Are “Stand Your Ground” Laws Racist and Sexist? A Statistical Analysis of Cases in Florida, 2005-2013

Abstract

Objective: I test for racial and gender bias in the enforcement of “stand your ground" (SYG) laws, controlling for potential confounders often invoked to reject claims of racism and sexism. Method: Regressions, simulations, and genetic matching are conducted using case-level data from 237 incidents in the US state of Florida between 2005 and 2013. Results: Controlling for potential confounders, the probability of conviction for a white defendant against a white victim is an estimated 90% with much error; for a black defendant it is nearly 100% with little error. For a male defendant in a domestic case, the probability is 40% whereas for a female defendant it is 80%. Conclusions: Enforcement of SYG laws appears biased against people of color in general and women specifically in the home. Policy implications are especially stark because these findings contradict recent research conducted for the US Senate.

“Stand your ground” (SYG) laws, which empower individuals to use any force necessary to defend themselves against anyone they believe to be an imminent threat, have become one of the most polarizing legal institutions in the United States. Supporters of SYG laws argue that they empower self-defense and deter crime (Lott 2013), however, a more critical view suggests that SYG laws enforce white supremacy over people of color and male supremacy over female domestic partners, as SYG laws appear more frequently to benefit white people relative to people of color (Hundley, Martin, and Humburg 2012; Martin, Hundley, and Humburg 2012) and to only infrequently benefit females (Carmon 2014) or female survivors of domestic violence in particular (Flatow 2014).

This article presents the first systematic statistical analysis of racial and gender bias in the outcome of SYG cases to control for a wide variety of contextual factors. The data is gathered from the *Tampa Bay Times* website, which reports information on 237 cases from the state of Florida in which an SYG defense was claimed. Two results from the analysis are notable. First, an SYG defense has *nearly zero* probability of succeeding when the victim is white and the defendant is a person of color. This finding remains true after accounting for more than ten objective factors related to the crime, suggesting that the racial disparity is not due to any commonly suspected objective factor correlated with race. Second, when attention is focused on domestic cases in particular, an SYG defense has a drastically lower likelihood of succeeding for female defendants relative to male defendants.

The article proceeds in five sections. The first section provides background on the controversy surrounding SYG laws and highlights the main findings of previous research, focusing on previous statistical analyses. The second section provides a detailed description of the data and modeling strategy used in this article. The subsequent section presents the main statistical findings, including two simulation exercises designed to shed light on two recent, high-visibility cases. The penultimate section assesses the robustness of the main findings and a final section concludes.

Background and Literature Review

"Stand your ground" laws, adopted by most US states, are laws which suggest that individuals have no duty to retreat from any place they have lawful right to be and may use any type of force to defend themselves, including lethal force, if they reasonably believe they face an imminent threat of bodily harm. Two recent legal cases dramatize the criticism of SYG laws. In the trial for the murder of black male teenager Trayvon Martin, George Zimmerman (an Hispanic male of 28 years) asked for immunity on SYG grounds. Although this request was not granted, George Zimmerman was acquitted by a jury and it has been shown that Florida's SYG laws helped Zimmerman's prospects throughout the legal process, from the initial police response to the wording of jury instructions (Coates 2013). On the other hand, Marissa Alexander (a 31-year-old black woman) was convicted of aggravated assault with a deadly weapon for shooting one warning shot to defend herself against her husband, despite her claims to self-defense under the same SYG laws which assisted George Zimmerman toward his acquittal.[1]

The *Tampa Bay Times* has organized several key facts regarding all the cases they could find in which someone from the state of Florida has claimed an SYG defense since 2005 ("Florida's Stand Your Ground Law" 2013). The *Tampa Bay Times* produced several analyses of their data, however, their analyses only look at descriptive cross-sections of the data. They explore the data revealingly, but because they do not control for other possible explanations their analyses remain vulnerable to many common, conservative retorts. In particular, it is commonly argued that bias in outcomes may be due to objective differences which are merely correlated with race, and that people of color are more likely to be convicted simply because they are more likely to engage in violent gun crime (Lott 2013). As the *Tampa Bay Times* must concede, "The *Times* analysis does not prove that race caused the disparity between cases with black and white victims. Other factors may be at play (Martin, Hundley, and Humburg 2012)."

The only previous statistical test of bias in the enforcement of SYG laws which sought to control for alternative explanations at the individual level was an analysis by gun advocate John Lott submitted in testimony to the US Senate Judiciary Committee (Lott 2013). Using the 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 analyses, 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

[1] Marissa Alexander originally appealed this verdict before ultimately accepting a plea deal.

“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 (2012) also find that SYG laws lead to an increase of homicides but that the victims are disproprtionately 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 control for several of the possibly non-racial reasons for this racial disparity.

