Lethal Election: Methodology

Death Penalty Information Center

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Introduction

At A Glance

This is an R Markdown (R Version 2023.12.1+402) document describing the methods, data collection, and data analysis for the DPIC's ***Lethal Election*** research project. We hope that those using this material will be able to reproduce our findings and/or contribute to further understanding of the impact of elections on the death penalty in the United States (US).

Suggested Citation

Lethal Election: How the U.S. Electoral Process Increases the Arbitrariness of the Death Penalty, Death Penalty Information Center, July 1, 2024.

Time Period

January 1st, 2013 - December 31st, 2022 (judicial analysis) | January 1st, 1976 - December 31st 2023 (executive clemencies analysis)

Spatial Domain

United States of America (USA); Georgia-US, Ohio-US, North Carolina-US.

Study Purpose

The purpose of this research project is to understand the dynamics and impact of elections (judicial and within the executive branch) on capital punishment in the US.

What Was Done and Why?

For statistical analysis, data assessment, and visualization, we used R, Flourish, and Tableau Desktop (2024.1). We simultaneously collected data and ran analyses for two different scopes of the project: **1) Judicial** and **2) Executive**; searching for causal relationships between variables that could reject or support our hypotheses. Being aware of the multifaceted circumstances that death penalty decisions involve, we controlled for socioeconomic factors such as crime and murder rates, and gross domestic product *per capita* (for the respective state depending on the spatial domain of our assessment). Additionally, we accounted for instances where elections remained uncontested, and we explored the impact of the transitional period—also referred to as the *lame-duck period*; though, we also acknowledge that this term has recently been criticized for its ableist connotations (e.g., Stones, 2017).

Primary data collection involved the creation of a comprehensive dataset of death penalty cases reviewed between 2013 and 2022 by the State Supreme Courts of Georgia, Ohio, and North Carolina. We chose these states for their similar size in population and because they are known as politically "purple" or "swing" states, which would (in theory) increase the likelihood of competitive elections and the political weight of judicial decision-making. While it is impossible to select an "average" death penalty state given the differences in use, procedures, and practices, these three states have sentenced to death and executed roughly similar numbers of people in the modern era (DPIC, n.d.). All three states of our focus elect Supreme Court justices, and at least one justice on each court is up for reelection every even-numbered year. In our review of the data, each case was coded for a variety of variables including outcome, each justice's vote, legal claims presented, facts of the crime, and characteristics of the prisoner.

The total sample included every death penalty case decided by the State Supreme Courts between 2013 and 2022, totaling 110 cases. The sample comprised 73 observations from Ohio, 24 from Georgia, and 13 from North Carolina. Justices' votes and case details were merged into one 'master spreadsheet' for further analysis. The master spreadsheet, which included DPIC original data cross-checked against the *Westlaw* database, was coded by two independent DPIC coders for justices' authorship, votes, dissents; whether the justice was in an election year, and for the criminal case details, such as aggravating factors, number of victims, and claims, e.g., of prosecutorial misconduct. Each person's data was then cross-examined by another team member. Additionally, various *Microsoft Excel* logical functions were performed to check for missing values and discrepancies to ensure data robustness.

Moreover, our socioeconomic information and criminal data came from the U.S. Census Bureau, Bureau of Economic Analysis, Bureau of Labor Statistics, Federal Reserve Bank of St. Louis, Federal Bureau of Investigation, and Centers for Disease Control and Prevention.

For the executive domain, we used existing DPIC data on clemencies, in addition to scholarly datasets compiled by Michael L. Radelet & Barbara A. Zsembik (1992) and Scott E. Sundby (2006). The dataset includes entries of executive clemencies (313 instances of clemencies for 146 observations—including instances of mass clemency in 2003 (167 cases) in Illinois and three federal/military clemencies).

This document contains the complete list of variables, datasets, and a detailed analysis description (with the respective R-script, as we hope to invite you to use our data and/or replicate our results). It also comes with significant and other findings that informed our analysis, however, a complete data of tests performed are available upon request and not included in this document.

Among the methods used for inferential statistics, we utilized linear and logistic regressions to examine the relationships between predictor variables and both continuous and categorical outcome variables. We also assessed the nature, distribution, and potential multicollinearity of the variables, and performed robustness checks and model diagnostics. Nonetheless, as the death penalty has been a declining phenomenon in criminal justice, we faced small-scale datasets and sample sizes, which may affect the generalizability of our findings.

Research Questions:

Justices: *How do outcomes for capital cases decided by State Supreme Courts during election years compare to cases decided during non-election years?*

Executives: *Whether executives are more likely to grant clemency to death-sentenced prisoners when up for re-election or at the end of their tenure?*

Hypotheses:

Hypothesis 1 (H1): *State Supreme Courts are less likely to grant relief to death-sentenced prisoners when one or more justices are facing re-election. (null hypothesis: State Supreme Courts are equally likely to grant relief to death-sentenced prisoners in election years as in non-election years)*

Hypothesis 2 (H2): *Elected Executive Officers (Governors and Presidents) exiting the office are more likely to grant clemencies and mass clemencies compared to when they are up for re-election. (null hypothesis: Elected Executive Officers (Governors and Presidents) exiting the office are equally likely to grant clemencies and mass clemencies as when they are up for re-election)*

Variables:

Dependent Variables

Variable Name	Coded as…	Description
Affirmed Sentences	affirm	a binary variable indicating whether the appellate court affirmed (upheld) the death sentence issued by the lower court coded as 0 for "no" (death sentence not affirmed) and 1 for "yes" (death sentence affirmed the death sentence)
Number of Cases	case	a continuous variable indicating the number of capital cases
State Prevailed	state_prev_all	indicating whether a state prevailed in the case coded as 0 for "no" (state did not prevailed) and 1 for "yes" (state prevailed) in the capital case
Defendant Prevailed	defe_prev_all	indicating whether a defendant prevailed in the case coded as 0 for "no" (defendant did not prevailed) and 1 for "yes" (defendant prevailed) in the capital case
Reversed Death Sentence	rev_ds	a binary variable indicating whether the appellate court reversed the death sentence without reversing the underlying conviction coded as 0 for "no" (death sentence not reversed) and 1 for "yes" (death sentence reversed)
Reversed Conviction	rev_con	a categorical binary variable indicating whether the appellate court reversed the defendant's conviction, irrespective of the sentence—coded as 0 for "no" (conviction not reversed) and 1 for "yes" (conviction reversed)

Variable Name	Coded as…	Description
Mass Clemency	mass_num	a binary variable indicating whether clemency was part of the mass clemency grant; coded as 0 for "no" when it was an individual clemency and as 1 for "yes" a mass-clemency grant

Independent Variables

Variable Name	Coded as…	Description
Election Year	election	a binary variable indicating election year; codes as 0 for non-election years and 1 for election years
Re-Election	re_el_num	a binary variable indicating whether the executive was up for re-election in the year clemency was granted; coded as 0 for "no", they were not running for re-election; and 1 for "yes", they were running for re-election
Last Year in Office	last_year_bin	a binary variable indicating whether the executive was last year in their office (ending their tenure for any reason) when clemency grant occurred

Control Variables

Variable Name	Coded as…	Description
Contested Election	contested_bin	a binary variable indicating whether the election was contested ; coded as 0 for "no" indicating a non-contested election, and 1 for "yes" indicated a contested-election
Population	pop	a continuous variable representing the total number of people living in a particular county/state
State/County Murder Rate *per capita*	smrpc, cmrpc	continuous variable indicating the number of murders relative to the population size in a sate or county
GDP *per capita*	gdp	a continuous variable measuring the gross domestic product (GDP) of a county divided by its population
Unemployment	unemp	a continuous variable representing the percentage of the labor force that is jobless
Appellant	app_pri and app_stat	a binary categorical variable (0,1) indicated whether the appellant was a state or a prisoner

Variable Name	Coded as…	Description
Dissent	diss_bi	a categorical binary variable indicating the presence of a dissenting opinion filed in the appellate decisions related to the case
Substantive Ruling	subst_rul	a categorical binary variable indicating whether the appellate court's decision in the case was based on substantive law coded as 0 for "no" (decision not based on substantive law), and 1 for "yes" (decision based on substantive law)
Procedural Ruling	proc_rul	a categorical binary variable indicating whether the appellate court's decision in the case was based on procedural law—coded as 0 for "no" (decision not based on procedural law), and 1 for "yes" (decision based on procedural law)
Reversed Non-Death Convictions	rev_other	a categorical binary variable indicating whether the appellate court reversed convictions that did not result in a death sentence, such as lesser felonies or misdemeanors associated with the case—coded as 0 for "no" (non-death convictions not reversed) and 1 for "yes" (non-death convictions reversed)
Multiple Offender	multiple_off	a categorical binary variable indicating whether the defendant/prisoner is considered as a multiple offender—coded as 0 for "no" (not a multiple offender) and 1 for "yes" defendant/prisoner is considered as a multiple offender
Number of Victim(s)	no_vict	number of victims in a capital murder case
Sexual Violence	sexual_violence	a categorical binary variable indicating the occurrence of sexual violence in a given incident or case. It is coded as 0 for "no" (no sexual violence occurred) and 1 for "yes" (sexual violence occurred)
Minor Victim	minor	a categorical binary variable indicating whether a victim was a minor (under the legal age of adulthood, which varies by jurisdiction), including the cases where sexual violence was perpetrated against minors. It is coded as 0 for "no" the victim

Variable Name	Coded as…	Description
		was not a minor and 1 for “yes” the victim was a minor
Partner	partner	a categorical binary variable indicating whether the victim was a romantic partner of the defendant coded as 0 for “no” the victim was a romantic partner of defendant/prisoner and 1 for “yes” the victim was a romantic partner of defendant/prisoner
Peace Officer	peace_officer	a categorical binary variable identifying whether the victim was a member of law enforcement or representing a broader category of ‘peace officer’, coded as 0 for “no” the and 1 for “yes”
Prosecutorial Misconduct Claim—Atkins	atkins	a categorical binary variable indicating whether the defendant has filed a claim of prosecutorial misconduct under the Atkins rule—coded as 0 for “no” (no claim filed) and 1 for “yes” (claim filed)
Prosecutorial Misconduct Claim—Brady	brady	a categorical binary variable indicating whether the defendant has filed a claim of prosecutorial misconduct under the Brady rule—coded as 0 for “no” (no claim filed) and 1 for “yes” (claim filed)
Prosecutorial Misconduct	pros_mis	a categorical binary variable indicating whether the defendant has filed a claim of other prosecutorial misconduct claim coded as 0 for “no” (no claim filed) and 1 for “yes” (claim filed)
Prosecutorial Misconduct Claim—Batson	batson	a categorical binary variable indicating whether the defendant has filed a claim of prosecutorial misconduct under the Batson rule—coded as 0 for “no” (no claim filed) and 1 for “yes” (claim filed)
Ineffective Assistance of Counsel Claim—Strickland	strickland	a categorical binary variable indicating whether the defendant has filed a claim of ineffective assistance under the Strickland rule—coded as 0 for “no” (no claim filed) and 1 for “yes” (claim filed)
Jury challenge—other	jury_ch_other	a categorical binary variable indicating whether the defendant has filed any other type of jury challenge not specifically

