Effects of Ideological Identification on Sentencing for Criminal Cases Involving Political Violence in Federal Cases

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Abstract

We aim to determine the effect of identification with various ideologies on federal prison sentencing. We utilize *The Prosecution Project*'s database of political violent criminals to examine 1,889 guilty verdicts. We isolate the effect of defendants' self-expressed political ideology on sentencing patterns (i.e., life sentences and length of sentences). We begin by modelling life sentences as a binary dependent variable. We proceed with a subset of the defendants' not given life sentences (1,864 observations). Using count models, we attempt to measure the effect of a defendant's ideological affiliation on the number of three-year prison increments to which the defendant is sentenced. We employ two-part and hurdle models to account for the large number of individuals who were sentenced to zero months in prison.

Introduction

Most empirical studies related to criminal sentencing focus on demographic factors, such as race and gender. By contrast, we examine the effects of ideological affiliation on sentencing in federal cases.[1] Specifically, we focus on the effects of defendant ideology in cases of political violence. Although politically motivated violence is relatively uncommon in the US, the American public appears perpetually fixated on the topic. Therefore, we recognize the opportunity to examine criminal cases that are of particular importance to the public and media.

This paper is organized into six sections. The first section of this paper outlines a literature review of the Federal Sentencing Guidelines and includes details on the relationship between race, religion, crime type, jurisdiction, etc. on criminal sentencing patterns. The second section discusses the data; its origin, structure, and relevant summary statistics. The third section outlines our theoretical framework of criminal sentencing and its relation to our data. The fourth section details the models we employ (i.e., logistic, two-part, hurdle) to isolate the effects of defendants' ideology on sentencing. The fifth section

[1] Our exclusion of state cases is discussed below

reports the results from our models, while the final section concludes the paper with a discussion of our findings.

Literature Review

During the sentencing process, a federal court uses a baseline offense to gauge a minimum sentencing. After further exploration of the crime, and after accounting for various characteristics of the relevant crime, the court arrives at a final offense level. Punishment is then determined on a scale from one to 43 (Craun, Purdy 2022). For reference, see table below.

For one level increase, a sentence may be increased anywhere from 3 months to a life sentence if an increase is present. In this analysis, we aim to measure the effect of ideological affiliation as one of the factors which contribute to a final offense level. Below we review the literature and federal standards for criminal sentencing as background for our study:

IDEOLOGY

Radical ideologies that were once on the fringes of the political spectrum are now more accessible through online media, influencing millions of Americans. Even with this rise in accessibility to radicalism, the media still overstates the prominence of political violence in the United States. For instance, only 1% of violent hate crimes reported were politically motivated (Westwood et al., 2022). Additionally, note that not all acts of political violence are classified as hate crimes.

RELIGION

Weinstein (2007) states that the effect of religion on sentencing has been subtle and indirect in United States courts. The effect's "subtlety" likely results from a lack of empirical evidence surrounding the relationship between religion and punishment (Ulmer et al. 2016). Additionally, Ulmer et al. (2016) find that moral and religious homogeneity effect sentencing through the election of state judges. While we only model within the scope of federal courts, future research may be interested in how moral and religious homogeneity effects sentencing patterns of federal judges, if there is any effect at all.

CRIMINAL METHOD.

Craun and Purdy (2022) examine the effect of firearm use on sentencing. According to 18 U.S.C. § 924(c), brandishing a firearm raises the baseline sentence for a given offense to 7 years. If the firearm is discharged, the baseline sentencing rises to 10 years. If the firearm falls under the category of machine gun, or if the firearm has any enhancements (e.g., silencer, muffler, etc.) then the baseline punishment rises to 30 years. Under this section, if any criteria of this code are met and the defendant is a repeat offender, a minimum sentence of 25 years must be issued.

To account for these discontinuous jumps in sentencing guideline, we discretize our dependent variable *Sentence Length*. This is further discussed in the *Methods* section. Discretizing *Sentence Length* allows us to predict our dependent variable despite the presence of unobserved variation between charges (such as firearm enhancement statutes regarding silencer).

REPEAT OFFENSES

Note below *Figure A* that repeat offenders are subject to lengthier sentences and, if the crime warrants, higher probability of receiving a life sentence.

HATE CRIME

Code §3A1.1 includes the Vulnerable Victims Enhancement of the Federal Sentencing Guidelines. Under this code, knowingly targeting aF vulnerable individual can elevate a sentence by two levels. Committing a hate crime, targeting a government official, or promoting terrorism can be reason to elevate to a life sentence (Craun and Purdy 2022). Many acts of political violence may fall under this code. An increase by two levels at a minimum in Zone B of the Federal Sentencing Guidelines can increase a max sentence by 6 months at a minimum or can increase to a life sentence at a maximum. See the table below, courtesy of the United States Sentencing Commission. Once again, the effect of repeat offenses on sentencing is obvious.

