Gun Laws and Justifiable Homicides: A Closer Look at Citizen and Police Lethal Force in the United States (1976-2020)[a]

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Abstract

Justifiable Homicide refers to instances where the intentional killing of an individual is legally sanctioned and exempt from criminal prosecution. This study investigates the potential effects of right-to-carry and stand-your-ground laws on both citizen and police justifiable homicides. Two sampling methods are employed, with negative binomial and zero-inflated negative binomial regressions estimating the impact of these laws in 50 US states, focusing on cases where a felon is killed by an armed citizen or police. If laws make it easier for the public to obtain guns, there is a possibility that justifiable homicides will increase. The analysis provides preliminary support for this claim, showing evidence that these laws contribute to a rise in citizen justifiable homicides. However, there is a contrasting effect on police justifiable homicides. Regarding stand-your-ground laws, the study finds a positive association with both police and citizen justifiable homicides. While this study cannot establish causality, it suggests that similar laws in the future may be linked to increased incidents of justifiable homicides. The authors believe that researchers in the fields of criminology and criminal justice should consider studying justifiable homicides singularly and not as a combined total of police and citizen occurrences, recognizing the unique nature of these events and how they may be affected in opposing ways by the same legislation.

Keywords: Justifiable Homicide, Right-to-Carry Laws, Stand Your Ground Laws, Gun Violence, Racial Disparities

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1 Introduction

Gun violence persists as a pressing public health crisis in the United States, underscored by the sharp rise in the number of firearm homicides following the arrival of the COVID-19 pandemic. The highest number recorded in 2021 was the greatest in over two decades (Braga, 2022; Centers for Disease Control (CDC), 2023). This alarming trend coincided with a nationwide shift towards the relaxation of laws governing the public carrying of concealed firearms (Donohue et al., 2022; Doucette et al., 2023).

1.1 Right-To-Carry (RTC) and Stand-Your-Ground (SYG) laws in the USA

Right-to-Carry (RTC) laws constitute state-level policies dictating the regulation or deregulation of concealed handgun carrying in public spaces. Categorized as no issue, may issue, shall issue, and permitless RTC laws, these regulations form a spectrum based on law enforcement discretion in determining eligibility for concealed weapon carry. While "no issue" laws bar citizens from carrying weapons in public, "may" and "shall" issue laws establish state permitting systems with varying degrees of discretion. "Permitless" laws grant lawful gun owners the freedom to carry concealed handguns in public.

Over the past four decades, these laws have shifted significantly from predominantly restrictive to more permissive, with all states permitting concealed carry in some circumstances and a notable rise in permitless carry states (Donohue et al., 2022; Doucette et al., 2023). In 1981, a total of 21 states unequivocally prohibited civilians from carrying concealed firearms in any situation (Donohue et al., 2022; Doucette et al., 2022, 2023). However, as of the current writing in 2023, there are no states that persist in maintaining a "no issue" stance. Presently, 25 states permit the permitless carry of concealed weapons, indicating a significant departure from the more restrictive policies of the past. Additionally, 17 states operate on a shall-issue basis, wherein eligible individuals are granted permits for concealed carry. The evolving landscape reflects ongoing debates surrounding public safety, individual rights, and the role of firearm regulation in American society (Donohue et al., 2022; Doucette et al., 2022, 2023). Previous evidence showed that may issue, shall issue, and permitless RTC laws are linked to a rise in violent crimes (Donohue et al., 2022; Van Der Wal, 2022; Doucette et al., 2023; Smart et al., 2023).

Stand-Your-Ground (SYG) laws, representing a departure from traditional self-defense doctrines, fundamentally reshape the legal framework governing individuals' use of force. These laws, enacted in various jurisdictions, nullify the longstanding duty to retreat, permitting individuals to confront threats without the obligation to seek safety (Yakubovich et al., 2021; Degli Esposti et al., 2022; NCSL, 2022). The core tenet of SYG laws lies in the elimination of the retreat requirement, authorizing individuals to stand their ground and employ force, even deadly force if they reasonably perceive an imminent threat of serious harm. SYG laws extend this legal framework to public spaces, challenging conventional notions that retreat is necessary for self-defense outside one's dwelling. Florida created the standard for SYG legislation by enacting it through statute in 2005, paving the way for 23 other states to adopt similar laws between 2006 and 2008.

While the initial adoption was primarily concentrated in the Southern region of the United States, the prevalence of SYG laws expanded considerably. As of 2021, thirty states have implemented SYG laws, and this figure is on the rise as numerous bills advocating for such measures navigate through state legislatures, indicating a continued trend toward the acceptance and integration of SYG principles across the nation (Degli Esposti et al., 2022). The proponents of SYG laws assert that they bolster public safety by dissuading potential criminals through the heightened threat of defensive violence. In contrast, detractors contend that these laws are unnecessary and may jeopardize public safety by encouraging the use of lethal force in situations where nonviolent resolution is feasible. Degli Esposti et al. (2022) found that SYG laws were associated with increased homicides each year and they suggest that the laws should be reconsidered to prevent unnecessary violent deaths. The intricate nuances of these laws demand an in-depth examination to discern their implications for public safety, the justice system, and individual behavior (Yakubovich et al., 2021; Degli Esposti et al., 2022; NCSL, 2022).

1.2 RTC laws, SYG laws and Justifiable Homicides (JH)

Justifiable Homicide (JH), within the framework of legal science, pertains to instances in which the intentional killing of an individual is deemed lawful and exempt from criminal prosecution. This classification typically arises when lethal force is employed as a means of self-defense or defense of others, contingent upon the reasonable perception of an imminent threat of severe harm or death (Macdonald and Parker, 2001). The evaluation of justifiable homicide involves a meticulous analysis of the specific circumstances surrounding the incident, considering factors such as the immediacy of the perceived threat, the absence of viable alternatives for preventing harm, and the proportional use of force (Macdonald and Parker, 2001).

Many studies have investigated the effect of right-to-carry laws on crime, with a substantial number focusing on the effect these laws have on homicides (Donohue et al., 2019, 2022; Van Der Wal, 2022; Doucette et al., 2023; Smart et al., 2023). Much fewer studies have investigated any relationship between right-to-carry laws and justifiable homicides, and even fewer have considered the effect of expanded stand-your-ground laws on defensive gun uses and justifiable homicides (Roman, 2013; Levy et al., 2020). Roman (2013) found that states with SYG laws have statistically significantly higher rates of justifiable homicides than non-SYG states. Similarly, Levy et al. (2020) reported that comparing periods pre- (2000 to 2004) and post-SYG (2005 to 2017) law enactment, SYG vs non-SYG states had increased JH rates of 54.9% vs 20.4%, respectively ($p<0.001$). Studies including a more extended timeframe, relevant covariates, and robustness checks are still lacking.