Variable Name	Coded as…	Description
		covered by other categories (such as discrimination or misconduct claims) coded as 0 for "no" (no other jury challenge filed) and 1 for "yes" (other jury challenge filed)
Financial Gain Aggravator	fin_gain	a categorical binary variable indicating whether the crime for which the defendant is being tried included a financial gain aggravator—coded as 0 for "no" (no financial gain aggravator involved) and 1 for "yes" (financial gain aggravator involved)
Felony Murder	felony_m	a categorical binary variable indicating whether the defendant is charged with felony murder, which occurs when a death results from the commission of certain felonies, regardless of intent to kill—coded as 0 for "no" (not charged with felony murder) and 1 for "yes" (charged with felony murder)
Accomplices	accompl	a categorical binary variable indicating whether the defendant had accomplices involved in the commission of the crime—coded as 0 for "no" (no accomplices involved) and 1 for "yes" (accomplices involved)
Public Pursuit	pursuit	a binary variable indicating whether the apprehension of the defendant involved a public pursuit or manhunt, signifying extensive law enforcement efforts to capture the defendant that engaged public attention—coded as 0 for "no" (no public pursuit or manhunt involved) and 1 for "yes" (public pursuit or manhunt involved)
Previous Capital Offender	prev_off	a categorical binary variable indicating whether the defendant has previously been convicted of a capital offense—coded as 0 for "no" (no previous capital offense conviction) and 1 for "yes" (has previous capital offense conviction)
Mental Disability	ment_diss	a binary variable indicating whether an individual has been diagnosed or identified as having a serious mental disability coded as 0 for "no" (no mental disability known) and 1 for "yes" (mental disability)

Variable Name	Coded as…	Description
History of Substance Abuse	substance	a binary variable indicating whether the defendant/prisoner has a history or current issue with substance abuse; it is coded as 0 for "no" (no history or current issue with substance abuse) and 1 for "yes" (history or current issue with substance abuse)
Domestic Violence Survivor	dom_viol	a binary variable (0/1) indicating whether the individual is a survivor of domestic violence; it is coded as 0 for "no" (not a survivor of domestic violence) and 1 for "yes" (a survivor of domestic violence)
Foster Care	foster	a binary variable (0/1) indicating whether the individual has been a client of the foster care system; it is coded as 0 for "no" (not a former foster care client) and 1 for "yes" (a former foster care client)
Sole Authority	sole_authority	a binary variable indicating whether the executive in power had a sole authority to grant clemency; it is coded as 0 for "no" (no sole authority, e.g., the clemency recommendation has to be given by a specific board), and as 1 for "yes" where an executive had the sole authority
Must Have Recommendation (to grant clemency)	must_have_recom	a binary variable indicating whether an executive must have recommendation to grant a clemency; it is coded as 0 for "no" (no sole authority, e.g., the clemency recommendation has to be given by a specific board), and as 1 for "yes" where an executive had the sole authority to grant clemency
Non Binding Recommendation	non_binding_recom	a binary variable indicating whether the executive receives a non binding recommendation on whether to grant the clemency; it is coded as 0 for "no" (no binding recommendation, e.g., the clemency recommendation given by a specific board is not binding), and as 1 for "yes" (the clemency recommendation given by a specific board is binding)
Board Clemency	board_clem	a binary variable indicating whether it was a Clemency Board to grant the clemency; it is coded as 0 for "no" (no board clemency

Variable Name	Coded as…	Description
		received), and as 1 for “yes” (board clemency received)

Other Variables

Variable Name	Coded as…	Description
Prisoner/Defendant Name	name	last, first name
Current Case Status	stage	direct appeal, post-conviction, other
Year of Death Sentence	first, second, third	year of the first and consecutive (if any) death sentences
Case Filed Date	filed	a variable indicating the date on which a legal case was officially filed in the court
Case Citation	title	name of the capital case
Jurisdiction	state	state, federal, military
Appellant (nominal)	appell	case appellant: prisoner, state, other
Election Year (nominal)	yr_el	an indication whether case filed-date is in the election year
Author	author	last and first name of the supreme court justice identifying the author of a judicial opinion related to the case
Majority	majority	last names of justices, or ‘all’ for *per curiam*
Dissenting Justices	dissent_jus	last and first name of dissenting justices identifying the author(s) of a judicial opinion related to the case
Number	no	number of cases
Month	month month when clemency was granted	
Year	year	year when clemency was granted
Name	name	defendant’s name
Race	race	defendant’s race
State	state	state name
Years Office	years_off	a nominal variable indicating the executive’s years in office
Years Run	year_run	a nominal variable indicating the year(s) executive was running for their office

Important Findings

Justices

To assess the election's impact on the dependent variables, we compared the outcomes across different units of analysis: 1) defendant/case; 2) election year. For the latter, we created a new dataset that aggregated data based on the date when the case was filed. By 'election year', we understood a 12-month period between a general election date in a particular state of focus, e.g., for Ohio, the elections in 2018 took place on November 6th, and the election year, which also encompassed primaries, commenced on November 7th, 2017. Political scientists and economists have discussed the 12 months' impact on a general election day. Especially considering primaries that may take place months prior to election day, the 12-month window is an adequate measure to indicate the potential effect of elections on judicial, prosecutorial, and executive decisions (Brookings, 1996; Gersen, 2011). In addition, we also controlled for the period where power is transitioned post-elections, a time that often allows for various—primarily unpopular or controversial—decisions to take place. This phenomenon has been widely discussed (e.g., Nagle, 2011), and in our research, it encompasses two months after the general election date.

Focus on an Election Year

We created new variables to indicate whether the case was filed during an election year. By 'election year', we understood a 12-month period between a general election date in a particular state of focus. For example, for Ohio, the elections in 2018 took place on November 6th, and the election year that also encompassed primaries commenced on November 7th, 2017. Please note that in Georgia, general elections for Supreme Court Justices take place in May (with an exception for 2020, when they happened in June).

