

Racial Bias in “Stand Your Ground” Cases in Florida, 2006-2013

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Abstract

In the United States, “stand your ground” laws have been adopted by most states with the stated intention of empowering self-defense, yet an increasing chorus of critics argue that they effectively enforce white supremacy. Surprisingly, the only previous statistical research to consider the issue at the level of individual cases is a short analysis submitted in testimony to the US Senate by conservative gun advocate John Lott. Though Lott finds no evidence of racial bias, I show that John Lott’s study was fundamentally flawed and, using the same data, I find very robust evidence of racial bias in “stand your ground” cases in Florida from 2006-2013. In particular, I find that cases with a white victim are far more likely to end with conviction than cases in which the victim is a person of color, even after accounting for up to 16 other factors including weaponry, whether the victim initiated, whether the victim died, etc.. Further, when one considers the race of the defendant, the bias toward conviction in cases of white victims is significantly greater for defendants of color than for white defendants. Finally, while in general a key predictor of conviction is whether the victim initiated the altercation, the fact of victim-initiation is more likely to lead to conviction when the victim is a person of color.¹

In 2012, when George Zimmerman went to trial for the killing of Trayvon Martin, his defense invoked Florida’s “stand your ground” law. Although he was not granted immunity on the basis of “stand your ground”, his acquittal is seen by many as a grave miscarriage of justice, in which a black teenager’s life was undervalued by the criminal justice system.

“Stand your ground” laws, adopted by most US states, are laws which suggest that “an individual has no duty to retreat from any place they have lawful right to be and [may use any level of force, including lethal](#), if they reasonably believe they face an imminent and immediate threat of serious bodily harm or death.”

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As far as I know, **this article presents the first statistical evidence of race (and gender) bias in the enforcement of stand your ground laws at the level of individuals.** It is also the first investigation with completely reproducible code (publicly available [here](#)) and data (publicly available [here](#)).

1. There is surprisingly little evidence that “stand your ground” laws have much to do with self-defense.

2. The “stand your ground” defense has *nearly zero* probability of succeeding when the victim is white and the defendant is a person of color.

Remember that this is true after accounting for more than ten objective factors related to the crime. The Tampa Bay Times made a similar finding but since they did not use a statistical model they could not infer racial bias. As they admit, “The Times analysis does not prove that race caused the disparity between cases with black and white victims. Other factors may be at play.’ While no honest statistician ever uses the word “prove,” the findings presented here do allow us to infer that people of color who claim “stand your ground” against white people have, on average, nearly zero chance of winning. Although there is uncertainty around that estimate, the model shows that we can be statistically confident (at a 95% confidence level) that “stand your ground” defenses against white victims are more likely to fail than against non-white victims in otherwise equivalent cases. We can also be statistically confident (a 94% confidence level) that a white defendant is less likely to be convicted against a white victim than a non-white defendant is against a white victim.

Background and Literature Review

“Stand your ground” laws, adopted by most US states, are laws which suggest that “an individual has no duty to retreat from any place they have lawful right to be and [may use any level of force, including lethal](#), if they reasonably believe they face an imminent and immediate threat of serious bodily harm or death.”

“Stand your ground” laws are supposed to be about empowering people to defend themselves against aggressors, but many argue that they serve to protect a racial order of white supremacy.

Most famously, George Zimmerman claimed a “stand your ground” defense for the killing of Trayvon Martin.

The [Tampa Bay Times](#) has organized a wealth of information regarding every case in which someone from the state of Florida has claimed a “stand your ground” defense since 2006. The Tampa Bay Times wrote up several excellent analyses of their data, however, their analyses only look at descriptive cross-sections of the data. They explore the data interestingly and revealing, but simply describing how the data breaks down into different groups always leaves the analyst vulnerable to counter-explanations (for instance, the what if black people are just more violent?” retort). As the [Tampa Bay Times concedes](#):