This study assesses whether the passage of right-to-carry laws and the expansion of the stand-your-ground doctrine subsequently influence citizen and police justifiable homicide rates. State-level data on justifiable homicides by civilians and police come from the Federal Bureau of Investigation's (FBI) Supplementary Homicide Reports (SHR) for the years 1976-2020. We pay close attention to stand-your-ground laws and other close variations of these laws which eliminate the "duty to retreat" when attacked since these laws can influence the number of justifiable homicides that occur within a given state.

1.3 The modern history of shall issue and SYG laws

The way states operate independently in the United States forces researchers to access the passing of laws state by state. The first state to ban concealed carry was Kentucky in 1813, and it was only in 1996 that it became a shall-issue state (Warner, 1938). Indiana banned it in 1820, and Georgia and Arkansas banned concealed carry in 1837, only then becoming shall-issue states in 1980, 1989, and 1995, respectively (Warner, 1938). The federal government started to regulate concealed carry in 1927 when a law was created requiring licenses to purchase pistols from mail orders, hoping to protect states that had banned concealed carry from citizens buying mail-order guns in other states (Warner, 1938).

1.3.1 Modern shall-issue laws

As states began proposing laws to regulate the licensing of concealed carry firearms, they diverged on the terminology of "shall" and "may." The former was used by states with a low amount of discretion when it comes to licensing, operating under more objective terms, while the latter applied subjective criteria, often requiring applicants to prove a hazardous occupation for the issuance of the permit (Grooms and McKinney II, 2018). Discretion may be extreme for some may-issue states. Cramer and Kopel (1995) explain that some states may issue an extremely low amount of permits since county sheriffs decide whether or not permits will be issued.

From 1900-1960, the only states considered to be shall issue were Vermont, classified that way due to a precedent decision by their state's Supreme Court on State v. Rosenthal (1903) that became the basis for future legal decisions and New Hampshire which passed a law in 1923 (Cramer and Kopel, 1995).[1]

From 1960 through 1986, seven other states enacted shall-issue laws[2] In the following 14 years, twenty-two states were added to the roster, mainly influenced by Florida, which passed its law in 1987.[3] The latest wave of states creating shall-issue laws happened after the year 2000, with 11 new states.[4] By 2020, the last year included in

[1]See NHRS XII § 159:6 and 1923 N.H. Laws 138, State v. Rosenthal, 75 Vt. 295, 55 Atl. 610 (1903).

[2]See ALA. CODE § 13A-11-75 (1975), Conn. Gen. Stat. § 29-28, Indiana Code § 35-47-2-3, Maine Code Title 25, §2003, North Dakota Century Code § 62.1-04-03, SD 23-7-7, RCW 9.41.070.

[3]See Alaska Stats. § 18.65.705, Arizona Revised Statutes § 13-3112, Arkansas Act 411 (1995), Florida Statutes Title XLVI § 790.06., Georgia Code § 16-11-126, § 16-11-129, and Op. Atty. Gen. U89-21 (August 25, 1989), I.C. § 18-3302, KRS 237.020 and Ky. Acts ch. 119, sec. 1, LRS 40:1379.3 S, Mississippi Code § 45-9-101, MCA § 45-8-321, NRS 202.3657, NC G.S. § 14-415.10. through § 14-415.23, OK § 21-1290, ORS 166.291, 18 Pa. C.S. § 6109, S.C. Code § 23-31-215 and Act No. 464, Section 1, Tenn. Code § 39-17-1351, Texas Concealed Handgun Act, 74th Leg., R.S., ch. 229, § 1, 1995, Utah Code § 53-05-704, VA. Code § 18.2-308, W.Va. Code § 61-7-4, Wyo. Stat. § 6-8-104.

[4]See MCL § 28.425b, Colo. Rev. Stat. § 18-12-203, MN Citizens' Personal Protection Act, ch. 28, art. 2, §§ 4–23, 2003 Minn. Laws 272, 274–87 and MN Session Laws 2005, chapter 83, RSMo 571.101, NM CONCEALED HANDGUN CARRY ACT OF 2003 29-19-4, O.R.C. 2923.125, K.S.A. § 75-7c03(a), Neb. Rev. Stat. § 69-2430, Iowa Chapter 714 WEAPONS, §724.7, Wis. Stat. § 175.60,

this study, only California, Delaware, Hawaii, Massachusetts, Maryland, New Jersey, New York, and Rhode Island were not operating under a shall-issue system. In summary, from 1960 through 2014 forty states enacted shall issue laws. The greatest wave happened after Florida enacted its law in 1987, with 32 states passing shall-issue laws afterward.

1.3.2 Modern SYG laws

From 1902 through 1960, the only states considered "stand your ground" were California (1951), Illinois (1902), New Mexico (1953), Virginia (1919), and Washington (1936) due to case law precedent.[5] From 1960 through the year 2000, the states of Colorado (1991) and Vermont (1997) were considered SYG due to case law precedent and the states of Oklahoma (1971) and Utah (1994) passed SYG laws.[6] From the year 2000 until 2016, 25 states became SYG.[7]

Although the states of North Dakota, Ohio, and South Dakota passed SYG laws in 2021, our study only runs from 1976-2020, so they were considered "duty-to-retreat" states, along with Arkansas, Connecticut, Delaware, Hawaii, Massachusetts, Maryland, Maine, Minnesota, Nebraska, New Jersey, Rhode Island, and Wisconsin.

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430 ILCS 66/10 Sec. 10., RCW 9.41.070

[5]See California Case Law - People v. Clark, 201 Cal.App.4th 235, 250 (2011); People v. Collins, 189 Cal. App. 2d 575, 588 (1961); Cal Crim Jury Instructions 505, 506, 3470, Cal. Penal Code § 198.5; People v. Hughes (1951) 107 Cal.App.2d 487, 493. Illinois Case Law - Hammond v. People, 199 Ill. 173, 182 (1902); People v. McGraw, 13 Ill. 2d 249, 256 (1958), People v. Rodriguez, 187 Ill. App. 3d 484, 490 (1989). New Mexico Case Law - State v. Horton, 57 N.M. 257, 261 (1953); State v. Anderson, 364 P.3d 306, 310 (2015); 14-5190 NMRA. Virginia Case Law - Foote v. Commonwealth, 11 Va. App. 61, 67 (1990); McCoy v. Commonwealth, 125 Va. 771, 775 (1919), McGhee v. Commonwealth, 219 Va. 560, 562 (1978); Commonwealth v. Cary, 271 Va. 87, 99 (2006); Adams v. Com, 163 Va. 1053 (1935). Washington Case Law - State v. Redmond, 150 Wn.2d 489 (2003); State v. Allery, 101 Wn.2d 591 (1984); State v. Hiatt, 187 Wash. 226, 237 (1936); Washington Pattern Jury Instructions–Criminal 16.08, RCW 9A.16.050; State v. Williams, 81 Wash. App. 738 (1996).