Data and Methodoloy

To test for the possibility of racial and gender bias in SYG cases, I gathered and processed all the relevant data made available on the *Tampa Bay Times* website ("Florida's Stand Your Ground Law" 2013).[2] The final result is a data matrix of 175 observations. The data matrix contains indicators for all the following factors related to each case, as determined by the questions asked and answered by the *Tampa Bay Times*, with the names I assigned each variable in parentheses. Did the victim initiate the incident (*Victim Initiated*)? Could the defendant retreat (*Defendant Could Retreat*)? Did the defendant pursue the victim (*Defendant Pursued*)? Did the defendant have a gun (*Defendant Gun*)? Did the incident take

[2] I began by downloading a spreadsheet made available on the *Tampa Bay Times* website, which included only a small subset of the relevant variables included elsewhere on their website. 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. All of the raw data and the code necessary to reproduce the findings below are available in the replication archive.

place on the defendant's property (*Defendant's Property*)? Was the victim killed (*Deaths*)? How old was the victim and defendant (*Victim Age, Defendant Age*)? Was there physical evidence (*Physical Evidence*)?[3] Was there at least one witness (*Witness*)?[4] Was the victim committing a crime (*Victim Crime*)? Were the victim and defendant white or non-white (*Victim Race, Defendant Race*)?[5] Were the victim and defendant female or male (*Victim Male, Defendant Male*)?[6] Was the incident a domestic dispute (*Domestic*)? Which county did the incident occur in (*County*)? Is there a time trend (*Year*)? Table 1 and Table 2 display summary statistics for the complete set of 175 cases used in the analysis.[7]

[Insert Table 1 about here]

[Insert Table 2 about here]

For the present analysis, conviction refers to any case in which the defendant received a guilty verdict or took a plea deal; non-convictions refer to any case in which the defendant

[3]What constitutes physical evidence? While the *Tampa Bay Times* indicates for each case whether there was physical evidence, I was unable to find any further documentation of how this was defined. However, their short case descriptions shed light on what is meant by physical evidence. For an exemplary case in which the *Times* reports the presence of physical evidence, consider the case of defendant Michael McAdams. In 2009, McAdams "fatally shot his estranged wife and her lover after he found them together at the former family home," according to the *Tampa Bay Times*. "McAdams claimed self defense saying Andrews wanted to fight and his wife was hitting him when he fired. Forensic evidence ran counter to the details McAdams provided however and a jury found him guilty." Another example is the case of defendant Johnny Davis. According to the *Times*, in 2010, "Johnny Davis stabbed Robert Davis, an unrelated neighbor, when Robert and others intervened in an argument he was having with his mother. Johnny Davis claimed self-defense saying Robert came into his mobile home and hit him in the head with a broom handle. But police found blood and other evidence to dispute that version of events."

[4]Presence of a witness could plausibly increase or decrease the probability of conviction, depending on whether witness testimonies are systematically patterned in a way that shapes the probability of conviction. Of course it is possible witness testimonies in favor of defendants cancel out testimonies against defendants. The variable is included as a control variable to investigate the matter empirically.

[5]The decision to consider Black and Hispanic people together is imperfect and arguable, but seems to me justified by two concerns. First, this seems theoretically justified given that the concept of white supremacy suggests the primary racial distinction is between white and non-white groups. Second, considering that the analysis is already concerned with multiple interactions and the sample of data is not exceedingly large, considering Black and Hispanic people together simplifies an already complex analysis and saves limited degrees of freedom. Future research may explore whether disaggregating the race variables leads to different results.

[6]Transgender identities were not gauged.

[7]For summary statistics of the raw data describing the full 237 cases, see Supplementary Information.

was acquitted, dismissed, granted immunity, or not charged. The inclusion of plea deals with guilty verdicts is not ideal because those who take pleas are not necessarily guilty. I considered removing plea deals row-wise but, given that they are almost as frequent as guilty verdicts (33, and 40, respectively), it does not seem that the improvement of the measure would be so great as to outweigh the loss of information from row-wise deletion. Furthermore, including plea deals with guilty verdicts is theoretically sensible because pleas are likely driven by the expectation that the defendant would be found guilty if tried. Of course, racial identity might shape whether a defendant fears they will be found guilty (innocent or not), but if that is the case then that is precisely why it is best to keep that information in the category of conviction. Ultimately, although plea deals and guilty verdicts are different paths to conviction, they are equally well captured by the concept of conviction insofar as they are both outcomes in which the criminal justice system classifies the defendant as guilty.

Many variables included different categories to indicate uncertainty, such as "disputed", "unknown", or "unclear." In these cases, I adopted a principle of giving benefit of the doubt to the individual in question, counting any uncertainty noted by the *Tampa Bay Times* as not applying to the individual (whether victim or defendant). For instance, the variable *Witness* is coded such that, if there is not *clearly* at least one witness confirmed by the *Tampa Bay Times*, then it takes a value of "No clear witness(es)" and otherwise takes a value of "Clear witness(es)." Likewise, the variable *Victim Crime* takes a value of "Victim was committing a crime" in unambiguous cases but a value of "Victim was not clearly committing a crime" whenever the *Times* noted uncertainty.

