuals to commit crimes motivated by their own bias. Lastly, we argue that SYG laws disproportionately increase the rates of justifiable homicides and hate crimes against racial minorities.[1]

For this analysis, to accurately estimate the effects of SYG law, we adopt a generalized difference-in-differences (*DiD*) methodology. This methodology is well-suited to evaluating the impact of policy changes, particularly in the case of SYG laws, which were implemented at different times in different states. We then address the concerns raised by recent literature on *DiD* setting with staggered treatment adoption (see among others, Sun and Abraham [2020], Callaway and Sant'Anna [2020], de Chaisemartin and D'Haultfœuille [2020a,b], Athey and Imbens [2021], and Goodman-Bacon [2021]) by adopting different time-varying estimates (Callaway and Sant'Anna [2020], Sun and Abraham [2020], de Chaisemartin and D'Haultfœuille [2020a,b]).

According to our main estimates, we find positive and statistically significant effects of the SYG laws on racial homicide rates. The magnitude of the increase, after controlling for covariates, is 1%. Similar results are found for justifiable homicide rates and racially driven justifiable homicide rates. Even though the magnitude of the increase is smaller, the direction and significance of the results are the same. The lower magnitude can be explained since the racial justifiable homicide rate is a subgroup of the justifiable homicide rate. The additional results related to hate crimes and racially driven hate crimes also report positive and statistically significant results. The increase in hate crime after the SYG law implementation is around 6%. The pattern of the results extends to intimidation, simple assault, and property damage hate crimes. All these subgroups of hate crimes show statistically significant increases post-SYG enactment. A notable exception is aggravated assault, where the data does not indicate a significant change. However, we suggest that the nature of SYG laws, which can shield actions under the label of self-defense, might obscure the real dynamics of such assaults.

This research relates to different strands of the empirical literature. Mainly, our findings contribute to the extensive literature on crime and punishment. First, it relates to a strand of literature on the probability of punishment (Doleac [2017], Anker et al. [2021], Menegatti [2023]) and the impact of crime. Our work differs from this literature since we investigate the reduction of the probability of punishment instead of its increase. Central to our study is its contribution to the law and economics literature, mainly through examining of SYG

[1] Lopez et al. [2023] provide an exhaustive review of the hate crime and bias-motivated crime literature.

laws from an economic perspective. By investigating how the reduction in the probability of punishment influences crime rates, we provide a novel economic analysis of legal frameworks designed to deter crime. This approach challenges traditional economic theories on crime and punishment and introduces a new dimension to understanding the interplay between legal policies and economic incentives in shaping individual behavior and societal outcomes. Our findings offer significant insights into the cost-benefit analyses of SYG laws, contributing to a more nuanced understanding of their economic implications on public safety and crime deterrence.

Additionally, our analysis extends the discourse on SYG laws and their societal repercussions. Despite the enactment of SYG laws over a decade ago, only a handful of studies, such as those by Ryan and Leeson [2011] and DeAngelo et al. [2018], have scrutinized their broader implications. Our research fills a critical gap by examining the policy's impact on justifiable and hate crimes, thus offering fresh insights into the nuanced effects of SYG laws on different crime categories. Our research makes an important contribution to public policy and criminal justice debates. By scrutinizing the real-world effects of SYG laws on justifiable and hate crimes, our work sheds light on the policy's broader societal impacts beyond its immediate legal ramifications. This analysis is crucial for policymakers, law enforcement agencies, and community leaders seeking to evaluate the effectiveness of SYG laws as a strategy for crime prevention and public safety enhancement. Furthermore, our exploration of the laws' differential impacts on various demographic and geographic populations underscores the importance of equitable justice and the potential for policy refinement to address disparities in the application and outcomes of SYG laws.

The remainder of the paper is organized as follows. In Section 2 we present the data involved in our estimates. Section 3 lays out the econometric strategy. Section 4 details the main results and the robustness analysis. In Section 4.1 we investigate the implication of the SYG law on several hate crime subcategories. Section 5 discusses findings and their implications. Section 6 concludes.

2 Data

We collect and construct a rich dataset using different sources to conduct this analysis properly. The information presented in this panel covers crime, demographic, and socioeconomic areas for the United States at the county level from 2000 to 2015. We gather data on homicides from the Supplementary Homicide Report (SHR) of the FBI's Uniform Crime Reporting

Program (UCR). In turn, this data is provided to the UCR by the local enforcement agencies[2]. They consist of detailed information on criminal homicides, such as the date, county location, circumstances, and demographic characteristics both for offender and victim. A primary limitation on SHR, as is often the case with crime data, is the well-known problem of under-reporting. Since participation in the Reporting Program is voluntary, several law enforcement agencies could not report events that occurred in their area. Even though under-reporting is the most common problem in this data, it is important to acknowledge other potential problems, such as variability in reporting practices or changes in reporting requirements. Despite these limitations, the SHR database represents one of the most reliable sources of information. Additionally, we collect data on criminal offenses from the UCR - county-level detailed arrest and offense data[3].

The main outcome variables included in this analysis refer to similar hate or discriminatory criminal offenses. The first one reports the homicide rate at the county level. Homicide is defined as the willful (non-negligent) killing of one human being by another. A second group of dependent variables in this analysis reports different specific crime rates, i.e., violent and property crimes. These criminal offenses include crimes against property and a person. Violent crimes include offenses such as murder, rape, robbery, and aggravated assault. Property crimes include burglary, larcenies, motor vehicle thefts, and arson. It can be seen that homicides are included in this more general aggregation of offenses. However, initially, we presented the homicide rate as a separate outcome variable due to its importance. Further in the analysis we include different variables from the UCR data such as justifiable homicide rates and hate crime rates with their respective subgroups. We define the racial homicide rate when the perpetrator is white and the victim is non-white.

We supplement the initial database with demographic characteristics such as population, non-white population, and male population information collected from the United States Census Bureau. In addition to this, we collect several variables related to socio-economic characteristics like income per capita, unemployment rate, Gini index, and high school and college attendance. The data for income per capita are obtained from the U.S. Department of Commerce, and the unemployment rate is produced by the Local Area Unemployment Statistics (LAUS) program from the U.S. Bureau of Labor Statistics. The data concerning educational attainment is provided by the updated version of Frank [2009] and constructed by the author using the perpetual inventory method. This variable represents the share of the population with at least a high school or college degree, respectively. To account for

[2] Florida does not report its data to the FBI. Moreover, several Alaska control variables are unavailable at the county level. Therefore, both states are excluded in our sample.

[3] The data is available up to 2016. However, the 2015 year is missing. To obtain 2015 data, we adopt linear interpolation.

political preferences, we construct a dummy coded as zero if a democrat candidate obtained the majority of the votes in the last presidential elections, one if republican[4]. The inequality measures are constructed using data published in the IRS's Statistics of Income on the number of returns and adjusted gross income (before taxes) by state and by the size of the adjusted gross income. The pre-tax-adjusted gross income reported by the IRS is a broad measure of income.

We examined various socio-demographic and crime-related factors across different counties. The summary of key statistics for the variables under consideration is presented in Table A.1.