Fig A: Federal Sentencing Guidelines

SENTENCING TABLE
(in months of imprisonment)

Zone	Offense Level	Criminal History Category (Criminal History Points) I (0 or 1)	II (2 or 3)	III (4, 5, 6)	IV (7, 8, 9)	V (10, 11, 12)	VI (13 or more)
	1	0–6	0–6	0–6	0–6	0–6	0–6
	2	0–6	0–6	0–6	0–6	0–6	1–7
	3	0–6	0–6	0–6	0–6	2–8	3–9
Zone A	4	0–6	0–6	0–6	2–8	4–10	6–12
	5	0–6	0–6	1–7	4–10	6–12	9–15
	6	0–6	1–7	2–8	6–12	9–15	12–18
	7	0–6	2–8	4–10	8–14	12–18	15–21
	8	0–6	4–10	6–12	10–16	15–21	18–24
	9	4–10	6–12	8–14	12–18	18–24	21–27
Zone B	10	6–12	8–14	10–16	15–21	21–27	24–30
	11	8–14	10–16	12–18	18–24	24–30	27–33
Zone C	12	10–16	12–18	15–21	21–27	27–33	30–37
	13	12–18	15–21	18–24	24–30	30–37	33–41
	14	15–21	18–24	21–27	27–33	33–41	37–46
	15	18–24	21–27	24–30	30–37	37–46	41–51
	16	21–27	24–30	27–33	33–41	41–51	46–57
	17	24–30	27–33	30–37	37–46	46–57	51–63
	18	27–33	30–37	33–41	41–51	51–63	57–71
	19	30–37	33–41	37–46	46–57	57–71	63–78
	20	33–41	37–46	41–51	51–63	63–78	70–87
	21	37–46	41–51	46–57	57–71	70–87	77–96
	22	41–51	46–57	51–63	63–78	77–96	84–105
	23	46–57	51–63	57–71	70–87	84–105	92–115
	24	51–63	57–71	63–78	77–96	92–115	100–125
	25	57–71	63–78	70–87	84–105	100–125	110–137
	26	63–78	70–87	78–97	92–115	110–137	120–150
	27	70–87	78–97	87–108	100–125	120–150	130–162
Zone D	28	78–97	87–108	97–121	110–137	130–162	140–175
	29	87–108	97–121	108–135	121–151	140–175	151–188
	30	97–121	108–135	121–151	135–168	151–188	168–210
	31	108–135	121–151	135–168	151–188	168–210	188–235
	32	121–151	135–168	151–188	168–210	188–235	210–262
	33	135–168	151–188	168–210	188–235	210–262	235–293
	34	151–188	168–210	188–235	210–262	235–293	262–327
	35	168–210	188–235	210–262	235–293	262–327	292–365
	36	188–235	210–262	235–293	262–327	292–365	324–405
	37	210–262	235–293	262–327	292–365	324–405	360–life
	38	235–293	262–327	292–365	324–405	360–life	360–life
	39	262–327	292–365	324–405	360–life	360–life	360–life
	40	292–365	324–405	360–life	360–life	360–life	360–life
	41	324–405	360–life	360–life	360–life	360–life	360–life
	42	360–life	360–life	360–life	360–life	360–life	360–life
	43	life	life	life	life	life	life

USSC, 2016

STATE SENTENCING

Jurisdiction of the case may well influence sentencing. The Federal Sentencing Guidelines created in 1984 (enacted in 1987) aim to reduce disparity across federal courts nationwide (Tiede, 2009). States were also given the opportunity to refer to these guidelines when sentencing. However, after the Federal Sentencing Guidelines took effect, states tended to ignore them, referring instead to pre-existing state sentencing guidelines and statutes. (Knapp and Hautley, 1991). State judges were given little incentive to prioritize federal guidelines over state-specific statutes (Knapp and Hautley, 1991). In fact, Mitchell (2017) states that no state has yet referred to the Federal Sentencing Guidelines. Instead, state judges utilize modern state statutes to apply appropriate sentences (Mitchell, 2017), which allows state judges to use higher levels of discretion when sentencing.

Due to marked differences between state and federal sentencing, we elect to remove state cases from our sample. Ultimately, removing these several hundred observations allows us to focus on sentencing disparities under one set of guidelines and statutes. We also recognize the differences in placement systems for state and federal judges.

JUDGES

Per the *United States Courts*, state judges are elected and are not typically appointed for life. Federal judges, on the other hand, are appointed by the President with confirmation by the senate and serve for life. By removing state cases, we eliminate the need to control for political motivations to be made by state judges which can vary by county or district.

RACE

As stated at the beginning of this section, most empirical research around sentencing disparities focuses on race and gender. Kamalu et al. (2010) state that generally, African Americans have and continue to endure longer prison sentences for similar crimes compared to whites. As the U.S. court systems tend to be male dominated, Goulette et al. (2015) find that females tend to receive lighter sentences as judges may relate defendants to women in their own lives. This paper is not a study of gender or racial disparities. However, acknowledging the differences in sentencing patterns for different demographic groups motivates us to control for them our models.

CLASSIFYING IDEOLOGICAL AFFILIATION

The main intent of this paper is to identify sentencing disparities between various ideologies.

LEFT VS RIGHT WING

Right-wing violence can be defined as violence committed be those promote human inequalities and target the progressive fight for an equal society (Wilson, 2020). Wilson states that racism and nationalism tend to be the driving factors but are not exclusive to the right. Loadenthal (2018) first examines the differences in classifications between left and right-wing political violence. He states that left-wing acts of political violence are often classified as terrorism, while right-wing acts of political violence are often defined as extremism. Loadenthal then states that left-wing acts of political violence are specifically designed to not injure a large proportion of the public. This design is to ensure the masses do not condemn them. This design segways into another discussion. What do we classify leftism acts of political violence as? Are leftism acts of political violence *terrorism*? Or are they a vehicle that attempts to drives political and social change? We do not attempt to classify leftism political violence here. Through this discussion, we begin to understand how leftism and rightism acts of political violence differ and fuel the analysis below.