[6]See Colorado Case Law - People v. Monroe, 2020 Colo. LEXIS 608 (June 29, 2020); People v. Garcia, 28 P.3d 340, 347 (Colo. 2001); Idrogo v. People, 818 P.2d 752 (Colo. 1991). Okla. Stat. Ann. tit. 21, § 1289.25(D), Utah Code Ann. § 76-2-402, Vermont Case Law - State v. Hatcher, 167 Vt. 338, 348 (1997).

[7]See Alabama Code Title 13A. Criminal Code § 13A-3-23, AS 11-81-335(b)(5). Ariz. Rev. Stat. §§ 13-405(B); 13-411(B). Fla. Stat. §§ 776.012(b); 776.031(b); 776.032(2). O.C.G.A. § 16-3-23.1. ID Code § 19-202A (2013). Ind. Code Ann. § 35-41-3-2(c). Iowa Code § 704.1(3). Kan. Stat. Ann. §§ 21-5222(c); 21-5230. Ky. Rev. Stat. Ann. §§ 503.050(4); 503.055(3), 503.070(3); 503.080(3). La. Rev. Stat. Ann. § 14:19(C), (D); 14:20(C), (D). Mich. Comp. Laws Serv. § 780.972(2). Miss. Code. Ann. § 97-3-15(4). Mo. Rev. Stat. § 563.031(3). Mont. Code. Ann. § 45-3-110. Nev. Rev. Stat. Ann. § 200.120(2). N.H. Rev. Stat. Ann. § 627:4(III)(a); State v. Etienne, 163 N.H. 57 (2011). N.C. Gen. Stat. § 14-51.2(f); 14-51.3. Oregon Case Law - State v. Sandoval, 342 Ore. 506, 513-514 (2007); State v. Lang, 215 Ore. App. 15, 18 (2007) and ORS § 161.219. 18 Pa. Cons. Stat. Ann. § 505 (2.3), (2)(ii); 506(b); 507(c)(3). S.C. Code § 16-11-440(C). Tenn. Code Ann. § 39-11-611(b)(2). Tex. Penal Code §§ 9.31(e); 9.32 (c). W. Va. Code § 55-7-22(c). Wyo. Stat. Ann.§ 6-2-602(a), (e), (f).

2 Methods

2.1 Data Source

We used Jacob Kaplan's Concatenated Files from the Uniform Crime Reporting (UCR) Program Data on Supplementary Homicide Reports (SHR) for the years 1976-2020. This database contained information on the circumstances of a homicide, which allowed us to see if the introduction of SYG and shall-issue laws affected the counts of justifiable homicides. In this table, we isolated the amounts of murders per state agency by year and circumstance.

We then got information from the CENSUS ACS Survey for the covariates of population (B01003_001E), poverty rate (DP03_0119PE), and unemployment rate (DP03_0005PE). Lastly, we acquired arrest data for all crimes and police personnel data for all states from the FBI Crime Explorer API.

When testing our justified homicides panel we found the presence of overdispersion, violating the assumptions of the Poisson regression model, thus we chose the Negative Binomial model. Further analysis with the specification test proposed by Hausman (1978) and the Lagrange Multiplier Test (Breusch and Pagan, 1980) indicated that fixed effects would be the most appropriate, leaving us with the selection of the FENB model for this study.

2.1.1 Fixed-Effects Negative Binomial Method

The Fixed-Effects Negative Binomial model (FENB) method was originally proposed by Hausman, Hall, and Griliches (HHG) in 1984, improving on the Poisson regression by adding a parameter θ that allows for the variance to exceed the mean (Hausman et al., 1984; Allison and Waterman, 2002). This method is ideal for models that exhibit overdispersion with count data as the dependent variable.

The probability function of the negative binomial model assumes the following convention:

$$
\begin{gathered}
P(Y_i = y_i) = \frac{\Gamma(y_i + \theta^{-1})}{\Gamma(y_i + 1)\Gamma(\theta^{-1})} \left(\frac{\theta^{-1}}{\theta^{-1} + \lambda_i}\right)^{\theta^{-1}} \left(\frac{\lambda_i}{\theta^{-1} + \lambda_i}\right)^{y_i} \\
\lambda_i = \mathrm{Exp}(X_i\beta + e_i) = \mathrm{Exp}(X_i\beta)\,\mathrm{Exp}(e_i)
\end{gathered} \tag{1}
$$

where θ is a shape parameter that quantifies the amount of overdispersion, Γ is the gamma function, and e_i is the variance heterogeneity.

Lastly, the log-likelihood function is:

$$
L = \sum_{i=1}^{n} \left\{ \ln\left[\frac{\Gamma(y_i + \theta^{-1})}{\Gamma(y_i + 1)\Gamma(\theta^{-1})}\right] - (y_i + \theta^{-1})\ln(1 + \theta\lambda_i) + y_i \ln(\theta\lambda_i) \right\} \tag{2}
$$

One of the vulnerabilities with joining Kaplan's database to ours is that his database is one of incidents, which means that if no homicides happened in a given month or year, then that row would be missing. This means that when we join these tables, we are left with many instances of "NA" for states that did submit information to the FBI. We solved this problem by substituting these "NA" values with a "0". This situation forced us to perform an additional test called the Zero-Inflated Negative Binomial (Greene, 1994; Famoye and Singh, 2022).

Lastly, we created another panel by using a different sampling method called the Multivariate Imputation by Chained Equations (MICE) with the Random Forest (RF) method for the imputation of missing values. MICE is a technique used to fill in missing data that occurs in more than one variable. It creates a number of datasets by imputing missing values on a variable-by-variable basis by a set of conditional densities, drawing from estimated conditional distributions of each variable based on all the others, taking the uncertainty into consideration (Buuren and Groothuis-Oudshoorn, 2011; Shah et al., 2014; Zhang, 2016). In addition, the combination of the random forest method used in the MICE imputation produces unbiased estimates with narrower confidence intervals than using parametric MICE (Zhang, 2016). RF is a machine learning technique that recursively subdivides the data based on the predictor variables, accommodating non-linear relations, and using a bootstrap aggregation of multiple regression trees, which reduces the issue of overfitting (Zhang, 2016). In chapter 3.3 we present the results of our study using this sampling method whilst running 50 iterations of 25 imputations to fill out missing data.