3 Empirical Strategy

This paper implements a generalized *difference-in-differences* (*DiD*) strategy to assess the impact of SYG on hate-crime-related outcomes. More precisely, we compare counties affected by the new policy before and after the SYG state law with counties without the new law implementation. We consider a balanced panel of US counties from 2000 to 2015, where different groups of counties are exposed to the policy at different times. Hence, in generalized *DiD* specification, we start by estimating a two-way fixed effect regression that follows:

$$Y_{cst} = \alpha_z + \gamma_t + \beta \times SYG_{cst} + X_{cst} + \epsilon_{cst}, \tag{1}$$

where Y_{cst} is one of the outcomes of interest[5]. SYG_{cst} is an indicator variable that is equal to 1 if the SYG law is implemented in a county c (belonging to the state s that implemented the law), X_{cst} is a matrix of time-varying controls. We include the geographic fixed effects (i.e., state fixed effects), α_z, to capture time-invariant geographical unobservables, and the time fixed effects, γ_t, to account for unobserved time-specific confounders. The ϵ_{cst} is the error term.

On the other hand, the identification assumption relies on the fact that the adoption of the SYG law is uncorrelated with any prior trend in our outcomes of interest. Notably, the parallel trend assumption in that setting is weaker than assuming that the treatment is randomly assigned. Hence, testing the parallel trends assumption is crucial. Adopting time-varying estimates, we test the pre-trend imbalance in the Subsection 4.2.

[4]Data available at the Massachusetts Institute of Technology Election Data website.

[5]We adopt several dependent variables: homicide rate, violent crime rate, property crime rate, racial homicide rate, justifiable homicide rate, racial justifiable homicide rate, anti-black homicide rate, and hate crimes (and its subcategories).

4 Results

As we detailed earlier, implementing the SYG law aimed to reduce barriers to self-defense to deter criminal victimization further. To check the overall effect of the SYG law and to provide some context, we first examine the SYG implications on key crime statistics, including homicide rate, violent crime rate, and property crime rates. Table A.2 presents these estimates and finds non-significant results of the reform on the homicide rate. Concerning the violent and property crime rate, we find negative and significant coefficients in the baseline models; however, the inclusion of the control variables shows a non-significant impact on the SYG.

While these findings offer valuable insights into the effects of the SYG law, our primary focus lies in exploring specific dimensions that might not be fully captured by these general crime variables. To delve deeper into the potential consequences of the SYG law, we explore the following dimensions:

Firstly, we investigate the possibility of the extended Castle Doctrine having a racial or discriminatory impact. There is concern that SYG laws may be exploited to target racial minorities, potentially contributing to the propagation of hate crimes. Our initial analysis examines whether the SYG law has any effect on the racial homicide rate, defined as the rate of homicides committed by white individuals against non-white individuals. Columns (1) and (2) in Table A.3 report positive and statistically significant coefficients for the racial homicide rate variable. In other words, states that adopted the SYG law witnessed an increase of approximately one percent in the racial homicide rate.

Secondly, we delve into the concept of 'justifiable' homicide, which could arise due to escalated violence resulting from the SYG law, potentially increasing the likelihood of citizens reacting forcefully when faced with a felon. For this analysis, information related to the justifiable homicide rate is included as a dependent variable. In this analysis, the definition of justifiable is limited to the killing of a felon during the commission of a felony by a private citizen or a peace officer in the line of duty. The results are also presented in Table A.3 with coefficients that report a positive and significant impact of the SYG on justifiable homicide.

These findings lead us to dig deeper into the impact of SYG laws on justifiable homicides, particularly concerning race, as we previously found a positive effect of the implementation of the law on racial homicide rates. The variables addressing the racial justifiable homicide rate and the anti-black justifiable homicide rate are included now as dependent variables. In this analysis, we find positive and barely significant coefficients only after including control variables. Coherently, the shooting of Miguel Antonio DeJesus and Diego Ortiz in 2007[6] or

[6]Two months after Texas's stand your ground law took effect, a 61-year-old white man called law enforcement to report a burglary in his neighbors' house by what he said were two black men. Despite being instructed by law enforcement to stay in his home and wait until they arrived, the man approached the

Trayvon Martin in 2012[7] represent two anecdotal examples of the use of SYG to target racial minorities.

4.1 Additional Results: Hate Crimes

From the main results presented in Table A.2 we found that the crime rates and its subgroups, i.e., violent and property crime rates, are not affected by the implementation of the SYG law. Our intuition for this is that the main motivations for these types of crimes are highly influenced by the socioeconomic situation of the offenders (e.g., robbery, human trafficking, etc.). In this section, we focus on other motivations that might play a role in committing a crime by exploiting the figure of "justifiable" actions previously discussed. These motivations involve hate and discriminatory behavior. In this analysis hate crime is defined as a criminal offense committed against a person or property which is motivated by the offender's bias against a race, religion, disability, sexual orientation, ethnicity, or nationality of origin. This is also known as a bias crime.

This analysis expands its focus to three main outcome variables, i.e., hate crimes, racial hate crimes, and anti-black hate crimes. We report the results obtained in Table A.4 in the appendix. Estimates reveal a positive and significant impact of the SYG law on the three hate crime rate-related variables. We observe a notable and positive effect of the policy, with a comparable magnitude of around 5% for average hate crimes and racial hate crime rates. Even though the estimates for anti-black hate crime rates are still positive and statistically significant, the magnitude of the results is lower, meaning the policy implementation led to only a 2.5% increase in this specific type of crime.

These findings suggest that the implementation of the policy has had a notable influence on hate-motivated criminal behavior. Building on this understanding, we now turn our attention to a more nuanced examination of hate crimes. Specifically, we delve deeper into related offenses such as intimidation, simple assault, damage, and aggravated assault, all of which are intertwined with the complex dynamics of hate crimes. By investigating these additional variables, we aim to gain a comprehensive understanding of the broader impact of the SYG law on various facets of hate-motivated actions.

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suspects and shot them in the back as they fled, killing them both.

[7]In Sanford, Florida, United States, Trayvon Martin, a 17-year-old African-American, walked back to his relative's house. A neighborhood watch coordinator reported what he said was a "real suspicious Black guy" to 911. The 911 operator told the perpetrator not to chase after Martin, but he got out of his car and pursued Martin, who was unarmed, and after a physical altercation, shot Martin.

4.1.1 Intimidation

Intimidation is defined as unlawfully placing another person in reasonable fear of bodily harm through the use of threatening words and/or other conduct, but without displaying a weapon or subjecting the victim to an actual physical attack. These types of crimes are well-known among minorities who suffer from them. However, a problem that these types of offenses experience is under-reporting. People might suffer these types of offenses in a general or discriminatory way, but because these do not result in actual injuries, there is the possibility that they remain unreported. Usually, this is due to fear of retaliation, vengeance, or shame. If the no-duty to retreat gives the right of extreme reaction using deadly force, one might expect an increase in intimation hate crimes.