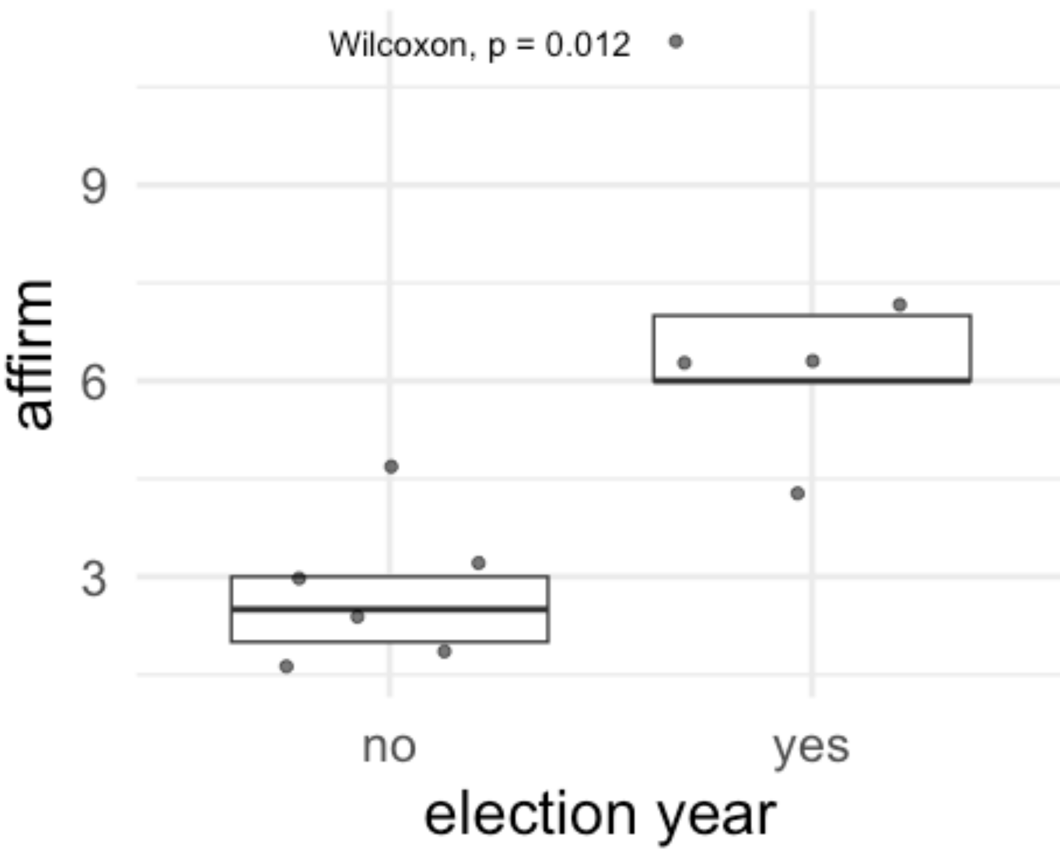
We created a dataset that enabled us to compare the values across election and non-election years with the election year as a unit of analysis (in opposition to the case/defendant as a unit of analysis used for the Master Spreadsheet). Thanks to the function 'mutate,' we could:

Mutate and collapse/summarize the variables and data points for Georgia, Ohio, North Carolina, and their respective election years that were converted into the code. To select respective cases falling into the ambit of an election year or not, we referred to the date when the case was filed. We also collapsed other variables, such as whether elections were contested (contested_bin); whether the state or defendant prevailed (state_prev_all_bi / defe_prev_all_bi), number of victims, number of dissents, affirmed or reversed death sentences (along with the distinction between reversed convictions and reversed sentences), and others.

For the dataset where variables were analyzed through the unit of analysis, the election-year, we observed a potential inflation of cases decided during election years (63 cases) compared to non-election years (37 cases). Only complete observations were used.

To analyze the impact of election years on the number of affirmed death penalty cases, a Wilcoxon rank-sum test (Mann-Whitney U Test) was performed for a variable indicating the number of affirmed cases ('affirm') and a categorical binary variable election ('election'). We chose this non-parametric test due to its robustness in handling non-normally distributed data and its ability to compare the central tendencies. It compared the distribution of affirmed cases between two groups: years with an election ('election'=1) and years without an election ('election'=0). The median of affirmed death penalty cases was higher in election years compared to non-election years. The findings were significant at a p-value of 0.012 (for an alpha of 0.05). The median value for the non-election year is about 3, while for an election year, it is 6. Using the measure of median values with the Wilcoxon test helped to control for outlier cases and their distribution. The significant difference in median values suggests that the central tendency 'shifts' depending on whether there is an election year or not. This shift may indicate that electoral cycles influence judicial behavior.

Figure 1. The Wilcoxon Test for Affirmed Death Penalty in State Supreme Courts (2013-2022)



We also corroborated these outcomes by performing both linear and logistic regressions on categorical outcome variables across different units of analysis and controlling for the number of cases as well as socioeconomic factors.

Figure 2. Logistic regression output for a categorical outcome variable 'affirm' (the number of affirmed death penalty sentences)

```
##          Term   Estimate Std.Error Odds.Ratio   Conf.Low Conf.High      P.
Value
## 1 (Intercept) -2.1222796 0.5658138  0.1197583 0.03950711 0.3630246 0.00017
62399
## 2    election  0.9723829 0.4362917  2.6442380 1.12440191 6.2184123 0.02583
08676
## 3     no_vict  0.8639054 0.2650085  2.3724079 1.41126829 3.9881286 0.00111
44520
```