After scraping, cleaning, and merging the data from the *Tampa Bay Times* website, I conducted a series of logistic regression analyses modeling the odds of conviction as a function of the independent variables listed above. Logistic regression analysis allows one to estimate the relationship between multiple independent variables on some dichotomous outcome.

Following in the spirit of "intersectional" perspectives on race and gender in critical legal research (Crenshaw 1991; Crenshaw 1989), I also consider the four possible interactions among the race and gender of defendants and victims (*White Victim X White Defendant*, *Male Victim X Male Defendant*, *White Victim X Male Victim*, *White Defendant X Male Defendant*). I then consider whether domestic cases may have different effects for male and female defendants (*Domestic X Male Defendant*), or for male and female victims (*Domestic X Male Victim*).

If previously perceived racial or gender bias is simply due to the fact that one racial group or gender commits more or worse crimes, or because one racial group or gender more often has to defend itself from certain types of crimes, then the coefficients related to race or gender should be statistically indistinguishable from zero while objective factors related to the incident should be statistically significant predictors of conviction (e.g., if the victim initiated the incident and was armed, this should be associated with a lower likelihood of conviction).

Analysis

Table 3 presents the results from three logistic regression analyses. Model 1 is a baseline model with all independent variables of interest included separately, whereas Models 2 and 3 introduce interaction terms to test whether race and gender condition the independent effects of certain primary variables. Each coefficient reflects the average change in log-odds of conviction associated with each corresponding independent variable. Specifically, each coefficient reflects the expected change in log-odds of conviction associated with the independent variable taking the value indicated by the variable's name, relative to the baseline category which is opposite the value indicated by the variable's name. Standard errors in parentheses reflect the statistical uncertainty of the coefficients. Starred coefficients are those which are very unlikely to be observed merely by chance, according to the conventional cutoff for statistical significance ($p<.05$). For instance, the coefficient for *Victim Initiated* in Model

1 suggests that, on average, a situation that the victim initiates has a log-odds of conviction 3.2 less than if the victim did not clearly initiate, assuming all the other independent variables are equal to their modal values. Because log-odds are not conveniently interpretable in terms of substantive effects, I postpone discussion of effect sizes until later in this section.

First, a series of objective factors related to the incident appear to have clear and intuitively sensible effects on the likelihood of conviction. Victim initiation has a statistically significant negative effect on the likelihood of conviction and is robust across all three models. On the other hand, also intuitively sensible, a clear ability for the defendant to retreat is associated with a greater likelihood of conviction in all three models. Death of the victim has a statistically significant and positive association with conviction. Defendants armed with a gun are less likely to be convicted, again to a statistically significant degree. This latter finding is interesting given that conservative critics sometimes suggest that racial disparities in outcomes are spurious evidence of racism because people of color may be more likely to use guns in violent crimes (Lott 2013), the assumption being that guns rather than colored skin tend toward convictions. Although it is purely speculative, one might hypothesize that the negative association between guns and conviction is due to the fact that other types of weapons (and unarmed assaults) require the defendant to engage in overtly active behavior toward the victim, whereas those armed with guns can assault a victim without obviously, actively moving toward the victim.

Several independent variables appear to have no relationship with the likelihood of conviction. It is interesting that, given SYG laws are often associated with the defense of homes, incidents taking place on the defendant's property do not appear any less likely to end in conviction. Witnesses and physical evidence also have no statistically distinguishable effects on the probability of conviction.

What do the models say about the key variables of interest, race and gender? In the baseline Model 1, white defendants appear to face a lower likelihood of conviction (compared to black defendants) and white victims appear to increase the likelihood of conviction (compared to black victims), at statistically significant levels, even after controlling for all of the objective factors considered already. However, if one considers how the race of both defendants and victims interact (Model 2), the race of the defendant per se does not appear to have any statistically distinguishable effect on the probability of conviction. However, crucially, Model 2 suggests that the extra likelihood of conviction in cases of white victims is greater for defendants of color compared to white defendants, also at a statistically significant level.[8] Model 2 also suggests that the extra likelihood of conviction in cases of white victims is greater for female relative to male victims, at a statistically significant level.[9]

The coefficients for *Domestic* in Models 1 and 2 suggest that in general, domestic disputes which involve SYG claims are less likely to result in conviction. But to test the claim that SYG laws are biased against women in cases of domestic violence (Flatow 2014), Model 3 introduces the interaction terms *Domestic X Male Defendant* and *Domestic X Male Victim* to identify whether the domesticity of an incident depends on the gender of the victim or defendant. The statistically significant and negative coefficient for *Domestic X Male Defendant* suggests that the tendency of defendants to escape conviction in domestic cases is greater for male defendants compared to female defendants. Furthermore, as evidenced by the coefficient for *Domestic* in Model 3, the effect of domesticity on conviction is statistically indistinguishable from zero when the defendant is female. The gender of the victim, however, has no statistically discernable conditioning effect on the relationship between domesticity and conviction.