Table A.5 documents that possibility. The estimates are strongly significant for all dependent variable specifications, namely, intimidation hate crime rates, intimidation racial hate crime rates, and intimidation anti-black hate crime rates. The coefficients suggest an increase in the intimidation hate crime rate and subcategories after the SYG implementation. Interestingly, even if we consider the potential under-reporting issues, these results suggest precise results about the increase of intimidation as a tool for discrimination, ranging from 1.6% to about 4%, depending on the outcome variable specification.

4.1.2 Simple assault

Following the intimidation offenses, we focus now on simple assault as a subgroup of hate crimes. Simple assaults are all assaults or attempted assaults that are not of an aggravated nature and do not result in serious injury to the victim. A similar problem of under-reporting can happen with simple assault. People might suffer these types of offenses in a general or discriminatory way, but because these do not result in serious injuries, there is the possibility that they remain unreported. However, we consider that this problem is lower as these are still assaults.

Once we focus on the simple assault hate crime rates, Table A.6, confirms the increase of that specific category of hate crime following the SYG implementation in columns (1) and (2). Moreover, the coefficient is also positive and significant in the case of racial simple assault hate crime rate as a dependent variable. Lastly, we do not find a significant impact on the anti-black simple assault hate crime rate (see column (6)).

4.1.3 Damage

The third subgroup studied in this section relates to property damage. Damage offenses are defined as willfully or maliciously destroying, damaging, defacing, or otherwise injuring real or personal property without the owner's consent or the person who controls it. Including these kinds of offenses is also important as they are highly connected with discriminatory actions. An interesting issue regarding damage crime rates is also under-reporting. In this subgroup in a slightly different sense. It might be expected that personal property suffers damage but is not reported as people usually do not know who did it, or there is no proof to sustain these accusations.

Considering the damage hate crime rate, we find the Castle Doctrine extension's positive and significant impact (see Table A.7). The coefficient suggests that, after the SYG implementation, there is an increase of 2% in the damage hate crime rate. When we isolate the effects of hate crimes that only involve race, the coefficients remain significant with a magnitude of 1.5% (see columns (3) and (4)). Lastly, by just considering damage offenses only against black individuals, in this case, the coefficients are barely significant and decrease in magnitude. Under the three scenarios, it can be observed that there is an increase in the respective crimes after the period of treatment.

4.1.4 Aggravated assault

Lastly, we focus on the aggravated assault hate crime rates. The FBI's Uniform Crime Rates define this crime category as an unlawful attack by one person upon another to inflict severe bodily injury, commonly by the use of a weapon. Table A.8 reports thetwo-way fixed effect model specification estimates. Here, the coefficients are no longer statistically significant. These results are consistent with the conjecture that, assuming racial bias, one could legally react using self-defense after provoking a physical altercation (thus avoiding aggravated assault as the first action).

4.2 Robustness

In assessing the robustness of our findings, we not only test for parallel trends but also delve into the dynamics of the treatment effect, employing an event-study version of the Two-Way Fixed Effects (TWFE) model as outlined in equation 1. This approach is crucial for understanding the temporal nuances of the SYG law's impact:

$$Y_{cst} = \alpha_z + \gamma_t + \beta \times \sum_{k=-10}^{10} D_{k(cst)} + X_{cst} + \epsilon_{cst} \tag{2}$$

where Y_{cst} is one of our variables of interest and $D_{k(cst)}$ is a set of indicator variables equal to one if, for county group c (belonging to the state s) in year t the adoption of the law was k years away. As summarized in section 1, the SYG law deviates from the standard

DiD setup because it has more than two time periods and heterogeneity in treatment time. This means the model in equation 1 could lead to biased estimates. In a staggered *DiD* setting, the coefficient of interest is calculated as a weighted average of all possible (2x2) comparisons. Specifically, the two-way fixed effect model identifies weighted sums of the average treatment effects in each group and period, where the parameter β in equation 1 is a weighted sum of the treatment effect. Negative weights can occur because $\hat{\beta}$ is a weighted sum of *DiD* estimates that also compare not-yet-treated and already-treated units, leading to negative weights. For example, Sun and Abraham [2020] shows that in cases of variation in treatment across units, the regression coefficients are not robust to the heterogeneous or dynamic treatment effects across groups and time. Recent literature highlighted the issue ([Callaway and Sant'Anna, 2020], [de Chaisemartin and D'Haultfœuille, 2020a,b], [Sun and Abraham, 2020], [Athey and Imbens, 2021], [Goodman-Bacon, 2021]) and proposed several ways to deal with the problem.

To address this concern, we propose event study figures adopting several estimators that are robust to the treatment heterogeneity (Callaway and Sant'Anna [2020], de Chaisemartin and D'Haultfœuille [2020a], Sun and Abraham [2020]). Figure A.4 presents the event-study figures for the following dependent variables: racial homicide rate, justifiable homicide rate, racial justifiable rate, and anti-black justifiable homicide rate. Regardless of the specific estimator employed, the coefficients for the years preceding the introduction of SYG law consistently hover around zero, showing no noticeable pre-existing trends. Similarly, in Figure A.5, we plot the estimates for the hate crime, racial hate crime, and anti-black hate crime. Again, the pre-trend imbalance is negligible. Moreover, Figure A.5 highlights the dynamics of the treatment effects: all proposed estimators demonstrate a positive and increasing effect of the SYG adoption on the hate crimes rate and its subcategories.

Lastly, we propose the dynamic plots for the hate crime rate, racial hate crime rate, and anti-black hate crime rate for the subcategories that follow: intimidation crime rate(A.6); simple assault crime rate(A.7); and damage crime rate(A.8). Again, the event-study plots show that the estimates are consistent with the parallel trends assumption (independently of the estimator used). Moreover, our analysis extends beyond confirming the absence of pre-trends. The event-study figures elucidate the dynamic nature of the SYG law's effects, revealing a discernible increase in hate crimes and justifiable homicides and its different subgroups following its enactment. Such findings underscore the law's unintended consequences, challenging the premise that SYG laws universally enhance public safety.

The event-study estimates confirm that the pre-trend imbalance issue is negligible. Also, the robustness checks not only validate our analytical approach but also offer a comprehensive view of the SYG law's impact.

5 Discussion

Several mechanisms could be driving the results of an increase in the variety of hate crimes and justifiable racial homicides after the implementation of the SYG laws in the US. For example the implicit bias, perception, and response around threats. In these circumstances, implicit biases are unconscious attitudes or stereotypes that affect our perceptions, decisions, and actions. People may hold implicit biases based on race, ethnicity, religion, gender, or other social identities. These biases can influence how people perceive threats and respond to them. For example, a person may be more likely to perceive a member of a minority group as threatening, even if that person is not posing a threat [Sower et al., 2023]. Combining this with the fact that SYG laws remove the duty to retreat in self-defense situations can create a perception of greater danger and a need for immediate action. This can result in individuals feeling more justified in using deadly force, even if the perceived threat is not imminent or severe. Another relevant factor involved is that the SYG laws may also increase the availability and use of firearms in self-defense situations [Chakraborty et al., 2022]. This can escalate violent encounters and make it more likely that someone will be killed or injured. Additionally, SYG laws may lower the threshold for what individuals perceive as a legitimate use of force in self-defense, potentially leading to more confrontations escalating into violence.