As far as I know, the only other direct statistical test of racism in the enforcement of “stand your ground” laws is one statistical analysis by gun advocate John Lott submitted in testimony to the US Senate Judiciary Committee (John R Lott 2013). Using data collected by the Tampa Bay Times, Lott conducts two logistic regression analyses on the probability a defendant will be convicted when SYG is argued. On the basis of these two regression analysis, Lott submits that there is no evidence of racial bias in SYG cases. However, Lott’s statistical analysis is problematic in several important ways. The first problem is that the analysis does not provide any discussion of how the Tampa Bay Times data were pre-processed for analysis. As will become clear in the section below on Data and Method, organizing the Tampa Bay Times data for statistical analysis requires the analyst to make several non-trivial and non-obvious decisions. However, the analysis submitted in the US Senate testimony provides no such discussion. As only one example, the Tampa Bay Times provides several categories for the legal outcome of cases, including “conviction” but also “plea”, “acquittal”, “immunity”, etc. The distinction between what should be counted as “conviction” and “not conviction” is far from obvious and, as with all statistical analysis, requires reasoned argument and transparency from the analyst. Yet, Lott provides no discussion. Second, his models only include as many as 78 of the total 237 cases. Because there is no discussion of the data cleaning process, it is unclear why the analysis is conducted on less than one third of the total cases, but it leaves open the significant question of whether one might find different results if more cases were to be included. Third, both of his two regression models are overfit, with each one having at least one case completely determined by the predictors. Regression analysis

assumes that the dependent variable is a function of several predictors and some error term or, in other words, it assumes a systematic and stochastic component in the process that generated the dependent variable. Overfitting means that for some cases there is no error or stochastic component; it is a problem because it effectively means that some of the predictors in the model are interpreting error (noise) as a systematic association with predictors (signal). For this reason, overfit models are known to have poor predictive performance. Fourth, he does not include several variables recorded by the Tampa Bay Times which are plausible predictors of outcomes, such as gender and age of victims and defendants, the county in which the incident occurred, weapon used by defendant, or whether the victim died.

Most published academic studies of SYG laws have focused on the effect of SYG laws on homicide rates rather than possible racism in enforcement. For instance, Cheng and Hoekstra (2013) find that SYG laws fail to deter burglary, robbery, or assault but increase murder rates by about 8 percent on net. McClellan and Tekin (McClellan and Tekin 2012) also find that SYG laws lead to an increase of homicides but that the victims are disproportionately white males.

The only previous study which focuses on the effect of SYG laws on racial disparities in legal outcomes is one by Roman (2013), which uses data from the Federal Bureau of Investigations Supplementary Homicide Report to model the ruling of justified homicides. Roman reports robust evidence of racial bias, finding that, compared to white-on-white homicides, black-on-white homicides have about half the odds of being ruled justified and that this disparity is worse in states with SYG laws. (Roman 2013, 9) While Roman's findings appear robust, that study has two key limitations. The first is that the effect of SYG laws is only considered at the state level as a factor which shapes individual rulings of justifiable homicide. For this reason the analysis does not give us direct insight into the subset of cases which specifically involve SYG claims. The second shortcoming is that Roman is unable to control for important facts related to the specific cases. This is crucial because—as many conservative pundits argue and Roman rightly acknowledges—if white-on-black homicides are more likely to be legitimate cases of self-defense than black-on-white homicides, then racial disparity in rulings of justifiable homicide may not reflect racism but rather objective differences in crime rates across racial groups. Because the Tampa Bay Times data contains information on precisely such contextual factors, the present study allows

us to account for the claim that people of color are more likely to engage in violent crime.

Data and Methodology

To test for the possibility of racial bias in SYG cases, I gathered all the available data made available on the Tampa Bay Times website.² The final result was a data matrix of Z cases and Y variables. The data matrix contains indicators for all the following factors related to each case, with the names I assigned each variable in parentheses.

- Did the victim initiate the incident?
- Could the defendant retreat?
- Did the defendant pursue the victim?
- Did the incident take place on the defendant's property?
- Was the victim killed?
- How old was the victim and defendant?
- Was there physical evidence?
- Was there at least one witness?
- Was the victim committing a crime?
- Were the victim and defendant white or non-white (Black, Hispanic, or "other")?
- Were the victim and defendant female or male? (Transgender identities were not gauged)
- Which county did the incident occur in?
- Is there a time trend?