JIHADISM

We are also interested in the effects of a defendant identifying with Jihad/Islamic Extremism on sentencing. The events of September 11th, 2001 changed how terrorists were investigated and prosecuted in the United States (more discussion below). Following 9/11, the United States has undertaken an aggressive war on terror and adopted a zero-tolerance policy for criminals suspected of association with a terrorist organization (Ahmed, 2018). Ahmed also states that the Federal Sentencing Guidelines - Terrorist Enhancement guidelines may treat hardened terrorists and Muslim youth who simply express support for terrorist groups equally. These new guidelines were enacted in 1995 following the Oklahoma City bombing. Wassenberg (2017) argues that Terrorism Enhancement was created using a set of crimes that is too broad. Wassenberg also states that this act is controversial because of the large increase in sentence if a crime falls under this broad set. Regarding the large increase in sentence length, Wassenberg states if a defendant has no prior criminal history (level I) and the defendant's case falls under the Terrorism Enhancement act, then the defendant's criminal history level will automatically increase to the maximum criminal history level (level VI). Referring to the table above, we notice the scale of impact of this act. Akram (2002) argues that U.S. laws have targeted Arab and Muslim non-citizens and courts have been quick to label them as terrorists. Akram states that the Patriot Act following 9/11 furthered stereotyping by the U.S. government.

In general, with a large political effort focused on the War on Terror following 9/11, Americans who identify Muslims as dangerous and untrustworthy are more willing to support the War on Terror (Sides, Gross, 2013). This may lead to biased prosecution in the federal court system. From above, the inclination to label individuals who identify with Jihad/Islam as terrorists under a zero-tolerance may result in biased sentencing. Overall, we leave the effect of 9/11 on sentencing for future research as the data set we use does not support propensity score matching (not enough observations before 9/11/2001). We do, however, recognize the effect 9/11 had on the legal system involving suspected terrorism and how these changes could be biased against Muslims. For more information, see *Appendix C.*

Data

The data utilized for this research comes from The Prosecution Project (TPP), an "open-source, long-term intelligence research database" founded by faculty and students at Miami University (Oxford, Ohio) in 2017 (Loadenthal, 2023). The Prosecution Project records felony crimes of terror and political motivated violence. Criminals that are included in the database must meet at least one of three criteria for inclusion:

1. They have expressed a socio-political aim
2. They have been charged under a state speech act
3. They support organized political violence

Each observation in the TPP dataset includes 60+ variables, including the demographic data on the defendant (race, age, sex, etc.), data on the crime (weapon or criminal method used, group affiliation, location, target of crime, the number of people killed or injured, etc.) data on the criminal case (involvement of law enforcement, charges brought against the defendant, plea, jurisdiction of case), and data on the expressed motivation of the criminal (link to a terrorist group, ideological affiliation, etc.).

Model

For our sample, we remove all state cases from our data. We assume our dependent variables of interest, both *Sentence Length* and *Life Sentences*, may be impacted by characteristics of the defendant, characteristics of the case, and characteristics of the crime. To that end, we use control variables from each of these three categories to isolate the effect of defendant *Ideology* on *Sentence Length* and *Life Sentences*:

Characteristics of the Defendant

- *Ideological Affiliation*: What is the defendants espoused ideological affiliation?
- *Age*: How old is the defendant?
- *Race*: What is the defendant's race?
- *US Citizenship*: Is the defendant a US citizen?
- *Veteran Status*: Is the defendant a veteran of the United States Military?

Characteristics of the Case

- *Plea*: Did the defendant plea guilty or not guilty?

Characteristics of the Crime

- *Number Killed*: How many people died from the crime?
- *Number Injured*: How many people were injured from the crime?
- *Cooffender*: Did another individual commit the crime in conjunction with the defendant?
- *Physical Target*: What type of location did the defendant target? (e.g., Mass transportation, medical facility, federal government facility, educational institution, etc.)
- *Criminal Method*: What criminal method did the defendant use? (e.g., firearms, explosives, kidnapping, etc.)

Note that we exclude the Prosecution Project's *Religion* variable in our identification strategy as we suspect it is highly correlated with the *Ideology* variable (in particular in cases of Jihad, Christian Nationalism, etc.)

We utilize two dependent variables derived from the dataset. We generate a binary variable *Life Sentence* indicating whether a defendant has at least one life sentence, creating our first dependent variable. We also discretize the *Months Sentenced* into 36 months (3 year) increments, creating our second dependent variable *Sentence Length.* Such a transformation is theoretically justified by the discontinuous jumps in the Federal Sentencing Guidelines (see above in Literature Review). Our two dependent variables answer the questions:

- *Life Sentences:* Was the defendant given a life sentence?
- *Months Sentenced:* How many three-year increments of prison time is the defendant sentenced to?

Below we report summary statistics for *Life Sentences* and *Sentence Length.*

Fig B: Summary Statistics for Life Sentences and Months Sentenced

Dependent Variable	Mean	Standard Deviation	Potential Values	Minimum	Maximum
Life Sentences	0.0105	0.102	0, 1	0	1
Sentence Length	2.4004	3.44	0 - 53	0	53

*Note that *Sentence Length* is discretized into 3-year increments. A mean of 2.4 suggests that the average sentence length issued to defendants was 7.2 years

Note that a large number of defendants were sentenced to less than 3 years of prison. Consequently, the *Sentence Length* is heavily skewed towards the left due a large volume of zeros. Below we show density plots using continuous data and histograms using discrete data.