2.1.2 Zero Inflated Negative Binomial Method

Two types of zeros can be found in our database, the first is for individual states that did submit data to the FBI but had zero occurrences of our dependent variable, which should enter into the counting process, and the other is for states that did not submit their data to the FBI and do not enter into the counting process (Hardin and Hilbe, 2018). The Zero-Inflated Negative Binomial (ZINB) is given by:

$$P(Y_i = y_i) = \begin{cases} \rho_i + (1+\rho_i)\left(1+\frac{\lambda_i}{\theta^{-1}}\right)^{-\theta^{-1}}, & y = 0 \\ (1-\rho_i)\frac{\Gamma(y_i+\theta^{-1})}{(y_i+1)\Gamma(\theta^{-1})}\left(1+\frac{\lambda_i}{\theta^{-1}}\right)^{-\theta^{-1}}\left(1+\frac{\theta^{-1}}{\lambda_i}\right)^{-y_i}, & y = 1, 2, \ldots \end{cases} \tag{3}$$

The ZINB distribution has $E(Y_i) = (1-p_i)\lambda_i$ as mean $var(Y_i) = (1-p_i)\lambda_i(1 + p_i\lambda_i + \frac{\lambda_i}{\theta^{-1}})$ and it relates p_i and λ_i to covariates given,

$$log(\lambda_i) = x_i'\beta \quad and \quad logit(p_i) = z_i'\gamma, (i = 1, ..., n) \tag{4}$$

where x_i and z_i are d- and q-dimensional vectors of covariates, with β and γ the regression coefficient vectors. Lastly, the ZINB (minus) log-likelihood is obtained by joining Equation 2 on Equation 3, given:

$$\begin{aligned} \mathcal{L}_z(\beta,\gamma,\theta^{-1},y_i,X,Z) = & \sum_{i=1}^{n}\log(1+e^{z_i'\gamma}) \\ & - \sum_{i:y_i=0}\log\left(e^{z_i'\gamma} + \left(\frac{e^{x_i'\beta}+\theta^{-1}}{\theta^{-1}}\right)^{-\theta^{-1}}\right) \\ & + \sum_{i:y_i>0}\left(\theta^{-1}\log\left(\frac{e^{x_i'\beta}+\theta^{-1}}{\theta^{-1}}\right) + y_i\log(1+e^{-x_i'\beta}\theta^{-1})\right) \\ & + \sum_{i:y_i\geq 0}\left(\log\Gamma(\theta^{-1}) + \log\Gamma(1+y_i)\right) \\ & - \log\Gamma(\theta^{-1}+y_i) \end{aligned} \tag{5}$$

where$X = (x_1, ..., x_n)$ and $Z = (z_1, ..., z_n)$.

This method allows us to compare our results to the FENB method when accounting for excess zeros.

2.2 Dependent and Independent Variables

The total police personnel, arrests (for all crimes), and murder offense counts were all divided by the total population and multiplied by 100,000 to find the rates per 100,000 population of each variable. We then did logs of the abovementioned variables and the population of states for every given year.

Our socio-demographic variables were taken from the United States Census Bureau's American Community Survey Data (ACS). These variables are the estimate of the percentage of families and people whose income in the past 12 months was below the poverty level, the estimate of the total population, the percentage of the unemployed civilian labor force, and lastly used in the robustness test were the estimates of the total population of males and females from 20 through 39 years of age. We used data from 50 states and removed from our dataset the locations of Puerto Rico, American Samoa, Guam, the United States Virgin Islands, the District of Columbia, and the Commonwealth of the Northern Mariana Islands.

The primary dependent variable in this analysis is homicide justification, divided into three different models: citizen justifiable homicides (CJH), police justifiable homicides (PJH), and a total (TJH) of the former two iterations. Justifiable homicides (JH) may be performed by citizens with a carry permit or by police officers. We set out to test all three models, hoping to understand if there were variations among them.

Our unbalanced panel has 50 states with data running from 1976-2020. Certain states such as Florida and Alabama had a considerable amount of years with missing data. Researchers have stated that the Supplementary Homicide Reports (SHR) data is not representative of all police departments, given that submission is voluntary by agencies all over the nation (Finch et al., 2022). However, both the FENB and ZINB models allow for unbalanced panels.

2.2.1 Summary Statistics

We use an unbalanced panel for this study containing data from the years 1976-2020 in 50 states of the United States of America.

Table 1: Summary Statistics

Variable	% of zeros	N	Mean	St. Dev.	Min	Max	NA
JH_cit	33.27%	2186	6.07	12.13	0	127	62
JH_pol	22.86%	2186	7.78	16.12	0	150	62
JH_tot	17.83%	2186	13.84	26.55	0	246	62
shall_issue	49.64%	2248	0.5	0.5	0	1	0
syg_law	71.75%	2248	0.28	0.45	0	1	0
unemp_rate	0%	2248	6.3	2.05	2.3	17.4	0
poverty_rate	0%	2198	11.86	3.94	2.9	27.2	50
log_arrest_rate	0%	2208	8.3	0.42	4.53	11.12	40
log_police_rate	0%	2203	5.61	0.27	3.63	6.69	45
log_murder_rate	0%	2186	1.76	0.51	0.11	3.6	62
log_popstate	0%	2248	15	1.01	12.51	17.48	0
pop_20_39	0%	2248	0.29	0.03	0.28	0.41	0

Source: Author, 2024.

The high percentage of zeros found on the JH variables led us to attempt the ZINB test as a secondary measure.

2.2.2 SYG and RTC laws until 2020

Our focus independent variables SYG and RTC are binary and identify when a law came into effect. If the state is shall-issue to residents or non-residents, or if the state is a constitutional carry, the value of RTC is "1". If the state is a may-issue or no-issue, the value is "0". States that received a value of "0" for every year were California, Delaware, Hawaii, Massachusetts, Maryland, New Jersey, New York, and Rhode Island. For states that went from no-issue to shall-issue or may-issue to shall-issue, we had a "1" for the year when the law came into effect and all subsequent years, and a "0" for previous years.