After scraping and wrangling the data from the Tampa Bay Times website, I conducted a series of what are called regression analyses to estimate which factors determine whether someone is convicted (the "stand your ground" defense fails) or not

²I began by downloading a spreadsheet made available by the Tampa Bay Times, which included a small subset of relevant variables. To supplement this spreadsheet with the other factors available only through the separate webpages for each individual case, I used Import.IO to crawl and scrape the webpage of each case automatically. I then merged, cleaned, and pre-processed the spreadsheet made available by the Times and the spreadsheet of scraped information.

convicted (the “stand your ground” defense succeeds). Regression analysis allows one to estimate the effect of many factors on some outcome, independent of (“controlling for”) all the other factors.

Below I present some key findings which estimate the effect of various factors on the probability that someone claiming “stand your ground” will be convicted.

To keep things simple, “convicted” refers to anyone who took a plea or was found guilty; “not convicted” refers to anyone who was acquitted, dismissed, granted immunity, or not charged.³

The reason why statistics are so valuable for complex phenomena such as legal outcomes is that they allow us to separate and estimate the different possible causes of something. *If* people of color are convicted more than white people simply because they commit more crimes or commit worse crimes, if we have data measuring race and the characteristics of crimes for large number of cases then we can look at a large number of cases and calculate how much crime and race are *independently* associated with an outcome after subtracting out the effect of the other.

In other words, if anyone says that my estimated effects aren’t real and that it’s only because some group is more likely to do/be more violent, more likely to be the attacker, or more likely to live in a poor county where crime in general is worse, you can say “No, these are the effects *after* subtracting whatever effect that correlation might have.”

Analysis

Conclusion

Cheng, Cheng, and Mark Hoekstra. 2013. “Does Strengthening Self-Defense Law Deter Crime or Escalate Violence? Evidence from Expansions to Castle Doctrine.” *Journal of Human Resources* 48 (3): 821–54.

³This is not perfect, especially because those who take pleas are not necessarily guilty. I considered dropping plea deals from the data but they are almost as frequent as guilty verdicts (33, and 40, respectively). So, for the present purposes it seems appropriate to consider pleas with guilty verdicts because the point is that pleas are likely driven by the expectation that someone would be found guilty. Of course, racial identity might shape whether someone fears they will be found guilty (innocent or not), but if that’s the case then that’s precisely why it is best to keep that information in the category of conviction.

Table 1:

	<i>Dependent variable:</i>	
	conviction	
	(1)	(2)
victim_initiatedVictim initiated	−2.933*** (0.745)	−2.357*** (0.539)
victim_crimeVictim was committing a crime	0.167 (0.904)	−0.258 (0.719)
victim_unarmedVictim clearly unarmed	1.116* (0.633)	0.592 (0.505)
defendant_pursuedDefendant pursued	−0.240 (0.640)	0.120 (0.501)
could_retreatDefendant could have retreated	1.711*** (0.661)	1.229** (0.516)
accused_weaponDefendant clearly had a gun	−1.656** (0.654)	−1.211** (0.495)
deaths	2.757*** (0.701)	1.390*** (0.484)
witnessClear witness(es)	−0.135 (0.613)	−0.111 (0.475)
physical_evidencePhysical evidence	−0.650 (0.552)	−0.645 (0.439)
defendant_propertyOn property of the defendant	−0.594 (0.633)	−0.743 (0.528)
victim_raceWhite victim	1.864** (0.733)	2.029 (1.745)
victim_genderMale victim	−0.655 (1.154)	1.203 (1.812)
victim_age	0.025 (0.022)	0.024 (0.018)
accused_raceWhite defendant	−1.359** (0.683)	0.185 (1.335)
accused_genderMale defendant	0.747 (0.878)	2.779 (1.836)
accused_age	−0.001 (0.020)	0.003 (0.017)
victim_raceWhite victim:accused_raceWhite defendant		−1.197 (1.088)
victim_genderMale victim:accused_genderMale defendant		−2.590