Fig C: Sentence Length Density Plot

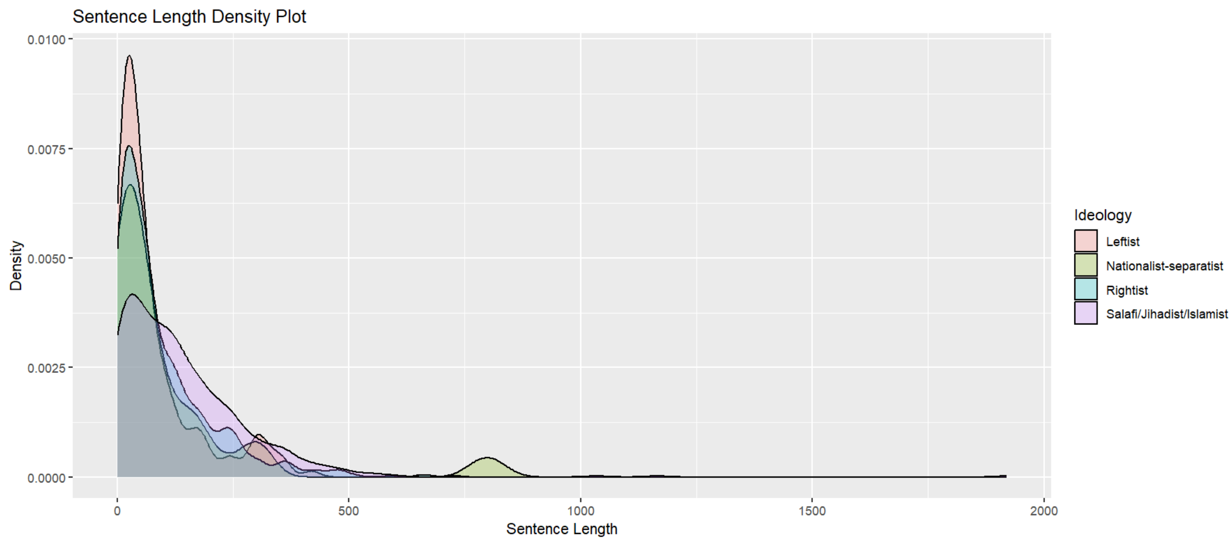
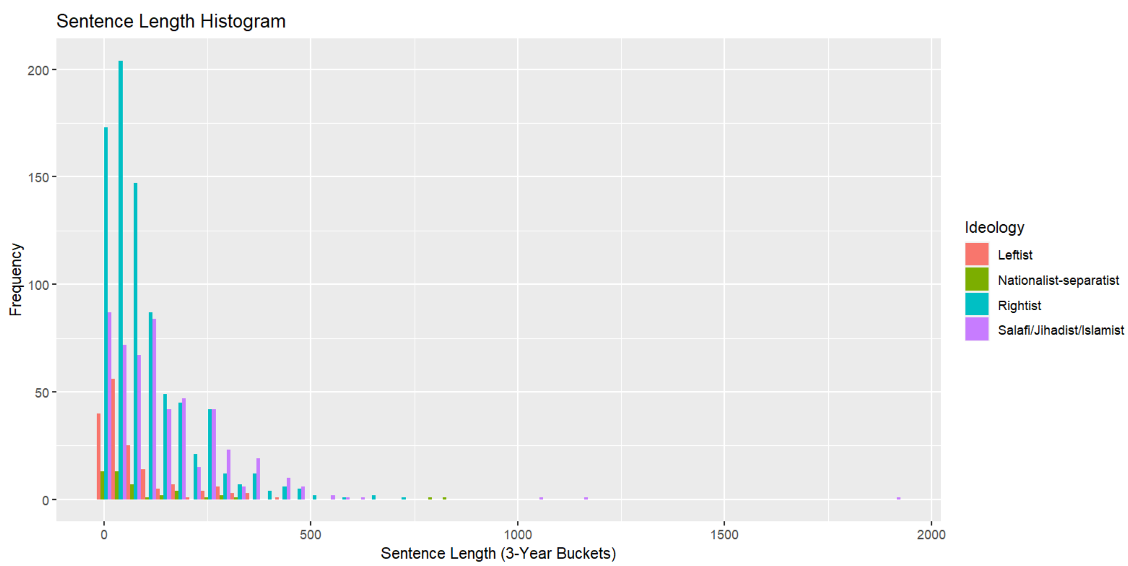


Fig D: Sentence Length Histogram



We notice that each ideology roughly follows an exponential distribution and a Poisson or negative binomial distribution (continuously and discretely respectively). We are not necessarily concerned with the differences in total count for each ideology, however, it is important to verify distributions visually. Next, we notice the majority of cases are bucketed into the "0" count. Visually, this motivates us to pursue zero-inflation and hurdle modeling. This concept is discussed further in the *Models* and *Discussion* section. Simply, we consider both modeling strategies since we do not discuss the structural differences in the processes of generating a zero. Below we report summary statistics for *Ideology.*