Before assessing the size of these estimated effects, it should be noted that in addition

[8] The statistically significant coefficient of 9.90 for *Victim White* reflects the expected change in log odds of conviction for when the victim is white compared to when the victim is a person of color, *while* the defendant is a person of color. The negative and statistically significant coefficient for *White Victim X White Defendant* suggests that the coefficient of 9.9 associated with a white victim decreases by an average of 4.2 for white defendants. See below for more conveniently interpretable effect sizes.

[9] The negative and statistically significant coefficient for *White Victim X Male Victim* suggests that the coefficient of 9.9, associated with a white victim, decreases by an average of 6.0 for male victims relative to female victims.

to the interaction of race across defendant and victim, and the interaction of domesticity and gender, it has been argued that race and gender interact in complicated ways specifically within cases of domestic violence. Crenshaw highlights in particular that women of color relative to white women may be less likely to challenge domestic abuse through the legal system because the home may be seen as a "safe haven" with respect to racism in society, and/or to avoid negative stereotypes about black communities (Crenshaw 1991, 1257; Crenshaw 1989, 71). Unfortunately, separate analyses attempting to explore this additional layer of complexity were found to be uninformative due to the limited size of the present sample.[10] However, future research using additional or different data, or alternative modeling strategies may very well generate valuable insights which further refine the general findings presented here.

[Insert Figure 1 about here.]

Figure 1 illustrates the key estimate of interest from Model 2 in terms of probability. As the graph reveals, the probability of conviction for non-white defendants against white victims is higher, and shows a strikingly smaller margin of error at a 95% confidence level, than for white defendants in otherwise equivalent cases. In other words, white defendants against white victims have, on average, about a 90% chance of conviction, but nonetheless there is a non-trivial subset of such defendants who are more likely to escape conviction than to be convicted; whereas, for non-white defendants in otherwise equivalent cases, there are no cases which are more likely to escape conviction than be to be convicted. As Model 2 reveals, this difference is substantial enough that there is less than a 5% probability we would observe this difference due to random chance alone.

[Insert Figure 2 about here.]

[10] Specifically, following in the spirit of Crenshaw's arguments, I considered four variations of Model 3, focusing on the domesticity-gender interaction for cases of white victims only and for cases of non-white victims only. With only 68 cases of non-white victims, full models similar to those reported in Table 3 lead to overfitting. Removing some independent variables could avoid overfitting but is typically a bad strategy because it increases the risk of omitted variable bias and introduces arbitrariness. In the absence of expert, *a priori* knowledge regarding the true data generating process, I judged it not worthwhile to examine these additional layers of complexity given the present data.

Figure 2 illustrates the key estimate of interest from Model 3 in terms of probability. As the graph indicates, male defendants in domestic cases are less likely to be convicted than female defendants in otherwise equivalent domestic cases. With respect to domestic cases, the gender bias is even more pronounced than the racial bias indicated in Figure 2. In otherwise comparable cases, the probability of conviction for male defendants is less than 40% whereas the probability of conviction for female defendants is greater than 80%.

How do these statistical findings speak to the justice of past and future legal cases? With caution, the analyses presented here can be used to consider how legal outcomes would be expected to change, on average, given different racial and gender identities for defendants and victims. To make the findings more substantively interpretable in light of publicly well-known cases, I consider two counterfactual questions. First, how would George Zimmerman's probability of conviction change had Trayvon Martin been white but all the other objective factors of the case had been the same as they were? Second, with respect to Marissa Alexendar's currently on-going appeal against her previous conviction, how would her probability of conviction change had she been a male defendant in an otherwise equivalent case?

To consider the case of George Zimmerman, I conducted 1000 simulations of Model 2 to estimate the probability distribution of conviction in a 2012 case where the defendant is non-white, the defendant is 28 years old, the victim is non-white, the victim is 17 years old, the victim died, the defendant clearly had a gun, the victim was clearly unarmed, the victim was not clearly committing a crime, the defendant actively pursued the victim, the defendant could have retreated, the defendant was not clearly on their own property, the victim did not clearly initiate, there were no clear witnesses, the defendant and victim were both male, and they were engaged in a non-domestic incident. Based on the results of the simulation, it is estimated that George Zimmerman's *ex ante* probability of conviction was 0.69 (sd = 0.21). In other words, according to Model 2, *ex ante* George Zimmerman was more likely to be convicted than not, but with a notable margin of error which made his odds not clearly very much better than those of a coin flip. In a hypothetical case in which all of these factors are exactly the same except the victim is white, the expected probability of conviction is 0.98 (sd = 0.05). In summary, had Trayvon Martin been white, George Zimmerman's *ex ante* probability of conviction would have changed by an average of 0.29 (sd=0.19).