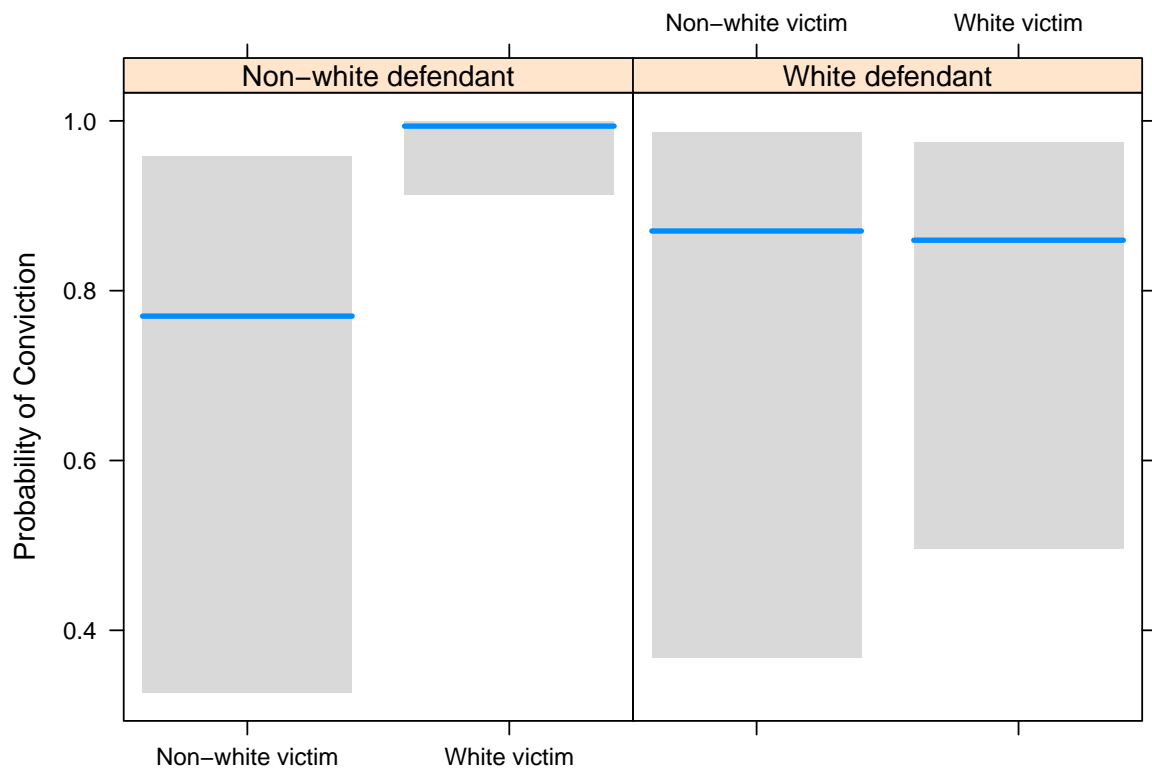


Figure 1: Effect of Victim's Race on Probability of Conviction for White and Non-White Defendants