Fig E: Frequencies of Ideologies

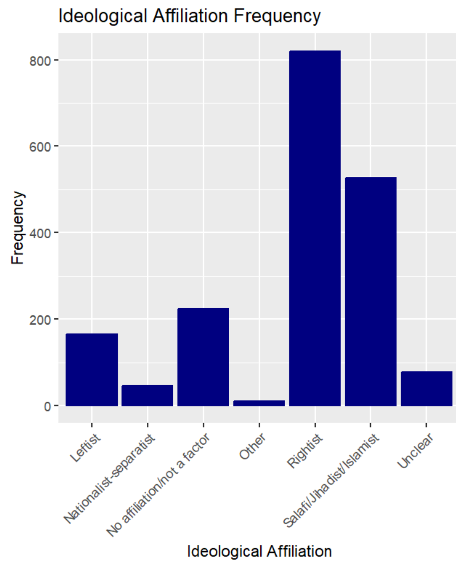


Fig F: Frequencies of Ideologies (Table)

Independent Variable	Frequency	Percent
Ideology	-	-
Rightist	829	43.96
Leftist	166	8.80
Nationalist	46	2.44
Jihadist	531	28.15
Unclear/Other	88	4.67
No Affiliation	226	11.98

"Rightist" ideological affiliations account for almost half of our sample, while "Leftists", the Rightist counterpart, represents less than a tenth of our sample. The "Nationalist" category also has a small number of observations. While outside the scope of this paper, future research might entail grouping nationalism with either leftism or rightism. Halikiopoulou et al (2012) argue that nationalism plays a vital role in extremism in both the left and the right. We do not participate in this discussion here and leave nationalism as a unique variable.

Methods

We use the *Life Sentences* variable as the dependent variable in a binary choice model to determine the likelihood that a defendant will receive a life sentence. We utilize a simple logit model to determine the effects of our independent covariates on *Life Sentences*. Specifically, we use the model to determine if a defendant is likely to have at least one life sentence. The models for *Months Sentenced* are more complex. As aforementioned, the *Sentence Length* variable has a high concentration at low and zero values: We use the *Months Sentenced* variable as a dependent variable in multiple count models designed to determine the number of months each defendant will be sentence to prison. In all models, we attempt to isolate the effect of the *Ideology* variable on the dependent variables.

This high density at near 0 months represents defendants who were given little to no prison time. To handle this nuance, we employ four distinct models able to accommodate large quantity of zeros. We begin with a two-part model, which separately models the zero-generation process. The first step in a two-part model is a dichotomous classifier (e.g., logit or probit) that distinguishes between observations with a high likelihood ($p \geq 0.5$) that $y > 0$ and those with a low likelihood ($p \leq 0.5$) that $y > 0$. Each observation is categorized accordingly ($y > 0$ or $y = 0$). If the dichotomous classifier determines $y > 0$ for a given observation, the observation is then funneled to the second step of the two-part model. A count model (e.g., poisson or negative binomial) is used to estimate the value of y for observations with $\hat{y} > 0$.

The first mechanism of our two-part models, a logit model, predicts whether *Sentence Length = 0* or if *Months Sentenced > 0.* For observations where *Sentence Length > 0,* the two-part model proceeds to a count model to determine the number of *Sentence Length.* We utilize three two-part models which each assume different underlying distributions: Poisson, negative binomial, and gamma. When estimating each model, we utilize robust standard errors. The zero-inflated model is given by:

$$P(Y = y_i) = \begin{cases} \pi_i + (1 - \pi_i)p(y_i = 0; \gamma_i) & y_i = 0 \\ (1 - \pi_i)p(y_i; \gamma_i) & y_i > 0 \end{cases}$$

where γ_i is vector of covariates and π_i represents zero-inflation. We see here that we assume the zeros stem from two different distributions and model as such (Feng, 2021). The second type of model we use to accommodate a large quantity of zeros is a hurdle model. Hurdle models also utilize two-stage process. First, a logit model predicts whether $y = 0$ or $y > 1$. Then, a truncated count model is utilized to count y for observations were $y > 0$. While hurdle models use a mixture, the critical assumption is that the data comes from the same source or process (Feng, 2021). The hurdle model is given by:

$$P(Y = y_i) = \begin{cases} p_i & y_i = 0 \\ (1 - p_i)\frac{p(y_i;\gamma_i)}{1 - p(y_i = 0;\gamma_i)} & y_i > 0 \end{cases}$$

where p_i represents the probability that observation i belongs to the zero-mass component. We notice that in the second line of this model, one component is the probability that observation i does not belong to the zero-mass component and the other is a zero-truncated representation of the specified probability mass function.

To compare the three model specifications, we utilize AIC, BIC, and log likelihood statistics. Since

$$AIC = 2k - 2\ln(L)$$

where L is the maximized value of the likelihood function, AIC is only dependent on the specification of the likelihood function and not the identification of the model. BIC is similarly measured.

To test each models' generalizability, we employ k-fold cross validation. The cross-validation (CV) method trains the model on a specific portion of the sample data (the training set) while leaving out a small group of observations for testing (the test set). In our CV procedure, we split the data into 10 equal subsections. The models are trained on nine of these subsections. The model is subsequently evaluated on the tenth subsection, which generates an error value. The process is then repeated, with each iteration excluding a different subsection of data to use as the test set. The errors from each of the of the iterations are averaged to produce mean error value for each type of model. K-fold cross validation emerges as the leading method to compare models since each model is identified in the same manner.