Figure 3. Coefficients Chart with Margins of Error for a categorical outcome variable 'affirm' (the number of affirmed death penalty sentences)

```
## Loading required namespace: broom.mixed
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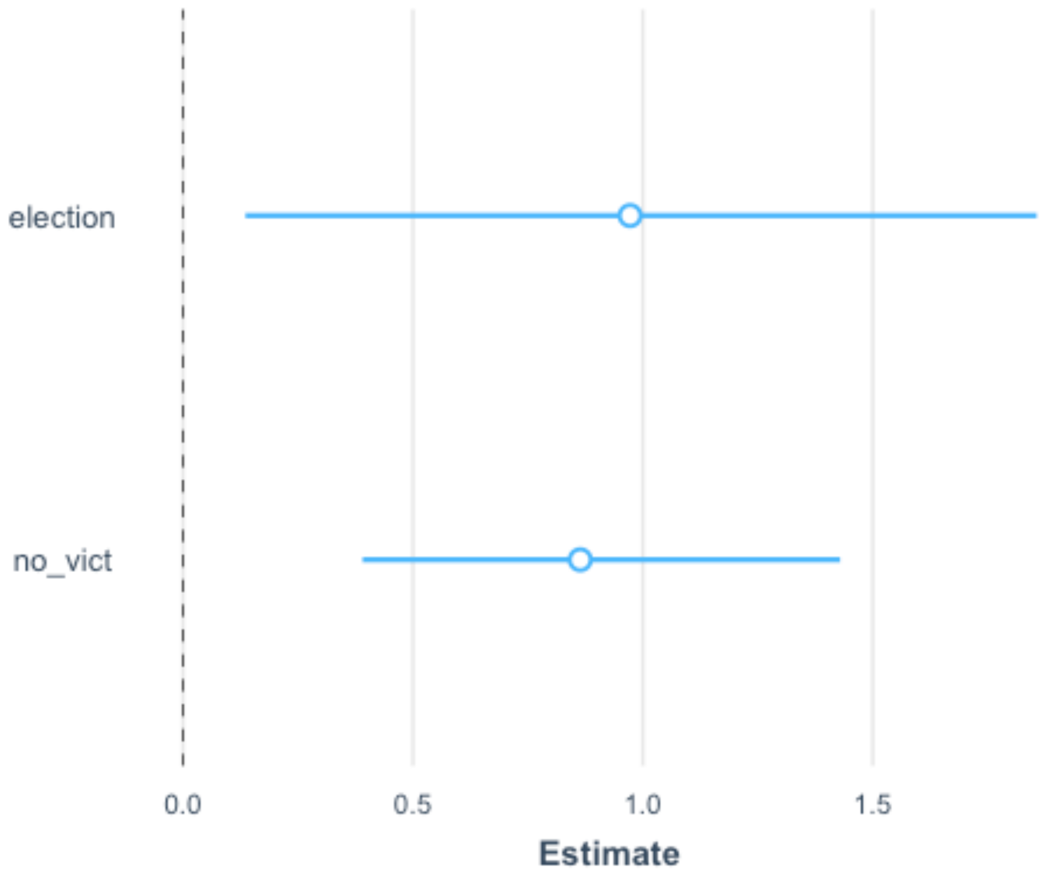


The above results suggest that the number of victims ('no_vict') and the election variable ('election') significantly influence the likelihood of the affirmed death penalty sentence, both being statistically significant and suggesting that election years significantly influence the likelihood of case affirmation. For each additional victim, the log odds of a case being affirmed increase by 0.86. During election years, the log odds of a case being affirmed increase by about 0.97.

Other Models:

Logistic Regression Models

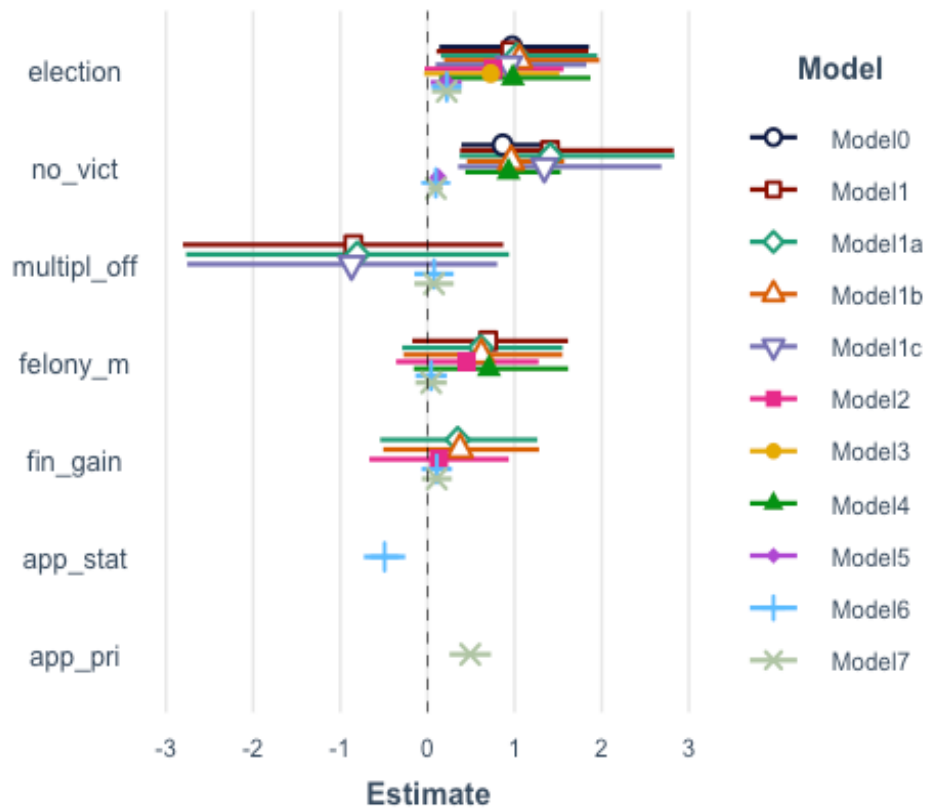
Figure 4. Regression Coefficients and Standard Errors

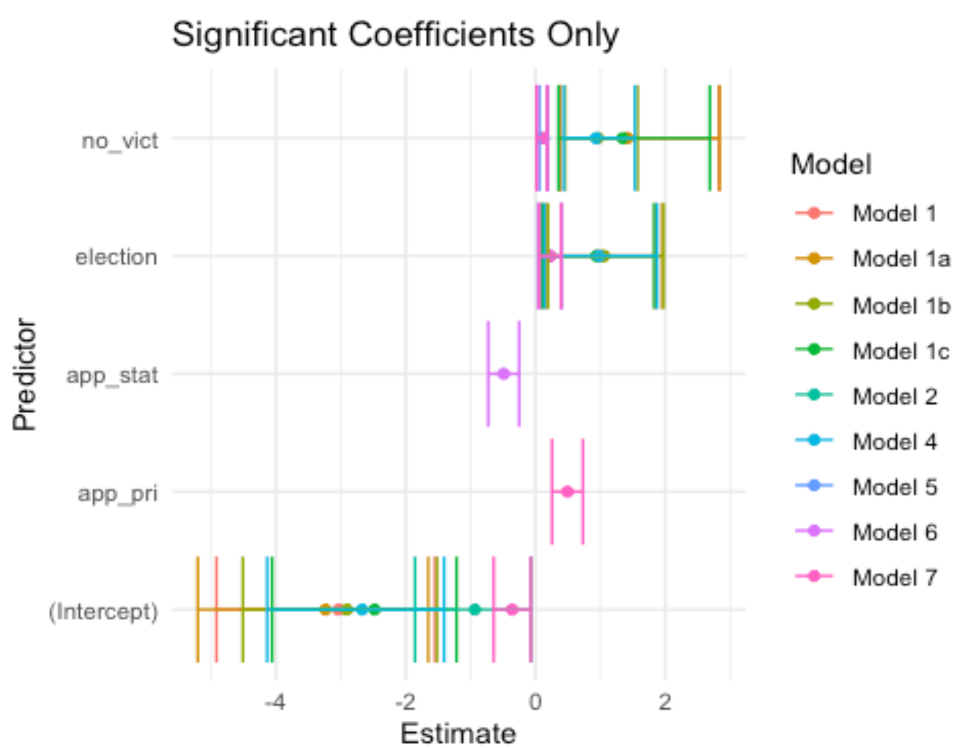
	Model 0	Model1	Model1a	Model1b	Model1c	Mode2	Model 3	Model4	Model5	Model6	Model7
(Intercept)	-2.12 ***	-3.04 ***	-3.24 ***	-2.91 ***	-2.48 ***	-0.93 *	-0.57	-2.67 ***	0.13	0.13	-0.36 *
	(0.57)	(0.85)	(0.90)	(0.76)	(0.72)	(0.45)	(0.30)	(0.69)	(0.09)	(0.12)	(0.15)
election	0.97 *	0.95 *	1.03 *	1.06 *	0.94 *	0.75	0.73	0.98 *	0.22 *	0.22 *	0.22 *
	(0.44)	(0.44)	(0.46)	(0.45)	(0.44)	(0.40)	(0.40)	(0.44)	(0.09)	(0.09)	(0.09)
no_vict	0.86 **	1.41 *	1.41 *	0.96 ***	1.34 *			0.93 ***	0.12 ***	0.10 *	0.10 *
	(0.27)	(0.63)	(0.63)	(0.29)	(0.60)			(0.28)	(0.03)	(0.04)	(0.04)
multipl_off		-0.85	-0.81		-0.87					0.08	0.08
		(0.94)	(0.94)		(0.91)					(0.11)	(0.11)
felony_m		0.70	0.61	0.62		0.45		0.71		0.04	0.04
		(0.45)	(0.47)	(0.46)		(0.42)		(0.45)		(0.09)	(0.09)