The same is done to regulate the stand-your-ground laws. We used "0" for states that have a duty-to-retreat (DTR) and/or a castle doctrine (CD) and "1" for states with stand-your-ground laws or that have a stand-your-ground case law precedent. SYG laws differ from the castle doctrine because CD allows the use of deadly force only within an individual's home. We used the same years in our analysis of RTC laws as Donohue et al. (2019) to define when our dummy variable should become "1", and regarding SYG laws, we performed our FENB and ZINB analysis by adding one year to the year the law passed or was enacted. This choice was made given that laws usually take several months to come into effect, and at times only become active in the following year.

Below we have a table describing when laws were enacted and the year our dummy variables became "1" in this study's panel.

Table 2: SYG and Shall-Issue Laws Until 2020

State	Stand-Your-Ground Laws (Year Law Was Enacted)	SYG Date (Used in FENB and ZINB Analysis)	RTC (Shall-Issue Laws) (Effective Date)	RTC Date (Used in FENB and ZINB Analysis)
Alabama, AL	2006	2007	1975	All years (study ranges from 1976 -2020)
Alaska, AK	2013	2014	10/1/1994	1995
Arizona, AZ	2010	2011	7/17/1994	1995
Arkansas, AR	Duty to Retreat	N/A	7/27/1995	1996
California, CA	1951 (Case Law/Precedent)	All years (study ranges from 1976-2020)	Rights Restricted / Limited Issue	N/A
Colorado, CO	1991 (Case Law/Precedent)	1992	5/17/2003	2003
Connecticut, CT	Duty to Retreat	N/A	1970	All years (study ranges from 1976-2020)
Delaware, DE	Duty to Retreat	N/A	Rights Restricted / Limited Issue	N/A
Florida, FL	2005	2006	10/1/1987	1988
Georgia, GA	2006	2007	8/25/1989	1990

Table 2: (Continuation) SYG and Shall-Issue Laws Until 2020

State	Stand-Your-Ground Laws (Year Law Was Enacted)	SYG Date (Used in FENB and ZINB Analysis)	RTC (Shall-Issue Laws) (Effective Date)	RTC Date (Used in FENB and ZINB Analysis)
Hawaii, HI	Duty to Retreat	N/A	Rights Restricted / Limited Issue	N/A
Idaho, ID	2013	2014	7/1/1990	1990
Illinois, IL	1902 (Case Law/Precedent)	All years (study ranges from 1976-2020)	1/5/2014	2014
Indiana, IN	2006	2007	1/15/1980	1980
Iowa, IA	2016	2017	1/1/2011	2011
Kansas, KS	2006	2007	1/1/2007	2007
Kentucky, KY	2006	2007	10/1/1996	1997
Louisiana, LA	2006	2007	4/19/1996	1996
Maine, ME	Duty to Retreat	N/A	9/19/1985	1986
Maryland, MD	Duty to Retreat	N/A	Rights Restricted / Limited Issue	N/A
Massachusetts, MA	Duty to Retreat	N/A	Rights Restricted / Limited Issue	N/A
Michigan, MI	2006	2007	7/1/2001	2001
Minnesota, MN	Duty to Retreat	N/A	5/28/2003	2003

Table 2: (Continuation) SYG and Shall-Issue Laws Until 2020

State	Stand-Your-Ground Laws (Year Law Was Enacted)	SYG Date (Used in FENB and ZINB Analysis)	RTC (Shall-Issue Laws) (Effective Date)	RTC Date (Used in FENB and ZINB Analysis)
Mississippi, MS	2010	2011	7/1/1990	1990
Missouri, MO	2007	2008	2/26/2004	2004
Montana, MT	2009	2010	10/1/1991	1992
Nebraska, NE	Duty to Retreat	N/A	1/1/2007	2007
Nevada, NV	2011	2012	10/1/1995	1996
New Hampshire, NH	2011	2012	1923	All years (study ranges from 1976-2020)
New Jersey, NJ	Duty to Retreat	N/A	Rights Restricted / Limited Issue	N/A
New Mexico, NM	1953 (Case Law/Precedent)	All years (study ranges from 1976-2020)	1/1/2004	2004
New York, NY	Duty to Retreat	N/A	Rights Restricted / Limited Issue	N/A
North Carolina, NC	2011	2012	12/1/1995	1996
North Dakota, ND	Duty to Retreat	N/A	8/1/1985	1986

Table 2: (Continuation) SYG and Shall-Issue Laws Until 2020

State	Stand-Your-Ground Laws (Year Law Was Enacted)	SYG Date (Used in FENB and ZINB Analysis)	RTC (Shall-Issue Laws) (Effective Date)	RTC Date (Used in FENB and ZINB Analysis)
Ohio, OH	Duty to Retreat	N/A	4/8/2004	2004
Oklahoma, OK	1971	All years (study ranges from 1976-2020)	1/1/1996	1996
Oregon, OR	2007 (Case Law/Precedent)	2008	1/1/1990	1990
Pennsylvania, PA	2011	2012	6/17/1989	1989
Rhode Island, RI	Duty to Retreat	N/A	Rights Restricted / Limited Issue	N/A
South Carolina, SC	2006	2007	8/23/1996	1997
South Dakota, SD	Castle Doctrine	N/A	7/1/1985	1985
Tennessee, TN	2007	2008	10/1/1996	1997
Texas, TX	2007	2008	1/1/1996	1996
Utah, UT	1994	1995	5/1/1995	1995

Table 2: (Continuation) SYG and Shall-Issue Laws Until 2020

State	Stand-Your-Ground Laws (Year Law Was Enacted)	SYG Date (Used in FENB and ZINB Analysis)	RTC (Shall-Issue Laws) (Effective Date)	RTC Date (Used in FENB and ZINB Analysis)
Vermont, VT	1997 (Case Law/Precedent)	1998	No permit required since 1903 (Case Law/Precedent)	All years (study ranges from 1976-2020)
Virginia, VA	1919 (Case Law/Precedent)	All years (study ranges from 1976-2020)	5/5/1995	1995
Washington, WA	1936 (Case Law/Precedent)	All years (study ranges from 1976-2020)	1961	All years (study ranges from 1976-2020)
West Virginia, WV	2008	2009	7/7/1989	1990
Wisconsin, WI	Duty to Retreat	N/A	11/1/2011	2012
Wyoming, WY	2008	2009	10/1/1994	1995

Source: Author, 2024. Data: Donohue et al. (2019), Perez (2021).