Results

In all regression results, we remove coefficients and standard errors for categorical variables with many categories (e.g., Completion of Crime, Race, Criminal Method, Physical Target) from the table below for simplicity. Readers interested in these results can find them in the appendix.

Below we report the results from logit model which attempts to predict whether a defendant will receive at least one life sentence. Because there were only 20 defendants in our sample who received life sentences, a number of covariates are excluded on the grounds they appear to perfectly predict *Life Sentences,* albeit erroneously (this includes a number of Ideology covariates).[2]

[2] For example,

Fig G: Life Sentences Logit Model

Ideology	
Salafi/Jihadist/Islamist	1.341
	(1.849)
Other/Unclear	1.557
	(2.132)
No Affiliation	-10.31
	(17.02)
Number Killed	3.803***
	(1.223)
Number Injured	-0.334
	(0.501)
Plea	-3.125**
	(1.505)
US Citizen	-1.779
	(2.211)
Veteran Status	5.243***
	(1.939)
Cooffender	-3.742**
	(1.649)
Hate Crime	-0.0699
	(2.040)
Previous Similar Crime	1.716
	(1.306)
Completion of Crime	-
Race	-
Physical Target	-
Constant	-8.355
	(5.400)
Observations	634

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Below we report the results from the three two-part models and the hurdle model used to predict *Sentence Length*. Each of the two-part models utilizes the same logit model:

Fig H: Sentence Length Count Models

RESULTS	(1) Logit	(1.A) Poisson	(1.B) Neg Bin	(1.C) Gamma	(2) Hurdle Logit	(2.A) Truncated Poisson
Ideology	-	-	-	-	-	-
Omitted = Rightist						
Leftist	-0.134	-0.175*	-0.202**	0.0426*	-0.134	-0.203**
	(0.264)	(0.101)	(0.0914)	(0.0239)	(0.271)	(0.0801)
Nationalist-Separatist	-0.862**	0.114	0.138	-0.0474	-0.862**	0.112
	(0.416)	(0.254)	(0.225)	(0.0451)	(0.415)	(0.113)
Salafi/Jihadist/Islamist	0.345	0.364***	0.317***	-0.0806***	0.345	0.397***
	(0.220)	(0.112)	(0.0845)	(0.0171)	(0.221)	(0.0591)
Other/Unclear	0.239	0.258**	0.230*	-0.0823***	0.239	0.287***
	(0.306)	(0.119)	(0.123)	(0.0284)	(0.305)	(0.0923)
No Affiliation	-0.334	0.191	0.150	-0.0308	-0.334	0.217**
	(0.288)	(0.131)	(0.128)	(0.0338)	(0.290)	(0.0933)
Number Killed	-0.200	0.186***	0.274**	-0.0842***	-0.200	0.190***
	(0.259)	(0.0656)	(0.110)	(0.0233)	(0.225)	(0.0447)
Number Injured	-0.0400	0.0334	0.112	-0.151**	-0.0400	0.0291
	(0.237)	(0.0416)	(0.132)	(0.0586)	(0.301)	(0.0264)
Plea	-1.133***	-0.581***	-0.589***	0.148***	-1.133***	-0.640***
	(0.179)	(0.0676)	(0.0601)	(0.0137)	(0.174)	(0.0365)
Gender	-0.371**	-0.264**	-0.287***	0.0638	-0.371*	-0.323***
	(0.177)	(0.116)	(0.0904)	(0.0411)	(0.196)	(0.0724)
US Citizenship	0.139	-0.0940	-0.0509	0.0229*	0.139	-0.103**
	(0.190)	(0.0698)	(0.0663)	(0.0121)	(0.186)	(0.0456)

Veteran Status	-0.103	0.0881	0.0804	-0.0291*	-0.103	0.0951
	(0.335)	(0.113)	(0.102)	(0.0158)	(0.311)	(0.0671)
Cooffender	-0.457***	-0.110*	-0.109**	0.0281**	-0.457***	-0.128***
	(0.152)	(0.0634)	(0.0551)	(0.0114)	(0.144)	(0.0389)
Hate Crime	-0.0163	0.176**	0.137	-0.0185	-0.0163	0.204***
	(0.238)	(0.0891)	(0.0855)	(0.0182)	(0.246)	(0.0713)
Previous Similar Crime	0.922***	0.172**	0.131**	-0.0234*	0.922***	0.198***
	(0.177)	(0.0710)	(0.0602)	(0.0132)	(0.173)	(0.0427)
Completion of Crime	-	-	-	-	-	-
Criminal Method	-	-	-	-	-	-
Race	-	-	-	-	-	-
Physical Target	-	-	-	-	-	-
Constant	-0.841	1.413***	1.678***	0.531***	-0.841	-12.57
	(1.134)	(0.462)	(0.535)	(0.137)	(1.091)	(746.6)
Observations	1,864	1,864	1,864	1,864	1,864	1,180

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Below we report statistical criteria used to evaluate the relative strengths of each of our two-part models, including AIC, BIC, Log Likelihood, and Mean Square Error derived from k-fold cross validation. For regression results of the appeared omitted categorical variables, see *Appendix B*.