fin_gain			0.35	0.37		0.13				0.11	0.11
			(0.46)	(0.45)		(0.41)				(0.09)	(0.09)
app_stat										-0.49 ***	
										(0.12)	

app_pri											0.49 ***
											(0.12)
N	110	110	110	110	110	110	110	110	110	109	109
AIC	138.01	138.58	140.00	138.77	139.03	154.96	152.45	137.45	149.97	137.97	137.97
BIC	146.11	152.08	156.20	152.27	149.83	165.76	157.85	148.25	160.78	159.50	159.50
Pseudo R2	0.22	0.26	0.26	0.25	0.23	0.06	0.04	0.25	0.19	0.37	0.37

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Figure 5. Coefficients Chart with Coefficients Chart with Confidence Intervals





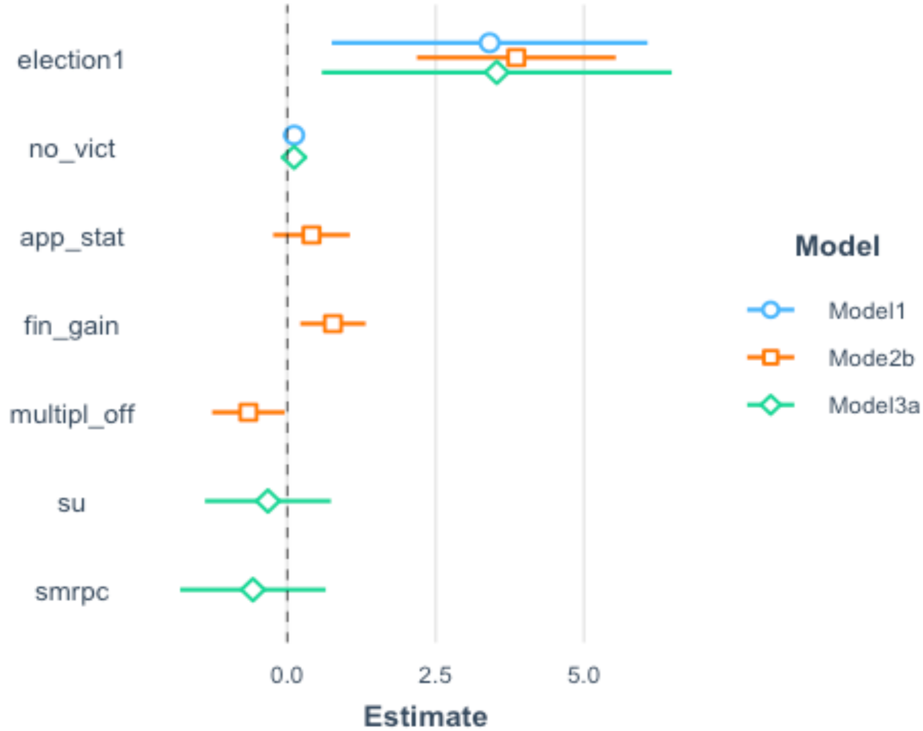
Linear Regression Models for Affirmed Cases (‘affirm’) — unit of analysis Election Year (‘election’)

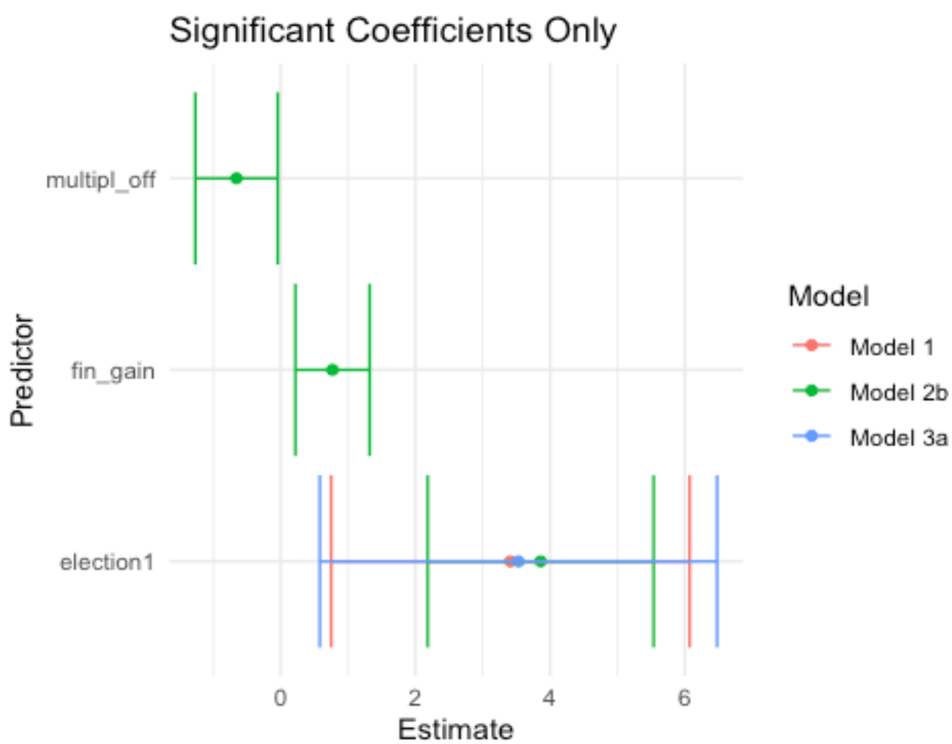
Figure 6. Regression Coefficients and Standard Errors

	Model1	Mode2b	Model3a
(Intercept)	1.10	1.03	6.50
	(1.36)	(0.95)	(4.36)
election1	3.41 *	3.86 **	3.53 *
	(1.15)	(0.69)	(1.21)
no_vict	0.12		0.11
	(0.08)		(0.09)
app_stat		0.41	
		(0.26)	
fin_gain		0.77 *	
		(0.23)	
multipl_off		-0.65 *	
		(0.25)	
su			-0.33
			(0.43)
smrpc			-0.58
			(0.50)
N	11	11	11
R2	0.66	0.91	0.73

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Figure 7. Coefficients Chart with Confidence Intervals





Further Linear Regression Models for Affirmed Cases ('affirm') — unit of analysis Election Year ('election') with different controls, e.g., number of cases

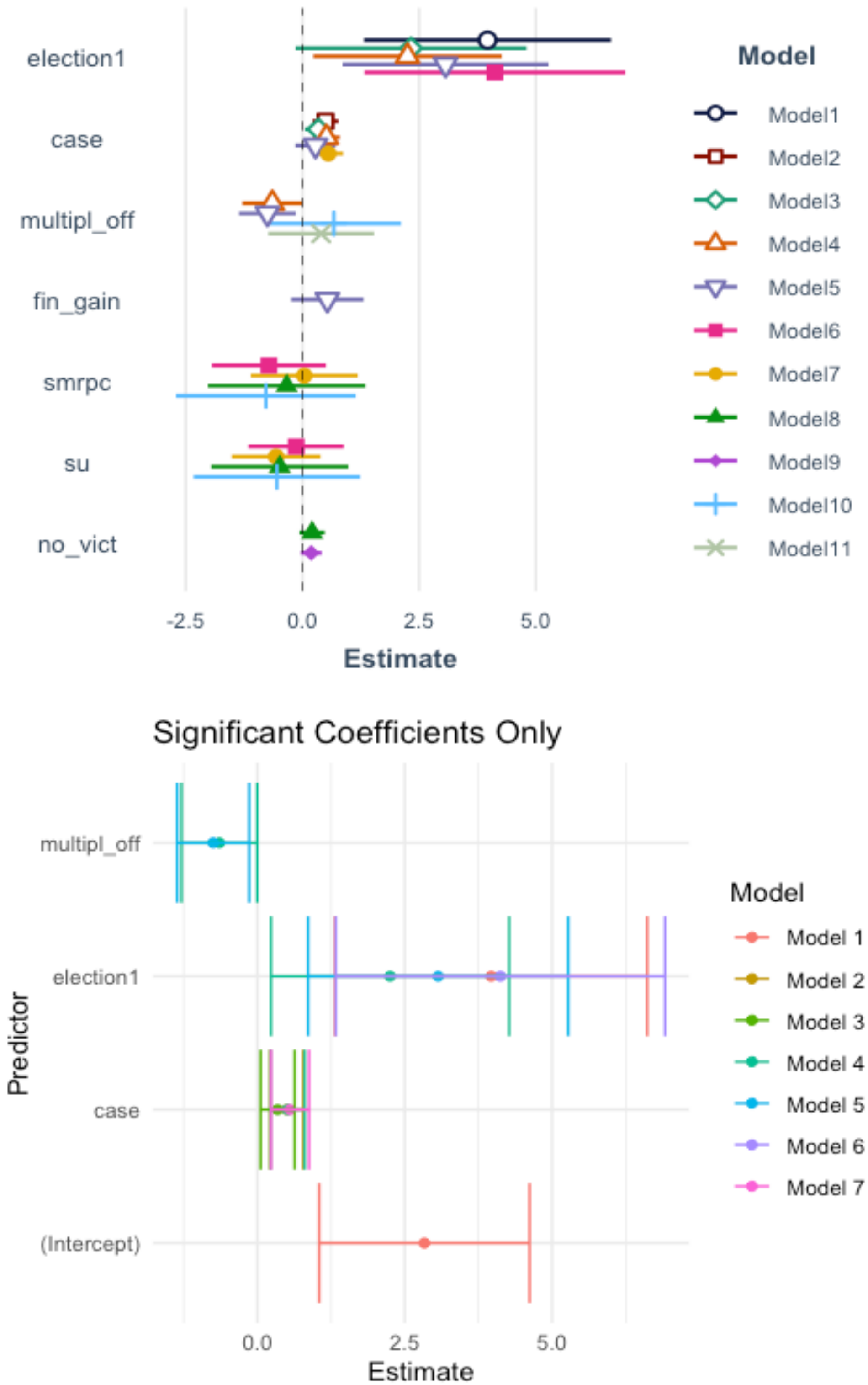
Figure 7. Regression Coefficients and Standard Errors

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8	Model9	Model10	Model11
(Intercept)	2.83 **	-0.31	0.14	1.18	0.80	8.04	1.86	5.85	1.42	9.72	2.95