To consider the case of Marissa Alexander, I conducted 1000 simulations of Model 3 to estimate the probability distribution of a defendant being convicted in a 2010 case where the defendant is non-white, the defendant is 31 years old, the victim is non-white, the victim is 34 years old, the victim did not die, the defendant clearly had a gun, the victim was clearly unarmed, the victim was not clearly committing a crime, the defendant did not clearly pursue the victim, the defendant could have retreated, the defendant was not clearly on their own property, the victim did not clearly initiate, there was at least one clear witness, and a female defendant and male victim were engaged in a domestic incident. Based on the results of this exercise, the *ex ante* expected probability of conviction for Marissa Alexander given the objective facts of her case was an estimated 0.55 (sd = 0.28). In other words, according to Model 3, *ex ante* Michelle Alexander was marginally more likely to be convicted than not but with a margin of error which made her odds statistically indistinguishable from those of a coin flip. In a hypothetical case in which all of these factors are exactly the same except the defendant is male, the expected probability of conviction becomes 0.14 (sd = 0.14). In summary, had Marissa Alexander been male, her *ex ante* probability of conviction would have changed by an average of -0.42 (sd=0.27).

Robustness

One common problem in regression analysis is that it is possible for unrepresentative cases to disproportionately drive model results. As the partial residuals in the effect plots above reveal some noticeable outliers, I calculate Bonferonni-adjusted p-values for the largest Studentized residuals in each model using normal distribution tests. In both models, the largest Studentized residual is not statistically significant, suggesting that the estimates above are unlikely to be artifacts of a few odd cases.[11]

A more complicated problem for drawing statistical inferences from observational data is the possibility that the units of analysis are distributed into the different values of an independent variable by other covariates. If some covariate systematically shapes the probability a unit will take a certain value on the independent variable of interest, estimates for that independent variable will be biased. To guard against this problem, I use a genetic matching search algorithm to automatically create a subset of the original sample which is optimally balanced on the other covariates (Diamond and Sekhon 2012; Sekhon 2011). The algorithm identifies the weights which need to be applied to each covariate (including scores for the propensity to be "treated") to limit the sample to those matched pairs of treatment and control units which optimize balance on the covariates. From these subsets of cases the estimated average treatment effect will approximate that which would be inferred from a randomized experiment, assuming of course that all relevant covariates have been included in the matching procedures.

Given that the main hypotheses relate to interaction terms, I conduct the matching procedures only on relevant subsets of the initial sample. For Model 2, the relevant subset includes only cases with white victims and the "treatment" effect to be estimated is the defendant being a person of color. For Model 3, the relevant subset includes only domestic cases and the "treatment" effect to be estimated is the defendant being female.

Before proceeding, note that a drawback of matching techniques is the significant loss of information that occurrs in the reduction of an initial sample to only matched pairs. In the present case, this sample attrition is especially severe for two reasons. First, the original sample of 175 cases is already small relative to the large number of covariates including interaction terms. Second, limiting the matching analysis to subsets in order to

[11]For the sake of brevity numerical results are not reported but are reproducible from the replication archive.

straightforwardly estimate treatment effects for interactive hypotheses reduces the original sample to 106 cases of white victims and 31 domestic cases. For Model 2, the matching procedures reduce the subset of white-victim cases to a subset of 18 matched observations and for Model 3 the subset of domestic cases is reduced to 8 matched observations.

Despite the drastic loss of information, matching estimates for both models are sized consistently with the estimates in the main regression models and statistically significant. For Model 2, the average treatment effect from being a defendant of color (in cases with white victims) is 0.26 (standard error = 0.12, p = 0.03). Note that this is a different effect than that which was estimated in the thought experiment related to the Trayvon Martin case. There it was asked what the expected effect would have been had Trayvon Martin been white (varying the race of the victim), whereas the matching estimates relate to the effect of being a defendant of color in a case with a white victim (varying the race of the defendant). Nonetheless the matching estimate of 0.26 appears consistent with the estimate from Model 2 (about .1) given that the difference between white defendants and defendants of color in Model 2 was compressed by the relatively high rate of conviction for all defendants in cases with white victims. Thus considering only matched pairs in only cases with white victims corroborates the results of Model 2, suggesting that, if anything, the estimated racial effect from Model 2 was biased downward.

For Model 3, the average treatment effect from being a female defendant (in domestic cases) is 0.62 (standard error = 0.21, p = 0.003). Here the matching estimate can be directly compared to the thought experiment relating to the case of Marissa Alexander. The estimated effect after matching is similar to that derived from Model 3 reported above, from which it was estimated that had Marissa Alexander been male her probability of conviction would have changed by -0.42 (sd=0.27). Again the matching estimate suggests that, if anything, the estimated gender effect from Model 3 is conservative.

Thus, it is unlikely the estimates presented here are merely artifacts of outliers or of imbalance in the propensity to be in one of the relevant treatment groups. The consistency of the effect sizes and their statistical significance in all cases increases confidence in both of the key findings.