Fig I: AIC, BIC, and Log Likelihood

Model	N	Log Likelihood	DF	AIC	BIC
Logit + Poisson	1,864	-3,742.29	110	7,704.59	8,312.95
Logit + Negative Binomial	1,864	-3,731.05	110	7,682.10	8,290.45
Logit + Gamma	1,864	-1.90e+09	111	3.80e+09	3.80e+09

Fig J: K-Fold Cross Validation

Two-Part Model	K-Folds	Mean Squared Error	MSE in Months (MSE *36)
Logit + Poisson	10	1.5509	55.83
Logit + Negative Binomial	10	1.4889	53.60
Logit + Gamma	10	1.6173	58.21

The Logit + Negative Binomial model performs best. The model has the lowest AIC, BIC, and Mean-Squared Error. The Logit + Gamma model performs noticeably poorly, with a remarkably large AIC and BIC. This result may explain the opposite signs than expected found throughout the results for the two-part gamma model.

Discussion

In terms of ideological effects on sentencing, we obtain results that align with the information provided in the literature review.

Note that leftists receive lighter sentences at a highly significant level even when controlling for characteristics of the crime, defendant, and case. We assume this results from the public's (and judges') perception of leftist crime. Recall that rightists are more likely to be classified as "extremists" while leftists are more likely to be classified as "freedom fighters" (or some variation). Additionally, leftists typically avoid violent acts against the general public to retain support.

All of our models suggests that Jihadist/Salafi/Islamist defendants will have higher sentence lengths than comparable defendants with rightist ideologies. However, note that we do not control for the Terrorism Enhancement Act in our model. The Terrorism Enchantment Act may be impactful even in cases that lack a material connection to official terror groups: even showing support for a terrorist organization online paired with a minor, unrelated crime unrelated to terrorist operations can invoke the penalty of the Terrorism Enhancement Act. For future research, controlling for cases that fall under the Terrorism Enhancement Act may be useful.

We did not find any significant results for nationalist ideologies. This may be due to our limited sample size. However, we note in our logit models that nationalists are less likely than rightists to receive a life sentence for a similar crime.[3] Future research on nationalism and sentencing may look at a broader data set of criminal cases. It may be possible to conduct a study using classification models which aims to classify defendant's with nationalist ideologies as rightist or leftist. Another possible avenue of research

[3] This may be in part due to nationalist's ability to fall under the categories of both the left and the right.

could utilize propensity score matching to determine the effect of various forms of nationalism (i.e., left wing versus right wing) using two independent statistical processes where causal inference is involved. Unlike most classification models where machine learning is used, causal inference and treatment models may give better insight.

Surprisingly, the number of people injured in a crime has no significant effect on sentence length. This may be due to the low incremental increase in our *Sentence Length* variable for people injured versus a more serious offense (i.e. people killed). For example, suppose in a hypothetical world an individual commits a crime and the sentencing judge is unaware of any injured persons. Suppose this judge issues a sentence of 37 months for this crime. However, right before the judge bangs the gavel, imagine it is revealed that one person was injured as a result of the crime. The judge reconsiders her sentencing decision and changes the sentence to 45 months. Because the *Sentence Length* variable is discretized into 3-year increments, both hypothetical sentences end up in the same bucket. Future research using smaller buckets may result in a significant relationship. However, this research should not be motivated with the sole purpose of obtaining significant *p*-value.

As expected, a defendant who has committed a prior crime using a previous similar method receives a harsher sentence. This is a product of how sentencing guidelines are structured. Note that we could not account for the nature of a defendant's criminal history more generally. In this case, the only insight we have is previous crimes committed if they used a similar method. For future research, a proxy or instrument variable may be needed since criminal history is protected information.From the results, we understand that a guilty plea has a negative effect on *Sentence Length*, and also has a negative effect on a defendant receiving any prison time at all.

Exogenous to the model, processes of the prosecution pre-trial may influence the sentence delivered (i.e., a defendant making a pre-trial deal to plead guilty in exchange for little to no prison time). We also understand that in cases where a defendant is a co-offender, they may be incentivized to share information that could further incriminate another co-offender of higher "value" to the DOJ. These hypothetical examples show how much of the process we cannot account for. Future research may be interested in answering philosophical questions regarding the discretizing of processes from arrest to indictment. Answering these questions can impact the selection of statistical models.

Conclusion

Overall, we begin the conversation on the effect of a defendant's ideological affiliation on their criminal sentencing in cases of politically or ideologically motivated violence. We model the length of time a defendant will be sentenced to prison as well as the probability of being given a life sentence using data on the defendant (e.g., demographic data), data on the case, and data on the crime itself. We utilized two-part models and hurdle models, which appropriately model defendants receiving no prison time as being a part of the same process as those who do receive prison time. Identifying the different processes can assist in informing results as well.

Most notably, our results suggest that leftists are more likely to receive lower sentences than rightists, even when controlling for variation between the defendants and their respective crimes. Other results are more predictable. Jihadist/Salafi/Islamist defendants are likely to receive high sentences than rightists, which we attribute to the unobserved yet influential impact of the Terrorism Enhancement Act. Also as expected, higher number of persons killed during a crime will increase a defendant's sentence length, as will committing the same crime multiple times (repeat offenses). By contrast, having a coofender in the crime or pleading guilty will lower a defendant's sentence length.

We are limited by the scope of the data set. There are only a select number of defendants that express a political or ideological motivation for their crime, and even fewer that do so while committing a violent act. Broader data sets would allow more for study of ideology at a lower level of detail (i.e., higher specificity) while more clearly establishing statistical trends in the data. Despite these limitations, we leverage this restricted data set to the best of our abilities knowing that observations in this data represent very rare occurrences with hopes that future research expands on the ideas presented in this paper. Using broader data sets than span multiple types of motivation for crime may introduce more robust results.