	(0.79)	(1.34)	(1.15)	(1.01)	(0.93)	(4.43)	(4.33)	(6.28)	(1.85)	(6.80)	(2.26)
election1	3.97 **		2.33	2.25 *	3.07 *	4.12 *					
	(1.17)		(1.07)	(0.85)	(0.90)	(1.18)					
case		0.49 **	0.34 *	0.51 **	0.28		0.55 **				
		(0.12)	(0.13)	(0.12)	(0.18)		(0.14)				
multipl_off				-0.64 *	-0.75 *					0.67	0.40
				(0.27)	(0.25)					(0.61)	(0.50)
fin_gain					0.53						
					(0.32)						
smrpc						-0.72	0.04	-0.34		-0.78	
						(0.52)	(0.48)	(0.71)		(0.81)	
su						-0.13	-0.56	-0.49		-0.55	
						(0.43)	(0.40)	(0.62)		(0.75)	
no_vict								0.21	0.19		

								(0.12)	(0.10)		
N	11	11	11	11	11	11	11	11	11	11	11
R2	0.56	0.64	0.77	0.87	0.91	0.66	0.72	0.35	0.29	0.20	0.07

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Figure 8. Coefficients Chart with Confidence Intervals



Based on the findings, **we were able to reject the null hypothesis and support H1 that the elected judges standing for re-election are less likely to grant relief to death row prisoners in election years**.

Executives

DPIC examined all state clemencies granted in death penalty cases from 1977-2023, for a total of 146 cases, excluding the mass clemency grant in Illinois in 2003. The latter (constituting more than 50% of the overall sample) were excluded from further analysis to prevent skewing our findings as well as ensure findings reliability and generalizability. These 146 cases include individual grants and "mass" grants of clemency for more than one person. We coded each case for a number of variables including election cycles, structure of clemency system, and defendant characteristics.