States that had a duty to retreat and/or castle doctrine until 2020 were Arkansas, Connecticut, Delaware, Hawaii, Massachusetts, Maryland, Maine, Minnesota, North Dakota, Nebraska, New Jersey, New York, Ohio, Rhode Island, South Dakota, and Wisconsin. In 2021, some of these states passed stand-your-ground laws, including Arkansas, North Dakota, Ohio, and South Dakota. However, our dataset only uses the years 1976-2020. States that are considered stand-your-ground by case law or by precedent are California, Colorado, Illinois, New Mexico, Oregon, Virginia, Vermont, and Washington. This means that at a certain year, there was a legislative contest resulting in a "no duty to retreat" that became a precedent law for future judicial decisions.

2.3 Data Analytic Plan

This study utilizes the FENB and ZINB methods to estimate the outcome of three models. The first, second, and third models estimate the effects of shall-issue and SYG laws on the amount of justifiable homicides performed by citizens, police, and a total of both in a particular state, respectively.

$$JH\_cit_{it} = \mu + \alpha_1(shall - issue)_i + \alpha_2(SYG)_i + \beta X_{it} + \epsilon_{it} \tag{6}$$

$$JH\_pol_{it} = \mu + \alpha_1(shall - issue)_i + \alpha_2(SYG)_i + \beta X_{it} + \epsilon_{it} \tag{7}$$

$$JH\_tot_{it} = \mu + \alpha_1(shall - issue)_i + \alpha_2(SYG)_i + \beta X_{it} + \epsilon_{it} \tag{8}$$

In these formulas, μ is the intercept, α_1 and α_2 are the interaction terms, βX_{it} includes the control variables, and ϵ_{it} is the random error term.

3 Empirical Findings

3.1 FENB Results of the Effects of RTC and SYG on JH

The results of fitting the FENB regression are shown in Table 3. We emulate the year fixed effects robustness check performed by Donohue and Ribeiro (2012), where they added the percentage of the population of adults from 20 through 39 years old. Donohue and Ribeiro (2012) mention that CJH could be influenced by higher crime rates where armed citizens would be more likely to be faced with criminals. We believe the same could apply to PJH. To circumvent this problem, they added covariates of the murder rate and the crack epidemic. In this study, we used the log of murder rate and log of arrest rates as a measure of crime in US states.

Except for RTC in models 2 and 3 and police rate in model 1, most of our independent variables hold their significance or lack thereof in the robustness check. For RTC laws, Model 2 that tests PJH has a negative influence. This means that states with shall-issue laws have fewer police justifiable homicides, implying that higher rates of armed citizens lessen the occurrence of justifiable homicides performed by police. The same RTC laws incur an increase in justifiable homicides performed by citizens and of the total of police and citizens together. However, there is a drop in significance for the TJH model during our robustness test.

On the other hand, SYG laws have positive estimates and maintain their significance during the robustness check for every model, indicating that stand-your-ground states have higher incidences of citizen and police justifiable homicides.

One argument that could be made about police justifiable homicides is the phenomenon of "suicide by cop" (SBC) impacting the incidence of PJH. Hutson et al. (1998), when reviewing 10 years of Los Angeles County Sheriffs' data on officer-involved shootings, found that 13% of all PJH were found to be SBC. In a more recent study, Mohandie et al. (2009) analyzed 90 US and Canadian police agencies from 1998 through 2006 and found that 36% of officer-involved shootings (lethal and non-lethal) were found to be SBC. They also found that SBC individuals had a firearm 60% of the time, with half of those discharging it at the police during the encounter, while 19% simulated having possession of a weapon to induce officers to discharge.

We believe that instances of "suicide by cop" could be getting reported as PJH to the FBI and inflating the statistics. Essentially, these are suicides that in our study are included as PJH. Finch et al. (2022) argue that there is undercounting in relation to PJH given that agencies report data voluntarily to the FBI. However, they do not mention the possibility of overcounting due to incidents of SBC.

The log of population, unemployment rate, log of murder rate, and log of arrest rate all have significantly positive estimates for all three models, suggesting that higher population, unemployment, murder, and arrest rates result in increases in citizen and police JH. This is in line with Donohue and Ribeiro (2012), where arrests are an indicator of higher criminal activity within a state, possibly creating more opportunities for situations where armed citizens and police are faced with criminals. This is also valid when we understand that police are more likely to be placed in a situation that leads to a justifiable homicide if they make more arrests yearly. But given that the log of arrest rate is also significant for citizen justifiable homicides, this implies that higher arrests are a symptom of greater criminal activity and not only of police effectiveness.

One of the main differences between our study, which ranges from 1976-2020, and Donohue and Ribeiro's study, which ranges from 1962-2007, is the poverty rate's influence on justifiable homicides. In their study, this covariate is not significant while being positive for CJH and negative for PJH. Here, we have negatively significant estimates, meaning that increases in poverty result in lesser CJH, PJH, and TJH. This is interesting given that unemployment and poverty are highly correlated, and yet in our study, they go in opposite directions, implying that unemployment is more connected to criminal activity than poverty itself.

Lastly, the log of police rate had non-significant results for our three models, presenting a negative influence in CJH and a positive influence in PJH, differing from Donohue and Ribeiro's research where CJH and PJH had negatively significant estimates. This covariate was significant for CJH during our robustness test, and both CJH and PJH maintained their respective signs, but TJH goes from a positive to a negative influence. This implies that higher police presence incurs in lesser situations where armed citizens are faced with criminals, thus resulting in less CJH. One could argue that this happens due to a deterrence effect. However, this is conflicting given that police presence has a positive effect on PJH. Different results could have been presented if our units were cities. However, given that we are using states as a unit, counties with higher police