Furthermore, hate and discrimination can be additional mechanisms that might influence the increase in hate crimes and justifiable racial homicides under SYG laws in the United States. In this case, additional discrimination might occur besides prejudice and stereotyping, which are forms of implicit bias. For example, institutional racism refers to how societal structures, policies, and practices perpetuate unequal treatment of different racial and ethnic groups [Mustard, 2001, Rehavi and Starr, 2014, Cohen and Yang, 2019, Topaz et al., 2023]. SYG laws may be more likely to be applied in ways that disproportionately affect members of marginalized groups, such as Black or Hispanic individuals. If SYG laws are applied inconsistently, with racial bias in legal proceedings, this could lead to an increase in racially motivated confrontations deemed justifiable. Additionally, SYG laws may make it more difficult to hold individuals accountable for their actions in self-defense situations. This can result in a lack of accountability for violence committed against members of marginalized groups, perpetuating a cycle of discrimination and violence. Furthermore, the SYG law might indirectly encourage racial profiling, where individuals or law enforcement officers may be more likely to view non-white individuals as potential threats. This could result in more confrontations that escalate into fatal encounters, contributing to the increased racial homicide rate.

An additional mechanism driving the results might be the role of legal precedents. For example, high-profile cases involving SYG defenses may set legal precedents that reinforce biases or suggest that using deadly force against racial minorities is more socially acceptable or legally justifiable. This could influence the behavior of individuals and potentially lead to an increase in racial homicides. Overall, the mechanisms driving the results are complex and diverse. Further research is needed to fully understand the impact of implementing these laws and their underlying mechanisms.

6 Conclusions

In recent years, over twenty states have expanded self-defense laws by adopting Stand Your Ground (SYG) policies, allowing lethal force in self-defense without the obligation to retreat, even in public spaces. Proponents argue that these laws deter crime by imposing higher risks on potential offenders. However, evidence from various incidents across the U.S. suggests that the broadened scope for using deadly force could escalate crime and non-negligent manslaughter rates [Cheng and Hoekstra, 2013].

Our study examines explicitly the unintended consequences of SYG laws. By analyzing the staggered adoption of the SYG law across different states, we initially assessed its impact on crime rates, including homicide, violent, and property crime. Contrary to the laws' intended purpose of crime deterrence, our findings do not find any significant impact on these crime rates following SYG's implementation. However, our research primarily sheds light on the subtler ramifications of this legislation, particularly its role in fostering discriminatory and biased crimes.

One key finding is the increase in racial homicide rates associated with SYG laws, pointing to a troubling trend where racial minorities are more likely to be victims of what is classified as justifiable homicide. Further analysis introduces a racial dimension to the study, examining race-specific variations in justifiable homicide rates. This analysis uncovers a concerning rise in homicides deemed justifiable that predominantly affect racial minorities.

Moreover, our research delves into hate crimes, defined here as crimes motivated by bias against race, religion, disability, sexual orientation, ethnicity, or national origin. The analysis reveals that SYG laws increase hate crimes and, more specifically, racial hate crimes. This pattern extends to various types of hate crimes, including intimidation, simple assault, and property damage, all of which show statistically significant increases post-SYG enactment. The notable exception is aggravated assault, where the data does not indicate a significant change. However, we suggest that the nature of SYG laws, which can shield actions under the label of self-defense, might obscure the fundamental dynamics of such assaults.

These findings challenge the intended benefits of SYG laws, casting doubt on their effectiveness in deterring crime. Instead, the evidence suggests that these laws may produce more harm than good, particularly by exacerbating racial tensions and potentially increasing discrimination against minorities. While our study introduces a novel causal inference approach to understanding the impact of SYG laws, it also underscores the need for further research. Future studies should aim to unravel the mechanisms behind these findings, offering deeper insights into the broader implications of SYG legislation.

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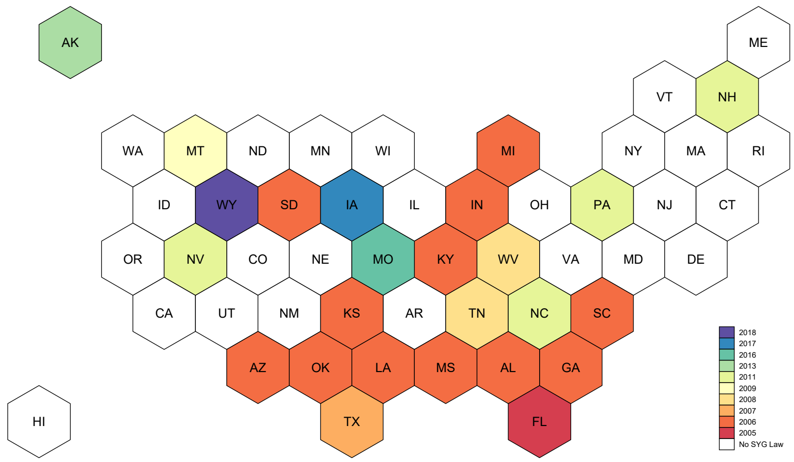
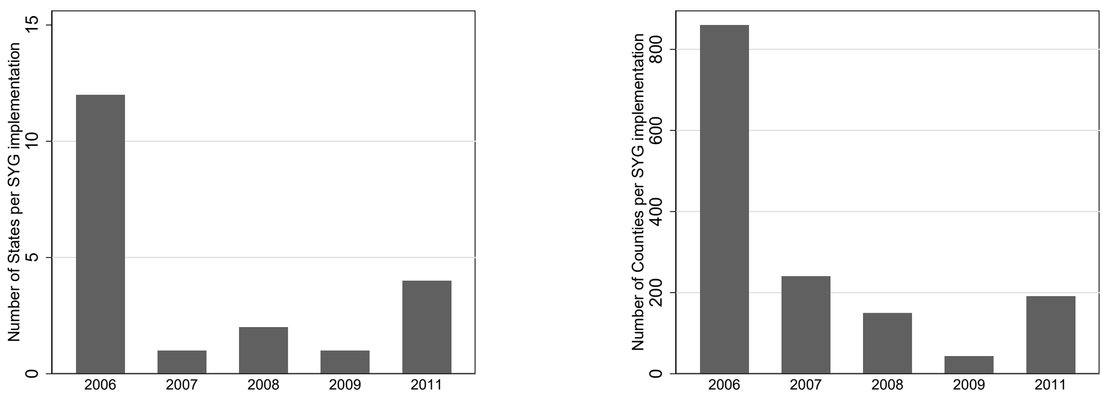
Appendix

Figure A.1: Stand-your-ground law implementation by state



Notes: The figure describes the year of implementation of the Stand-your-ground law in the U.S. for each state between 2000 and 2018.