Data Citation

Loadenthal, Michael, Lauren Donahoe, Madison Weaver, Sara Godfrey, Kathryn Blowers, et. al. "The Prosecution Project Dataset," *the Prosecution Project*, 2023 [dataset]. https://theprosecutionproject.org/

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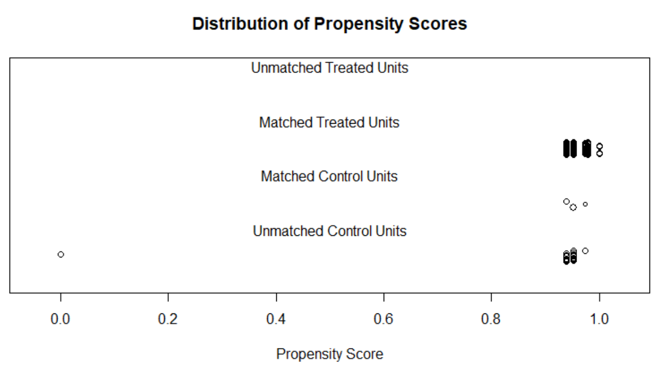
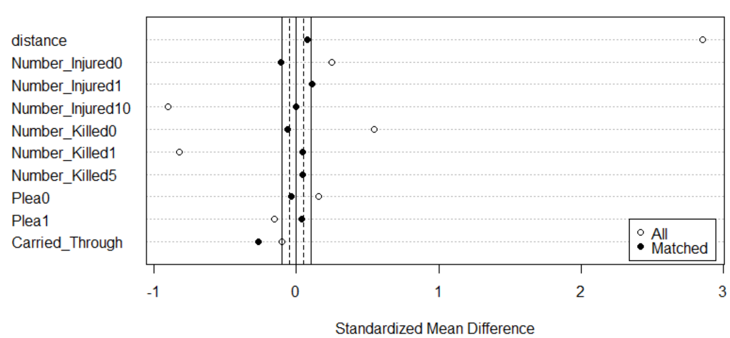
APPENDIX A

Propensity Score Matching

We turn to propensity score matching to measure the effect of 9/11 on sentencing in cases where no life sentences were issued, and the defendant identifies with Jihad/Islamic Extremism. With only 26 control observations, we expect that this process will produce results with large standard errors and confidence intervals. We proceed in a naïve manner with hopes of motivating future research. By leveraging nearest neighbor matching and replacement matching, we find that only three control group observations got matched with a treatment observation. With an initial sample size of 531, we eliminate 23 observations for a matched sample of 508. We must use replacement matching as a final sample size of 26 is far too small. In addition, if we force the other 23 observations to match with a treatment group observation, the matches will be far too unbalanced. We are currently naïve; however, we are still motivated to produce the best possible model. Below are charts of the distribution of propensity scores along with standardized mean differences.





We notice that due to the lack of sample size in the control group, this process results in overly confident propensity scores along with unbalanced standardized mean differences. Notice that the independent variables are a parsimonious set of variables used to describe the nature of a crime. As expected, no sensible results present themselves and we leave a stronger modeling approach for future research. Without reporting a table, the estimated coefficient for the 9/11 intervention attained from a weighted linear regression is statistically insignificant with a confidence interval from –85.7 to 152.2.

Appendix B

Post-9/11 Sentencing

Two key aspects emerge regarding Jihad/Islamic Extremism sentencing post-9/11. (1) How investigations changed, and (2) how prosecution changed. In terms of prosecution, two main strategies were adopted: *Explicit Politicality*, a middle-ground approach, and exceptional vagueness (Shields et al., 2009). Shields et al. Argue that 9/11 did not change prosecution strategies, but the extent to which each strategy is used. *Explicit Politicality* is a strategy which paints the defendant as a terrorist and as someone who has committed an act of political violence. This strategy utilizes the public media and contains lengthy discussions of motive and conspiracy. *Exceptional Vagueness*, on the other hand, is a strategy where prosecution refrains from labeling the defendant as a terrorist. In this scenario, the defendant's case is comparable to a traditional criminal investigation. In between, the middle-ground approach is where prosecution will subtly inform the court that the defendant may be linked to a terrorist organization. In terms of investigations, the FBI decentralized their investigations of terror and referred this duty to field offices post-9/11 (Shields et al., 2009). During this process, the FBI shifted their focus to prevention, and began narrowing in on criminal activity that terrorists would potentially engage in before an attack (specifically, immigration and financial fraud). By shifting their focus to crime categories and not individuals, the FBI would report "prevented terrorist attacks". While investigations are not necessarily the area of significance to this study, we note that differences in investigation strategies pre- and post-9/11 effect the pool of defendants charged with acts of political violence

Following 9/11, new critiques of the DOJ annual reports boasting success against terrorist threats emerged. Shields et al. (2009) state that people critiqued the data reliability as some cases reported have no link to terrorism, and that defendants who were found guilty and identified with a terrorist organization received softer sentences. These critiques may be byproducts of the investigation efforts mentioned above. If a suspected terrorist is charged with a crime unrelated to terrorism before an attack, then the DOJ would be incentivized to claim they have successfully prevented a potential attack and report it. We acknowledge prosecution differences in an effort to show how changes in prosecution strategy, along with a national fear of terror post-911 effect sentencing of defendants associated with Jihad.