Table 3: FENB and FENB Robustness Test Results

Variables	FENB			FENB Robustness Test		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
RTC	0.453∗∗∗	-0.088∗	0.136∗∗∗	0.380∗∗∗	-0.154∗∗∗	0.065!
	(0.044)	(0.038)	(0.033)	(0.050)	(0.043)	(0.038)
SYG	0.369∗∗∗	0.442∗∗∗	0.407∗∗∗	0.363∗∗∗	0.443∗∗∗	0.403∗∗∗
	(0.044)	(0.040)	(0.034)	(0.044)	(0.040)	(0.034)
Unemployment rate	0.049∗∗∗	0.037∗∗∗	0.042∗∗∗	0.046∗∗∗	0.034∗∗∗	0.039∗∗∗
	(0.010)	(0.009)	(0.008)	(0.010)	(0.009)	(0.008)
Log of murder rate	1.602∗∗∗	0.821∗∗∗	1.150∗∗∗	1.643∗∗∗	0.858∗∗∗	1.192∗∗∗
	(0.061)	(0.052)	(0.045)	(0.062)	(0.054)	(0.046)
Log of police rate	-0.099	0.109	0.059	-0.175∗	0.031	-0.019
	(0.082)	(0.074)	(0.064)	(0.082)	(0.078)	(0.067)
Log of arrest rate	0.282∗∗∗	0.546∗∗∗	0.412∗∗∗	0.310∗∗∗	0.577∗∗∗	0.441∗∗∗
	(0.053)	(0.053)	(0.043)	(0.053)	(0.054)	(0.043)
Poverty rate	-0.015∗	-0.041∗∗∗	-0.031∗∗∗	-0.013∗	-0.039∗∗∗	-0.030∗∗∗
	(0.006)	(0.005)	(0.004)	(0.006)	(0.005)	(0.004)
Log of state population	1.124∗∗∗	1.032∗∗∗	1.059∗∗∗	1.129∗∗∗	1.034∗∗∗	1.061∗∗∗
	(0.026)	(0.022)	(0.019)	(0.026)	(0.022)	(0.019)
Population 20 through 39				-2.792∗∗	-2.600∗∗∗	-2.746∗∗∗
				(0.926)	(0.786)	(0.685)
Fixed Effects	Y	Y	Y	Y	Y	Y
Log Likelihood	-4,263.5	-4,931.5	-5,708.4	-4,258.9	-4,926.0	-5,700.3
Adjusted R2	0.235	0.209	0.220	0.236	0.210	0.221
BIC	8,595.8	9,931.8	11,485.6	8,594.3	9,928.4	11,477.1
Theta	2.687	2.904	3.547	2.712	2.925	3.585

Notes: *** p<0.001, ** p<0.01, * p<0.05, ! p<0.1

presence would displace criminal activity to nearby locations (Donohue et al., 2014), thus nullifying any possible deterrence effect that would or could have been present.

3.2 ZINB Results of the Effects of RTC and SYG on JH

The results of fitting the ZINB regression model to the RTC and SYG study are shown in Table 4. The murder and arrest rate covariates are significant in both parts of the ZINB regression model, suggesting that the counts of citizen, police, and the total justifiable homicides increase as the murder and arrest rates get higher, while the excess of justifiable homicides decreases. The unemployment rate is also significant in both parts of the regression model except for citizen justifiable homicides. This implies that the amount of justifiable homicides increases, while the excess of PJH and TJH decreases. The police rate is significant for PJH and TJH, meaning that the count of these variables increases the more personnel are present, whilst the excess of TJH also increases. This result conflicts with the FENB that showed no significance for all three models, also because the TJH is a sum of citizen and police JH, both of which are not significant for the binomial logit link, as well as the fact that both parts of the ZINB model share the same sign.

The poverty and state population are only significant for the negative binomial part of our study, implying that the higher rate of poverty accompanies a decrease in CJH, PJH, and TJH, whereas the higher population increases the same dependent variables.

Table 4: ZINB Results

Variables	Neg bin with log link			Binomial with logit link		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
RTC	0.391∗∗∗	-0.139∗∗∗	0.094∗∗	-12.177	-20.950	-0.735
	(0.045)	(0.038)	(0.032)	(244.314)	(10640)	(0.480)
SYG	0.346∗∗∗	0.410∗∗∗	0.379∗∗∗	-2.696∗	-16.76	-1.047
	(0.043)	(0.038)	(0.032)	(1.230)	(745.8)	(0.877)
Unemployment rate	0.052∗∗∗	0.042∗∗∗	0.048∗∗∗	0.156	0.443∗∗	0.244∗
	(0.010)	(0.009)	(0.007)	(0.192)	(0.141)	(0.102)
Log of murder rate	1.523∗∗∗	0.739∗∗∗	1.059∗∗∗	-4.426∗	-4.696∗∗∗	-2.650∗∗∗
	(0.061)	(0.052)	(0.045)	(2.047)	(1.345)	(0.793)
Log of police rate	-0.004	0.183∗	0.148∗	0.070	1.915!	2.202∗∗
	(0.081)	(0.072)	(0.061)	(1.462)	(1.128)	(0.790)
Log of arrest rate	0.218∗∗∗	0.484∗∗∗	0.352∗∗∗	-2.044∗	-2.457∗∗	-1.144∗∗
	(0.053)	(0.052)	(0.041)	(0.841)	(0.829)	(0.395)
Poverty rate	-0.015∗	-0.039∗∗∗	-0.029∗∗∗	-0.439	-0.005	0.006
	(0.006)	(0.005)	(0.004)	(0.315)	(0.085)	(0.063)
Log of state population	1.127∗∗∗	1.033∗∗∗	1.047∗∗∗	1.412	-0.196	-0.445
	(0.026)	(0.022)	(0.021)	(1.450)	(0.495)	(0.340)
Log of theta	1.073∗∗∗	1.191∗∗∗	1.482∗∗∗			
	(0.063)	(0.059)	(0.061)			
Fixed Effects	Y	Y	Y	Y	Y	Y
Log Likelihood	-4,263	-4,885	-5,643	-4,263	-4,885	-5,643
Theta	2.925	3.292	4.402	2.925	3.292	4.402

Notes: *** p<0.001, ** p<0.01, * p<0.05, **!** p<0.1

Lastly, RTC and SYG laws are only significant in the negative binomial part of our study, except for CJH on SYG laws. This suggests that SYG laws increase CJH, PJH, and TJH, while there is a decrease in the excess of CJH. On the other hand, RTC laws increase CJH and TJH but have the opposite effect on PJH which is in line with our FENB results.

3.3 Multivariate Imputation by Chained Equations Using Random Forest Method

Boehme and Mourtgos (2024), when studying the influence of de-policing on police traffic stops and crime in the city of Los Angeles, use the Multivariate Imputation by Chained Equations with the random forest (RF) method for the imputation of missing values. Herein we utilize the "MICE" R Package, running 50 iterations of 25 imputations (Buuren and Groothuis-Oudshoorn, 2011). For this database, we did not perform any imputation of "0" on "NA", even though Kaplan's database is a table of incidents, which would have missing values if the incident did not occur. We present the results for the table created with RF and compare them with the results from our previous table to avoid any bias in the imputation of missing values. Given that we do not create an excess of zeros in the database this time, we only perform the negative binomial test in Section 3.2.

Table 5 presents the results for the panel created with the random forest method, and the summary statistics can be found in Appendix A. When analyzed with the specification test proposed by Hausman (1978), this database indicated that random effects would be the best approach, so all models are tested with random effects in this section. Further analysis with the Lagrange Multiplier Test (Breusch and Pagan, 1980) suggested a fixed effects model. The results (not presented here) were the same in terms of significance and sign for the main explanatory variables.