Figure A.2: Number of States and Counties implementing the SYG law

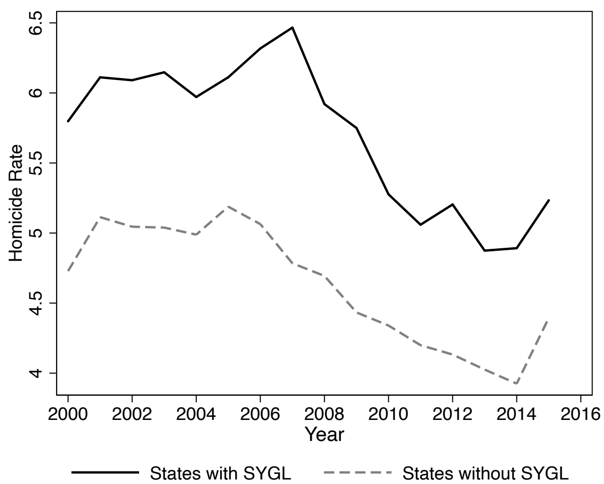


Panel A. States

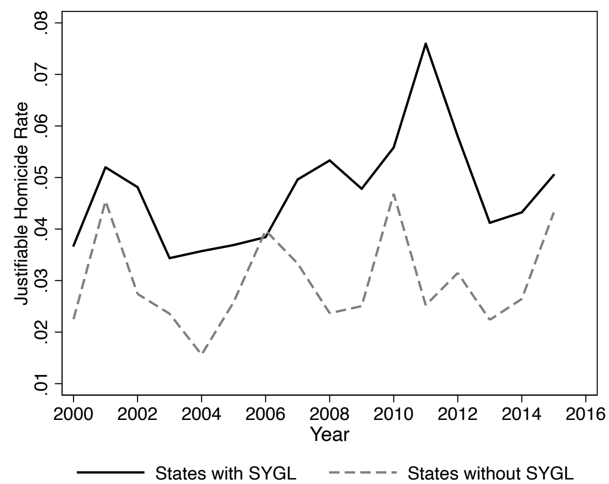
Panel B. Counties

Note: The bar graph displays the number of states that adopted the SYG law in a given year. The bar graph displays the number of counties in states that adopted the SYG law in a given year.

Figure A.3: Evolution of Homicide Rate in the U.S.



(a) Homicide Rate



(b) Justifiable Homicide Rate

Note: The graph reports the evolution of (a) homicide and (b) justifiable homicide rates in the U.S. between 2000 and 2015. Homicide rates are the number of homicides per 100,000 inhabitants.

Table A.1: Summary Statistics

	Mean	Min.	Max.	St.Dev.
Homicide rate per 100,000 population	3.23	0.00	233.64	6.16
Not white homicide rate per 100,000 population	0.15	0.00	83.19	1.03
Violent crime rate per 100,000 pop.	133.84	0.00	2299.41	112.01
Property crime rate per 100,000 pop.	418.92	0.00	2838.39	275.19
Justifiable homicide rate per 100,000 pop.	0.040	0.00	61.087	0.493
Justifiable racial homicide rate per 100,000 pop.	0.005	0.00	11.317	0.129
Justifiable anti-black homicide rate per 100,000 pop.	0.004	0.00	11.317	0.118
Hate crime rate per 100,000 pop.	1.45	0.00	365.76	4.72
Racial Hate crime rate per 100,000 pop.	0.78	0.00	152.72	2.74
Anti-black Hate crime rate per 100,000 pop.	0.50	0.00	152.72	1.99
Dummy republicans political preferences	0.77	0.00	1.00	0.42
Income per capita	31958.85	10254.00	2.0e+05	10070.60
Unemployment rate	6.47	1.10	29.40	2.74
Population	1.0e+05	403.00	1.0e+07	3.2e+05
Not white population	20773.28	2.00	2.9e+06	91637.23
Fraction of male in population	0.50	0.43	0.73	0.02
Gini index	0.60	0.52	0.71	0.03
High School Attendance	0.63	0.53	0.75	0.04
College Attendance	0.18	0.11	0.46	0.04
Observations	42528			

Table A.2: SYG policy, Homicide, Violent and Property Crime rates

	Homicide rate		Violent crime rate		Property crime rate	
	(1)	(2)	(3)	(4)	(5)	(6)
SYG Policy	-0.0145	-0.0001	-0.1010***	-0.0074	-0.0577***	0.0014
	(0.016)	(0.016)	(0.022)	(0.014)	(0.022)	(0.007)
Controls		Yes		Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
N	42528	42528	42528	42528	42528	42528
R^2	0.36	0.36	0.61	0.82	0.65	0.95

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Robust standard errors clustered at the county level in parenthesis. The dependent variables are log-transformed. Control variables include dummy for Republican political preferences (in the last presidential election), income per capita, unemployment rate, crime rate, non-white population, population, male population, high school attendance, college attendance, and Gini inequality index.

Table A.3: SYG policy, Racial and Justifiable Homicide rates

	Racial Homicide rate		Justifiable Homicide rate		Racial Justifiable Homicide rate		Anti-black Justifiable Homicide rate	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SYG Policy	0.0087*	0.0095**	0.0056**	0.0056**	0.0013	0.0015*	0.0013	0.0014*
	(0.005)	(0.005)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Controls		Yes		Yes		Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes		Yes	Yes	Yes		Yes
N	42528	42528	42528	42528	42528	42528	42528	42528
R^2	0.23	0.23	0.16	0.16	0.10	0.10	0.10	0.10

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Robust standard errors clustered at the county level in parenthesis. The dependent variables are log-transformed. Control variables include dummy for Republican political preferences (in the last presidential election), income per capita, unemployment rate, crime rate, non-white population, population, male population, high school attendance, college attendance, and Gini inequality index.

Table A.4: SYG policy and Hate Crime rates

	Hate crime rate		Racial hate crime rate		Anti-black hate crime rate	
	(1)	(2)	(3)	(4)	(5)	(6)
SYG Policy	0.059***	0.054***	0.051***	0.049***	0.025***	0.024**
	(0.015)	(0.015)	(0.011)	(0.012)	(0.009)	(0.010)
Controls		Yes		Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
N	42528	42528	42528	42528	42528	42528
R^2	0.43	0.43	0.36	0.36	0.34	0.34

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Robust standard errors clustered at the county level in parenthesis. The dependent variables are log-transformed. Control variables include dummy for Republican political preferences (in the last presidential election), income per capita, unemployment rate, crime rate, non-white population, population, male population, high school attendance, college attendance, and Gini inequality index.

Table A.5: SYG policy and Intimidation Hate Crime rates

	Intimidation Hate crime rate		Intimidation Racial hate crime rate		Intimidation Anti-black hate crime rate	
	(1)	(2)	(3)	(4)	(5)	(6)
SYG Policy	0.0397***	0.0346***	0.0279***	0.0249***	0.0163***	0.0156***
	(0.008)	(0.008)	(0.006)	(0.006)	(0.005)	(0.005)
Controls		Yes		Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
N	42528	42528	42528	42528	42528	42528
R^2	0.35	0.35	0.30	0.30	0.27	0.27

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Robust standard errors clustered at the county level in parenthesis. The dependent variables are log-transformed. Control variables include dummy for Republican political preferences (in the last presidential election), income per capita, unemployment rate, crime rate, non-white population, population, male population, high school attendance, college attendance, and Gini inequality index.