Conclusion

Though many critics argue that "stand your ground" (SYG) laws are characterized by racism and sexism in their outcomes, almost all research on this question has been unable to control for a wide variety of other factors which defenders of SYG laws commonly invoke to explain away the implication of racial or gender bias. The critique of SYG laws has remained vulnerable to the conservative defense that SYG laws are not, but only seem to be, racist or sexist because certain racial or gender types are more or less likely to be involved in certain types of cases which are objectively more or less likely to end in legitimate convictions. Indeed, the only previous statistical analysis which sought to control for a wide variety of objective factors concluded precisely that there is no racial bias in the outcome of SYG cases after controlling for other objective factors relevant to each case (Lott 2013).

This article provides the first properly documented and systematic, article-length statistical analysis of racial and gender bias in SYG cases which controls for a wide variety of objective factors possibly correlated with race and/or gender. In stark contrast to John Lott's analysis submitted in testimony to the US Senate Judiciary Committee, I find evidence of both racial and gender bias in a sample of Florida SYG cases from 2005-2013 reported by the *Tampa Bay Times* ("Florida's Stand Your Ground Law" 2013).

In particular, the probability of conviction for a white defendant against a white victim in a typical case was found to be high at 90% (though with a relatively large margin of error) but the probability of conviction for a black defendant in an otherwise objectively equivalent case was found to approach 100% (with a relatively small margin of error). The gender bias in domestic cases appears to be even more pronounced. Conviction for a male defendant in a typical domestic case was found to be about 40%, but for a female defendant in an otherwise objectively equivalent case, the probability of conviction was found to be around 80%.

To put the findings in perspective, I also used simulations to consider how the probability of conviction would change in response to changes in racial and gender identities in two well-known and recent cases. In the case of George Zimmerman's killing of unarmed black teenager Trayvon Martin in 2012, I found that if Trayvon Martin had been white the probability of a conviction would have increased by an estimated 0.29, from 0.69 to 0.98. With respect to the case of Marissa Alexander's warning shot against husband Rico Gray in a 2010 domestic dispute, I found that if Alexander had been a male the probability of a conviction would have decreased by an estimated 0.42, from 0.55 to 0.14. This statistical exercise is especially concerning for Michelle Alexander's case because it reveals that she is not only more likely to be convicted than a man would, but that *ex ante* her most likely outcome is qualitatively different than a man's would be in an equivalent case: Alexander was altogether more likely to be convicted than not, whereas a man in an objectively equivalent case would not simply be less likely to be convicted but would also be altogether more likely to go free than be convicted. Thus, the statistical analysis presented here indicates an alarmingly high probability that Marissa Alexander's initial conviction (currently under appeal) was an artifact of institutionalized sexism (i.e. patriarchy).

In summary, the analysis presented here provides striking evidence of both racial and gender bias in the outcomes of Florida cases between 2005-2013 in which "stand your ground" laws are invoked. It reveals fundamental flaws in a previous analysis submitted in testimony to the US Senate Judiciary Committee (Lott 2013) and finds unreliable its conclusions of no racial bias. Finally, this article informs important public debate about the possibility of racism and sexism in the application of SYG laws, suggesting that lawmakers and judges have paid inadequate heed to the racial and gender implications of "stand your ground" laws.

Table 1: Summary Statistics for Numerical Variables

Variable	**n**	**Min**	$\widetilde{\mathbf{x}}$	$\bar{\mathbf{x}}$	**Max**	**s**
Victim Age	175	15	30	32.1	79	12.8
Defendant Age	175	14	35	37.1	81	14.6
Year	175	2005	2009	2009.1	2013	2.0

Table 2: Summary Statistics for Categorical Variables

Variable	**Levels**	**n**	%
Victim Initiated	Victim did not clearly initiate	96	54.9
	Victim initiated	79	45.1
Victim Crime	Victim was not clearly committing a crime	137	78.3
	Victim was committing a crime	38	21.7
Victim Unarmed	Victim not clearly unarmed	50	28.6
	Victim clearly unarmed	125	71.4
Defendant Pursued	Defendant did not clearly pursue	126	72.0
	Defendant pursued	49	28.0
Defendant Could Retreat	Defendant could not clearly have retreated	72	41.1
	Defendant could have retreated	103	58.9
Defendant Gun	Defendant did not clearly have a gun	63	36.0
	Defendant clearly had a gun	112	64.0
Deaths	Victim was not killed	75	42.9
	Victim was killed	100	57.1
Witness	No clear witness(es)	63	36.0
	Clear witness(es)	112	64.0
Physical Evidence	No clear physical evidence	80	45.7
	Physical evidence	95	54.3
Defendant's Property	Not clearly on property of the defendant	117	66.9
	On property of the defendant	58	33.1
Domestic	Non-domestic	144	82.3
	Domestic	31	17.7
Victim Race	Non-white victim	69	39.4
	White victim	106	60.6
Victim Gender	Female victim	9	5.1
	Male victim	166	94.9
Defendant Race	Non-white defendant	65	37.1
	White defendant	110	62.9
Defendant Gender	Female defendant	20	11.4
	Male defendant	155	88.6

Note: Due to space constraints, the variable *County* is omitted.