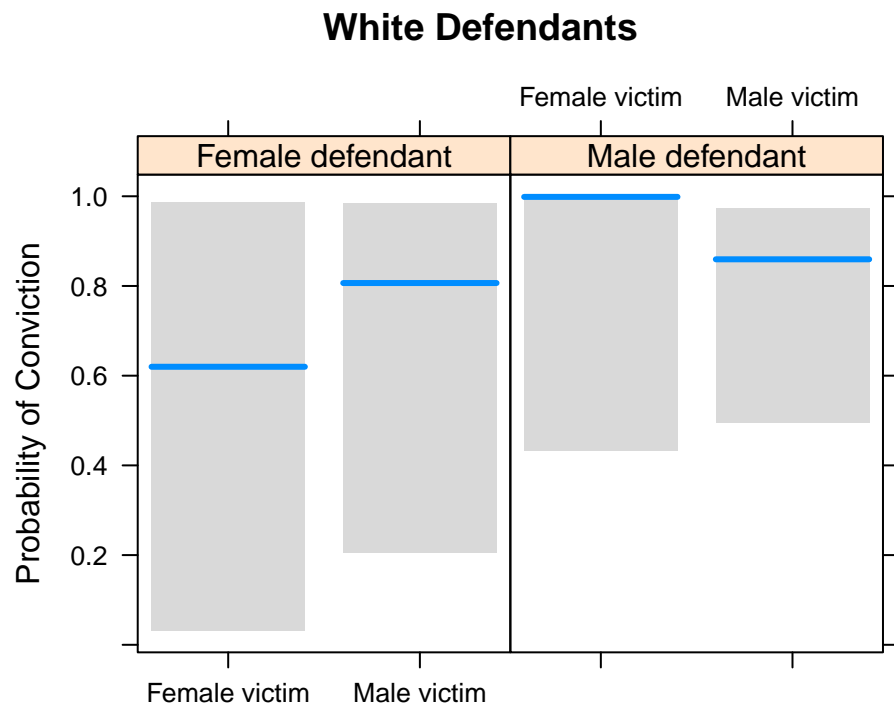


Figure 2: lskjdfklkj

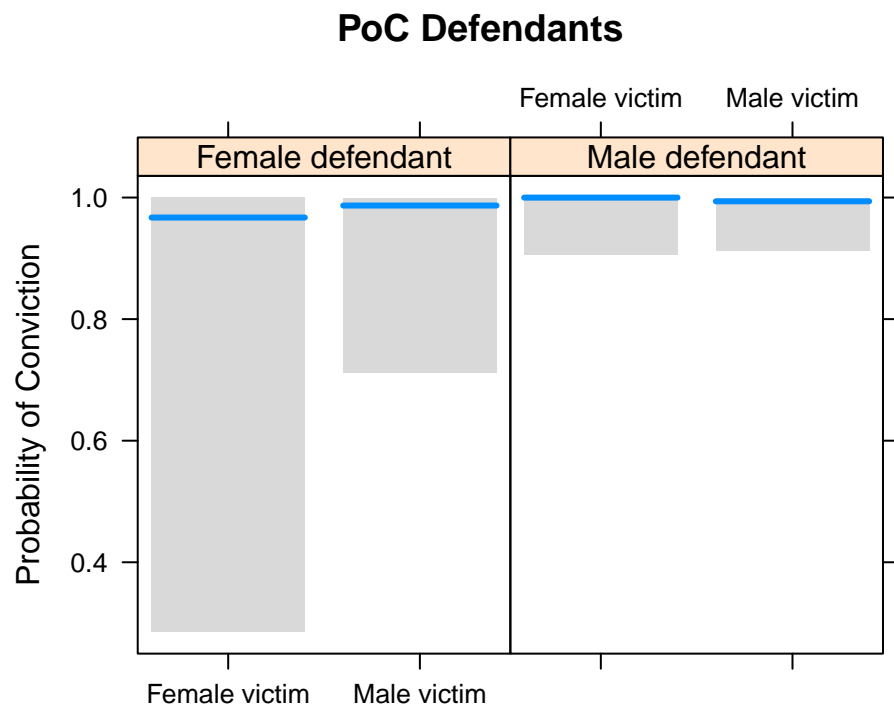


Figure 3: lskjsdfsdfflkj

John R Lott, Jr. 2013. "Testimony Before the Senate." In *Hearing on "'Stand Your Ground' Laws: Civil Rights and Public Safety Implications of the Expanded Use of Deadly Force*.

McCellan, Chandler, and Erdal Tekin. 2012. "Stand Your Ground Laws, Homicides, and Injuries." *NBER Working Paper*, June.

Roman, John K. 2013. "Race, Justifiable Homicide, and Stand Your Ground Laws: Analysis of FBI Supplementary Homicide Report Data."