Table 5: NB and NB Robustness Test Results for Table Created with RF

Variables	NB			NB Robustness Test		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
RTC	0.184∗∗∗	-0.138∗∗∗	0.060∗	0.162∗∗∗	-0.172∗∗∗	0.006
	(0.033)	(0.031)	(0.027)	(0.038)	(0.034)	(0.031)
SYG	0.328∗∗∗	0.373∗∗∗	0.366∗∗∗	0.327∗∗∗	0.374∗∗∗	0.365∗∗∗
	(0.035)	(0.032)	(0.029)	(0.035)	(0.032)	(0.029)
Unemployment rate	0.027∗∗∗	0.028∗∗∗	0.033∗∗∗	0.025∗∗	0.026∗∗∗	0.031∗∗∗
	(0.008)	(0.007)	(0.006)	(0.008)	(0.007)	(0.006)
Log of murder rate	0.918∗∗∗	0.536∗∗∗	0.884∗∗∗	0.927∗∗∗	0.553∗∗∗	0.911∗∗∗
	(0.042)	(0.038)	(0.034)	(0.043)	(0.039)	(0.035)
Log of police rate	0.031	0.133∗	0.092!	0.009	0.097	0.038
	(0.061)	(0.057)	(0.051)	(0.064)	(0.059)	(0.053)
Log of arrest rate	0.151∗∗∗	0.355∗∗∗	0.272∗∗∗	0.159∗∗∗	0.369∗∗∗	0.292∗∗∗
	(0.039)	(0.038)	(0.033)	(0.040)	(0.038)	(0.033)
Poverty rate	0.003	-0.024∗∗∗	-0.017∗∗∗	0.004	-0.023∗∗∗	-0.016∗∗∗
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Log of state population	0.805∗∗∗	0.861∗∗∗	0.932∗∗∗	0.806∗∗∗	0.862∗∗∗	0.933∗∗∗
	(0.019)	(0.018)	(0.016)	(0.019)	(0.018)	(0.016)
Population 20 through 39				-0.812	-1.307∗	-2.099∗∗∗
				(0.672)	(0.616)	(0.550)
Fixed Effects	N	N	N	N	N	N
Log Likelihood	-10338.925	-11011.569	-12524.392	-10337.544	-11007.184	-12510.590
AIC	10359	11032	12544	10360	11029	12533
Theta	3.962	4.476	4.958	3.969	4.497	5.013

Notes: *** p<0.001, ** p<0.01, * p<0.05, ! p<0.1

The effect of the shall-issue laws has opposite significant effects on justifiable homicides. If performed by citizens, the effect of right-to-carry laws is positive and significant, however, if performed by police, the effect is negative and significant. These effects almost nullify each other when we run the total of justifiable homicides. All of the results found when using a database created with the random forest validate the original results found in Section 3.1 that used a different sampling method. Although the estimate of our two explanatory variables may differ, the results are validated by significance and sign. Unlike right-to-carry, we observe a significant and positive relationship between stand-your-ground laws and justifiable homicides for all the models involved.

4 Discussion and Conclusion

We attempted to understand if the passing of right-to-carry and stand-your-ground laws affects the occurrence of justifiable homicides performed by citizens and police. We used two different missing data procedures and performed a year fixed effects robustness check for every model by adding the population of 20 through 39 years old. We also performed tests with negative binomial fixed effects and random effects and with zero-inflated negative binomial. All our results for citizen justifiable homicides indicated that RTC and SYG laws have a positive effect on CJH, suggesting that these laws are connected to an increase in situations where a felon is killed by an armed citizen.

SYG laws have a significant and positive relationship with justifiable homicides for all the models involved. On the other hand, shall-issue laws have opposite significant effects on justifiable homicides whether the perpetrator was a citizen or a police officer. If performed by citizens, the effect of right-to-carry laws is positive and significant; however, if performed by police, the effect is negative and significant. Although both are justifiable homicides, these situations differ greatly in terms of all the situational variables that lead to an event of justifiable homicide. It is easy to understand why this would affect citizen justifiable homicides, meaning that if a higher number of citizens are carrying guns, there will be more situations where an armed citizen will be confronted by a felon. However, why would the effect be negative for police justifiable homicides? It is possible that shall-issue laws, which cause a greater amount of guns to be in circulation, create a deterrent effect to police justifiable homicides. Whether officers are not as inclined to escalate situations because of the higher possibility of a confrontation with an armed citizen or because the higher amount of guns in circulation themselves work as a deterrent effect on crime decreasing the situations where officers are confronted by armed criminals is something that we cannot infer from this research. There is even the possibility that the higher circulation of guns is having some negative effect on incidents of suicide-by-cop, thus lowering the number of police justifiable homicides. What we see is that right-to-carry laws create a lower amount of justifiable homicides performed by police, and the effect is the opposite for citizens.

4.1 Methodological Contribution

Our research adds a relevant point to the literature as to whether researchers should study justifiable homicides as a whole or separately. Our results indicate that justifiable homicides, whether performed by citizens or police, should be studied singularly to avoid potential nullifying effects such as what we encountered in our explanatory variable of RTC laws. We also believe further research is needed to account for suicide-by-cop situations that may or may not be impacting the counts of police justifiable homicides.

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Appendix

A Summary statistics for panel created with RF imputation method

Herein we present the summary statistics for the panel from Section 3.3. We use a balanced panel in Section 3.3 containing data from years 1976-2020 in 50 states of the United States of America.

Table 6: Summary statistics for panel created with RF imputation method

Variable	% of zeros	N	Mean	St. Dev.	Min	Max	NA
JH_cit	0%	2250	6.69	12.11	1	127	0
JH_pol	0%	2250	8.23	15.85	1	150	0
JH_tot	0%	2250	14.43	26.41	1	246	0
shall_issue	49.6%	2250	0.5	0.5	0	1	0
syg_law	71.73%	2250	0.28	0.45	0	1	0
unemp_rate	0%	2250	6.3	2.05	2.3	17.4	0
poverty_rate	0%	2250	11.86	3.94	2.9	27.2	0
log_arrest_rate	0%	2250	8.3	0.42	4.53	11.12	0
log_police_rate	0%	2250	5.61	0.28	3.63	6.69	0
log_murder_rate	0%	2250	1.76	0.52	0.01	3.6	0
log_popstate	0%	2250	15	1.01	12.51	17.48	0
pop_20_39	0%	2250	0.29	0.03	0.22	0.41	0

Source: Author, 2024.