Table 3: Logistic Regressions for Dependent Variable *Conviction*

	Model 1	**Model 2**	**Model 3**
Victim Initiated	−3.20***	−3.30***	−3.60***
	(0.79)	(0.85)	(0.86)
Victim Crime	−0.44	−1.20	−0.14
	(0.98)	(1.10)	(1.00)
Victim Unarmed	0.83	1.50*	0.70
	(0.64)	(0.77)	(0.66)
Defendant Pursued	−0.29	−0.33	−0.50
	(0.67)	(0.72)	(0.71)
Defendant Could Retreat	1.70**	2.00***	1.90***
	(0.69)	(0.74)	(0.73)
Defendant Gun	−1.80***	−1.90***	−2.10***
	(0.68)	(0.74)	(0.75)
Deaths	2.60***	2.70***	2.90***
	(0.71)	(0.79)	(0.77)
Witness	−0.32	−0.12	−0.20
	(0.63)	(0.71)	(0.67)
Physical Evidence	−0.95	−0.96	−0.96
	(0.60)	(0.63)	(0.61)
Defendant's Property	−0.13	0.36	−0.25
	(0.71)	(0.81)	(0.74)
Domestic	−1.70*	−2.40**	3.90
	(0.88)	(1.00)	(3.00)
Victim White	2.10***	9.90**	1.80**
	(0.77)	(3.90)	(0.78)
Victim Male	−1.40	4.50	−1.40
	(1.30)	(3.80)	(2.00)
Victim Age	0.02	0.04	0.02
	(0.02)	(0.03)	(0.02)
Defendant White	−1.90**	−0.13	−1.90**
	(0.78)	(1.90)	(0.81)
Defendant Male	0.17	5.50	1.60
	(0.94)	(4.10)	(1.40)
Defendant Age	0.001	−0.01	0.002
	(0.02)	(0.02)	(0.02)
White Victim X White Defendant		−4.20**	
		(1.80)	
Male Victim X Male Defendant		−6.10	
		(4.00)	
White Victim X Male Victim		−6.00*	
		(3.50)	
White Defendant X Male Defendant		0.53	
		(1.80)	
Domestic X Male Defendant			−4.30**
			(2.10)
Domestic X Male Victim			−2.60
			(2.90)
N	175	175	175
Log Likelihood	-58.00	-52.00	-55.00
AIC	208.00	204.00	206.00

***p < .01; **p < .05; *p < .1
County and Year variables included in the models but not displayed. Robust (Huber-White) standard errors in parentheses.