Table A.6: SYG policy and Simple Assault Hate Crime rates

	Simple Assault Hate crime rate		Simple Assault Racial hate crime rate		Simple Assault Anti-black hate crime rate	
	(1)	(2)	(3)	(4)	(5)	(6)
SYG Policy	0.0201**	0.0203**	0.0182***	0.0183***	0.0072*	0.0064
	(0.008)	(0.008)	(0.006)	(0.006)	(0.004)	(0.004)
Controls		Yes		Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
N	42528	42528	42528	42528	42528	42528
R^2	0.26	0.26	0.19	0.19	0.17	0.17

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Robust standard errors clustered at the county level in parenthesis. The dependent variables are log-transformed. Control variables include dummy for Republican political preferences (in the last presidential election), income per capita, unemployment rate, crime rate, non-white population, population, male population, high school attendance, college attendance, and Gini inequality index.

Table A.7: SYG policy and Damage Hate Crime rates

	Damage Hate crime rate		Damage Racial hate crime rate		Damage Anti-black hate crime rate	
	(1)	(2)	(3)	(4)	(5)	(6)
SYG Policy	0.0207**	0.0201**	0.0154**	0.0148**	0.0090*	0.0091*
	(0.008)	(0.009)	(0.006)	(0.006)	(0.005)	(0.005)
Controls		Yes		Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
N	42528	42528	42528	42528	42528	42528
R^2	0.35	0.35	0.27	0.27	0.24	0.24

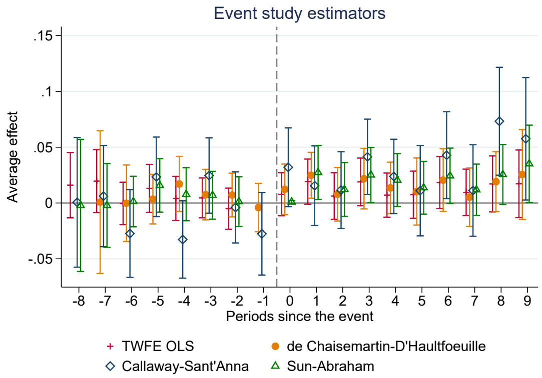
Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Robust standard errors clustered at the county level in parenthesis. The dependent variables are log-transformed. Control variables include dummy for Republican political preferences (in the last presidential election), income per capita, unemployment rate, crime rate, non-white population, population, male population, high school attendance, college attendance, and Gini inequality index.

Table A.8: SYG policy and Aggravated Assault Hate Crime rates

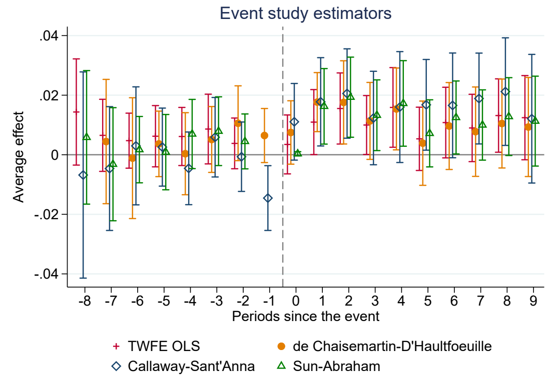
	Aggravated assault Hate crime rate		Aggravated assault Racial hate crime rate		Aggravated assault Anti-black hate crime rate	
	(1)	(2)	(3)	(4)	(5)	(6)
SYG Policy	0.0083	0.0092	0.0057	0.0069	0.0036	0.0043
	(0.005)	(0.006)	(0.004)	(0.004)	(0.003)	(0.003)
Controls		Yes		Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
N	42528	42528	42528	42528	42528	42528
R^2	0.18	0.18	0.14	0.14	0.12	0.12

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the county level in parenthesis. The dependent variables are log-transformed. Control variables include dummy for Republican political preferences (in the last presidential election), income per capita, unemployment rate, crime rate, non-white population, population, male population, high school attendance, college attendance, and Gini inequality index.

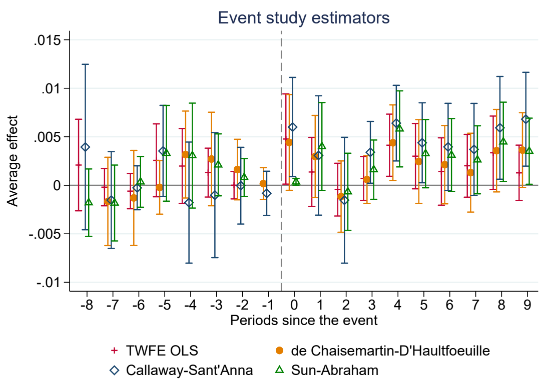
Figure A.4: Stand-your-ground, Racial and Justifiable Homicide rates: time-varying estimates



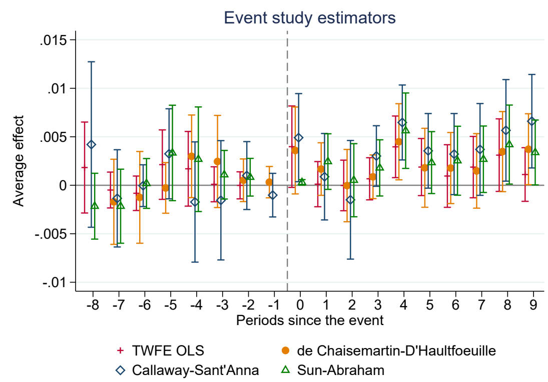
Panel A. Racial Homicide rate



Panel B. Justifiable Homicide rate



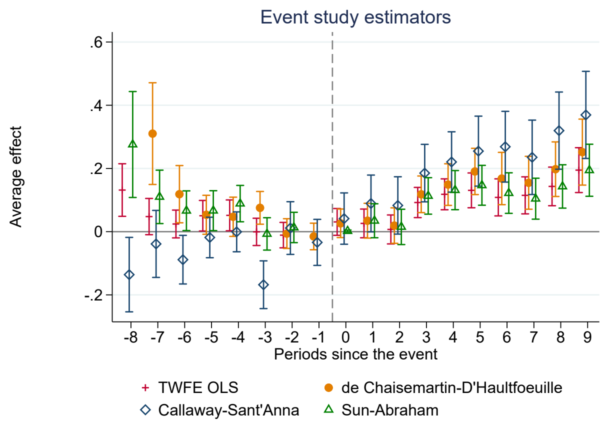
Panel C. Racial Justifiable Homicide rate



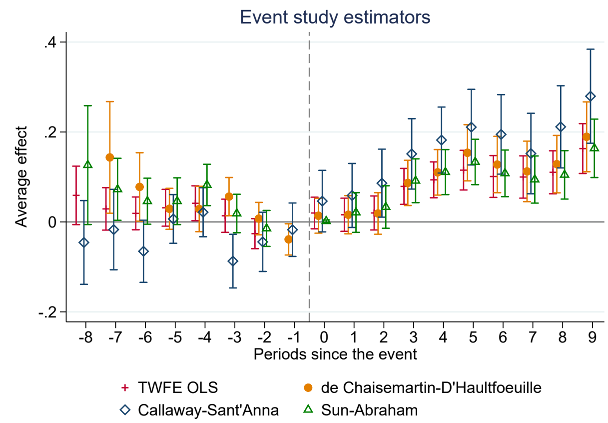
Panel D. Anti-black Justifiable Homicide rate

Notes: The graphs overlay the time-varying estimates of four estimators: a time-varying estimate of the TWFE model, equation 1 (in red with cross markers); de Chaisemartin and D'Haultfœuille [2020a] (in orange with circle markers); Callaway and Sant'Anna [2020] (in blue with diamond markers); Sun and Abraham [2020] (in green with triangle markers). The outcome variables (in log terms) are, respectively, the racial homicide rate, the justifiable homicide rate, the racial justifiable homicide rate, and the anti-black homicide rate. The estimates include the following control variables: dummy for Republican political preferences (last presidential election), income per capita, unemployment rate, crime rate, non-white population, population, male population, high school attendance, college attendance, and Gini inequality index. We also control for county FE and year FE. Vertical bars refer to the 95 percent confidence intervals. Standard errors are clustered at the state-county level.

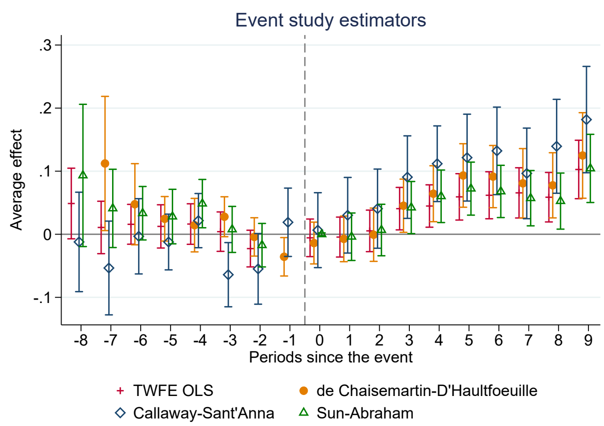
Figure A.5: Stand-your-ground and Hate crime rate: time-varying estimates



Panel A. Hate crime rate



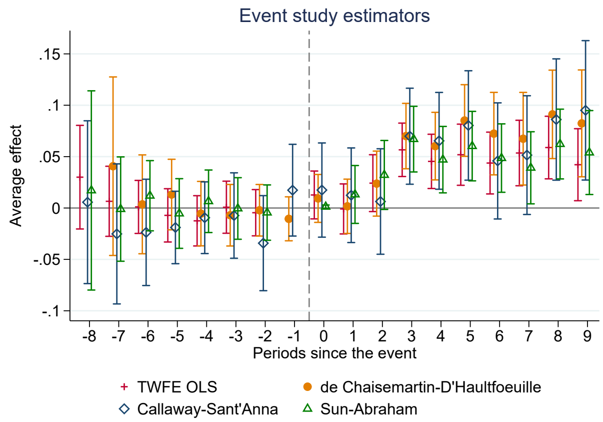
Panel B. Racial hate crime rate



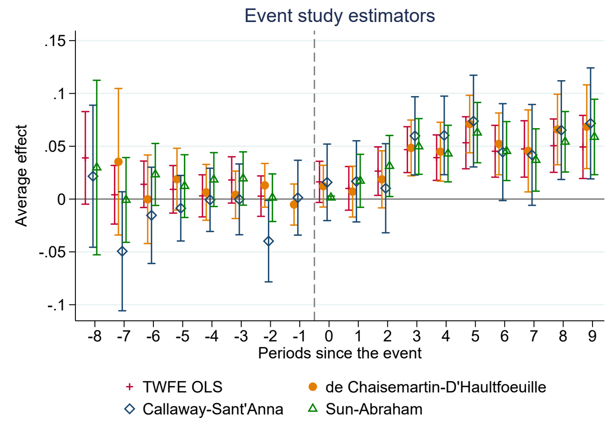
Panel C. Anti-black hate crime rate

Notes: The graphs overlay the time-varying estimates of four estimators: a time-varying estimate of the TWFE model, equation 1 (in red with cross markers); de Chaisemartin and D'Haultfœuille [2020a] (in orange with circle markers); Callaway and Sant'Anna [2020] (in blue with diamond markers); Sun and Abraham [2020] (in green with triangle markers). The outcome variables (in log terms) are, respectively, the hate crime rate, the racial hate crime rate, and the anti-black hate crime rate. The estimates include the following control variables: dummy for Republican political preferences (last presidential election), income per capita, unemployment rate, crime rate, non-white population, population, male population, high school attendance, college attendance, and Gini inequality index. We also control for county FE and year FE. Vertical bars refer to the 95 percent confidence intervals. Standard errors are clustered at the state-county level.

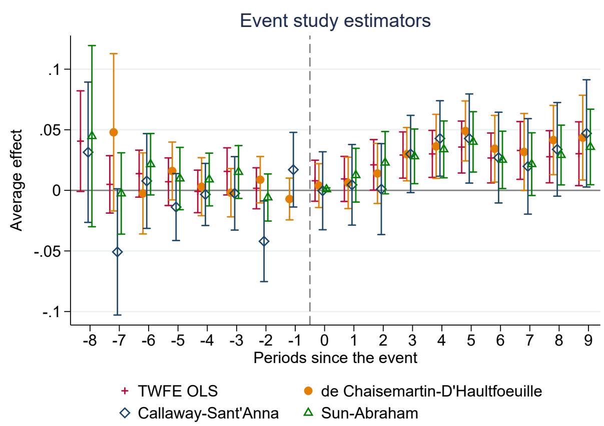
Figure A.6: Stand-your-ground and intimidation hate crime rate: time-varying estimates



Panel A. Intimidation hate crime rate



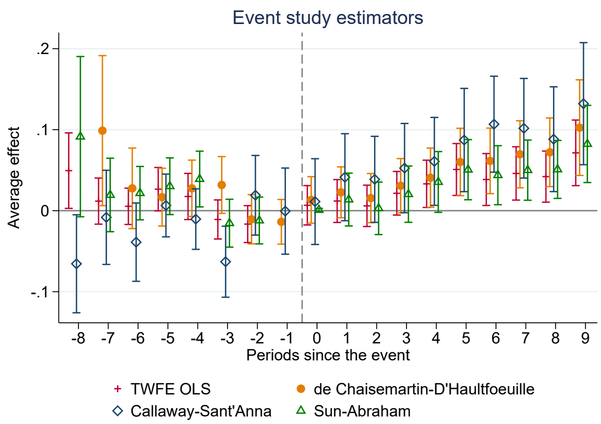
Panel B. Racial intimidation hate crime rate