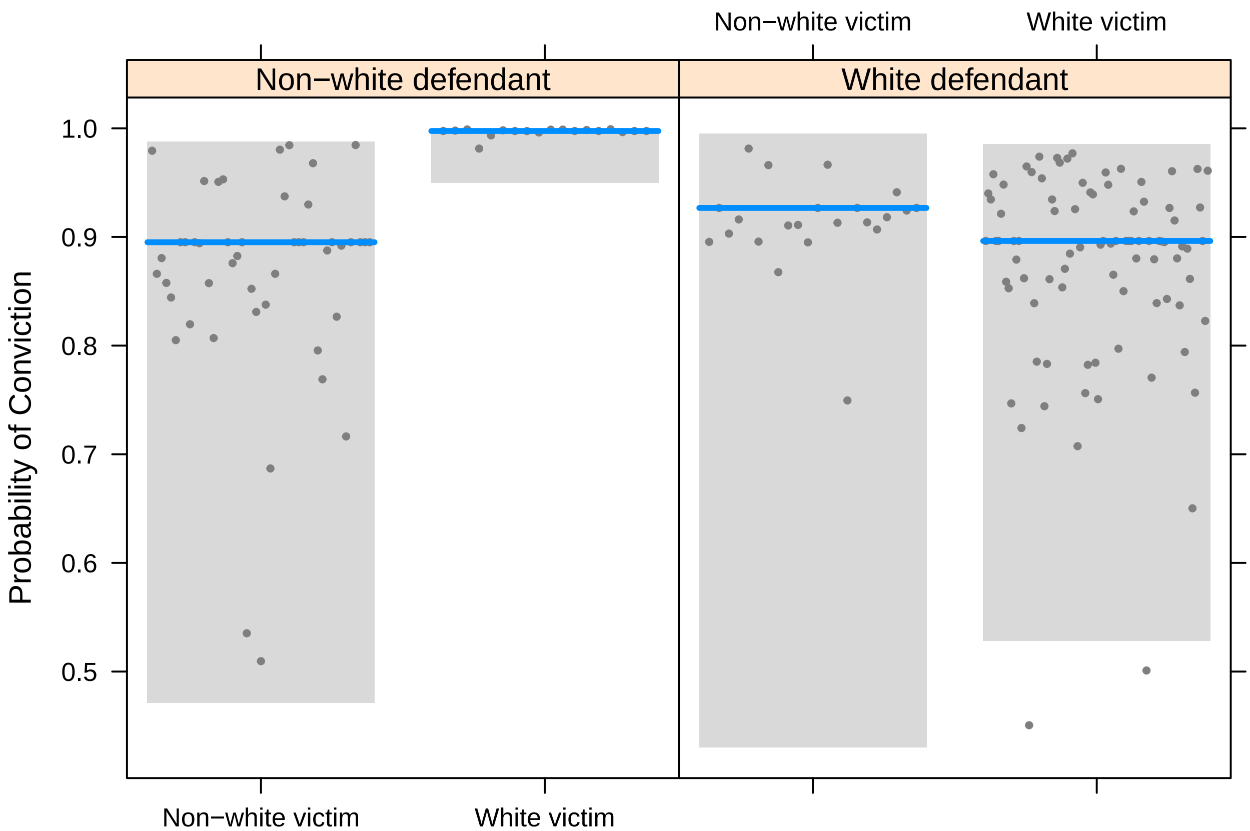

Figure 1: Effect of Victim's Race on Probability of Conviction for White and Non-White Defendants (95% Confidence Intervals and Partial Residuals in Grey)

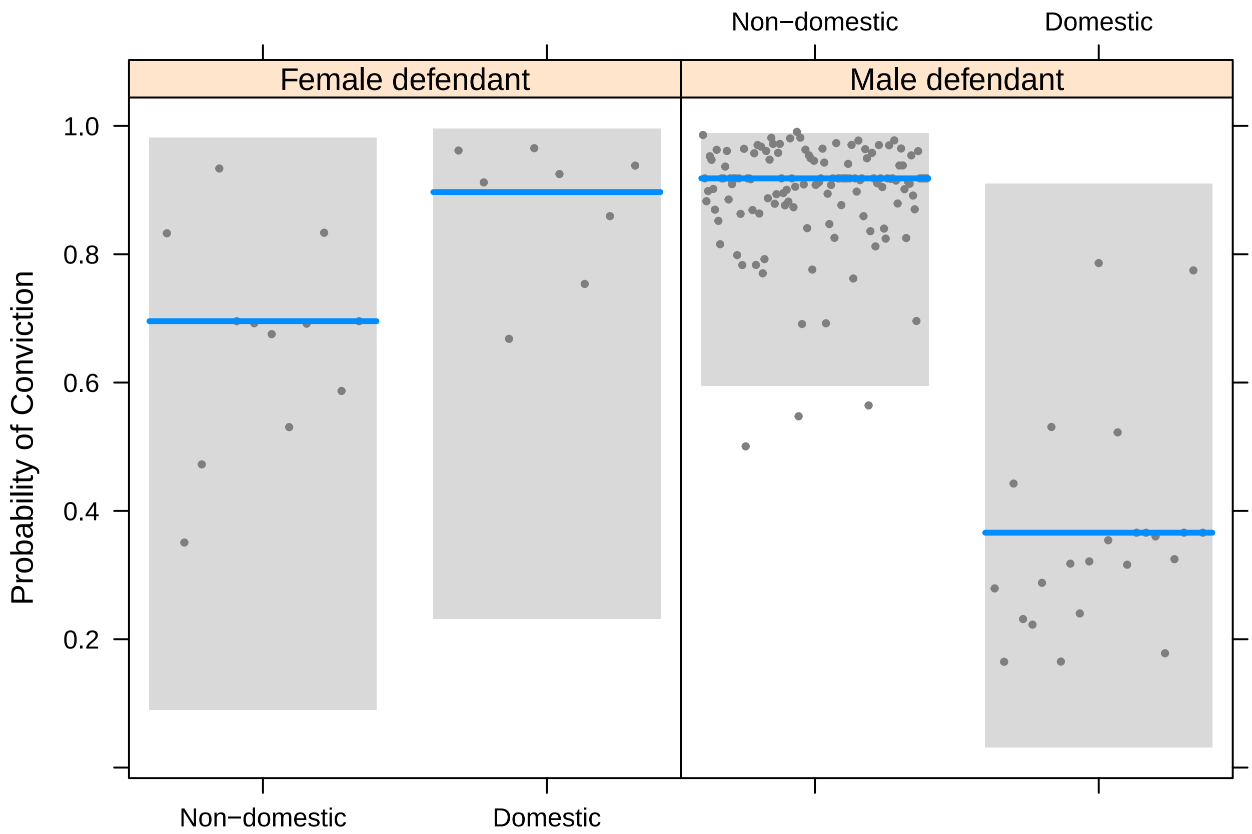

Figure 2: Effect of Domesticity on Probability of Conviction for Male and Female Defendants (95% Confidence Intervals and Partial Residuals in Grey)

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