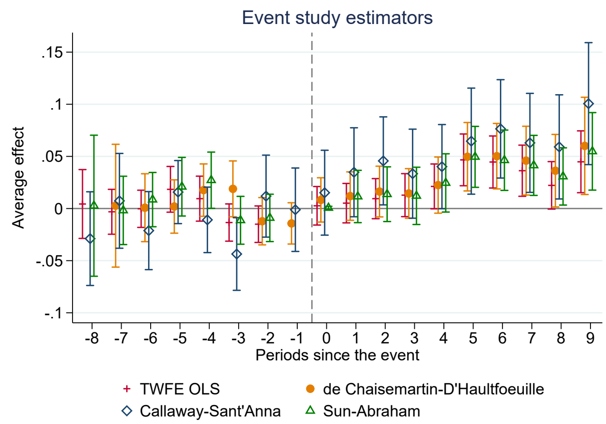
Panel C. Anti-black intimidation hate crime rate

Notes: The graphs overlay the time-varying estimates of four estimators: a time-varying estimate of the TWFE model, equation 1 (in red with cross markers); de Chaisemartin and D'Haultfœuille [2020a] (in orange with circle markers); Callaway and Sant'Anna [2020] (in blue with diamond markers); Sun and Abraham [2020] (in green with triangle markers). The outcome variables (in log terms) are, respectively, the intimidation hate crime rate, the racial intimidation hate crime rate, and the anti-black intimidation hate crime rate. The estimates include the following control variables: dummy for Republican political preferences (last presidential election), income per capita, unemployment rate, crime rate, non-white population, population, male population, high school attendance, college attendance, and Gini inequality index. We also control for county FE and year FE. Vertical bars refer to the 95 percent confidence intervals. Standard errors are clustered at the state-county level.

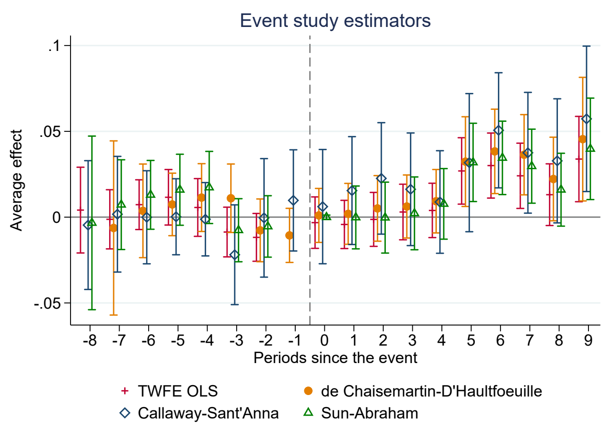
Figure A.7: Stand-your-ground and simple assault hate crime rate: time-varying estimates



Panel A. Simple assault hate crime rate



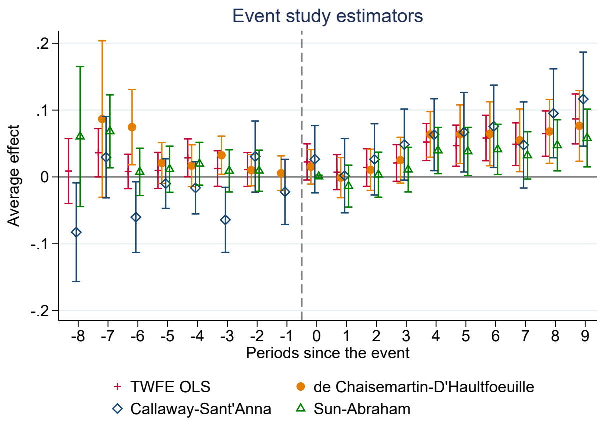
Panel B. Racial simple assault hate crime rate



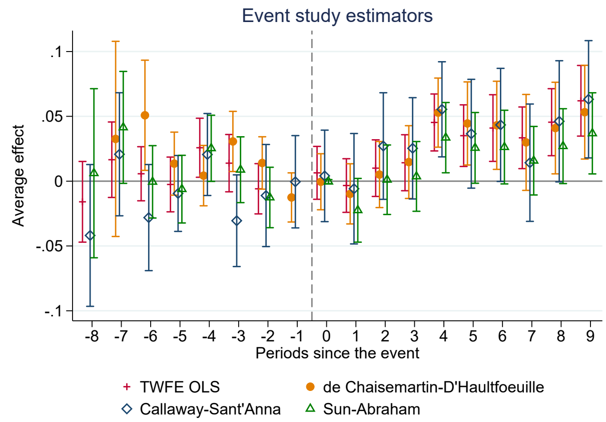
Panel C. Anti-black simple assault hate crime rate

Notes: The graphs overlay the time-varying estimates of four estimators: a time-varying estimate of the TWFE model, equation 1 (in red with cross markers); de Chaisemartin and D'Haultfœuille [2020a] (in orange with circle markers); Callaway and Sant'Anna [2020] (in blue with diamond markers); Sun and Abraham [2020] (in green with triangle markers). The outcome variables (in log terms) are, respectively, the simple assault hate crime rate, the racial simple assault hate crime rate, and the anti-black simple assault hate crime rate. The estimates include the following control variables: dummy for Republican political preferences (last presidential election), income per capita, unemployment rate, crime rate, non-white population, population, male population, high school attendance, college attendance, and Gini inequality index. We also control for county FE and year FE. Vertical bars refer to the 95 percent confidence intervals. Standard errors are clustered at the state-county level.

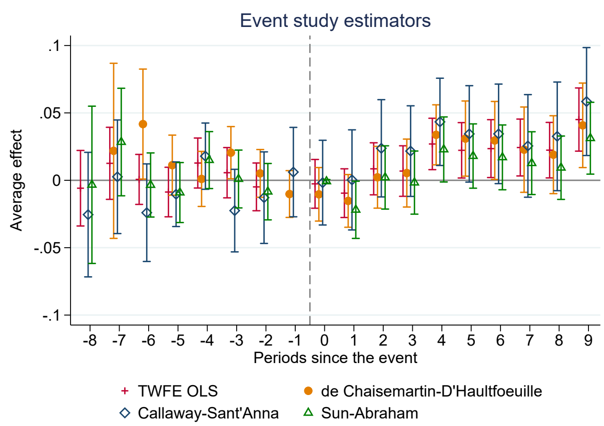
Figure A.8: Stand-your-ground and Damage Hate crime rate: time-varying estimates



Panel A. Damage hate crime rate



Panel B. Racial damage hate crime rate



Panel C. Anti-black damage hate crime rate

Notes: The graphs overlay the time-varying estimates of four estimators: a time-varying estimate of the TWFE model, equation 1 (in red with cross markers); de Chaisemartin and D'Haultfœuille [2020a] (in orange with circle markers); Callaway and Sant'Anna [2020] (in blue with diamond markers); Sun and Abraham [2020] (in green with triangle markers). The outcome variables (in log terms) are, respectively, the damage hate crime rate, the racial damage hate crime rate, and the anti-black damage hate crime rate. The estimates include the following control variables: dummy for Republican political preferences (last presidential election), income per capita, unemployment rate, crime rate, non-white population, population, male population, high school attendance, college attendance, and Gini inequality index. We also control for county FE and year FE. Vertical bars refer to the 95 percent confidence intervals. Standard errors are clustered at the state-county level.