In the logistic regression analysis output below, we tested factors influencing executives' mass clemency decisions. Sole authority ('sole_authority') and the final year of tenure ('last_year_bin') are significant predictors; the fact of being up for re-election ('re_el_num') was not significant. Sole authority and the last year in office significantly increase the odds of mass clemencies. The model explained a reasonable proportion of the variance based on the pseudo-R2 values.

Logistic Regression

Figure 8. Logistic Regression Results

```
##             Term   Estimate Std.Error Odds.Ratio   Conf.Low  Conf.High
## 1    (Intercept) -2.6222904 0.5419471  0.0726363 0.02510956  0.2101205
## 2      re_el_num  0.5304289 0.4790390  1.6996611 0.66465476  4.3463887
## 3 sole_authority  3.1189326 0.4930318 22.6222204 8.60712376 59.4582893
## 4  last_year_bin  1.2822412 0.6207449  3.6047096 1.06777941 12.1691159
##        P.Value
## 1 1.307264e-06
## 2 2.681742e-01
## 3 2.515543e-10
## 4 3.886162e-02
```

Logistic Regression analysis showcases that the executive's sole authority ('sole_authority') in making a clemency decision and their last year of tenure ('last_year_bin') are significant predictors of the outcome variable mass clemency ('mass_num').

Chi-Square Tests for Mass Clemencies

The Chi-Square Test showcased a significant association between the sole authority and granting clemency. The strong association between sole authority and mass clemencies highlights the individual executive power in clemency practices. The Cramér's V value of about 0.6 indicates a strong association between these two variables.

Based on the logistic regression findings, **we were able to reject the null hypothesis and support H3 that the elected executive officers (governors and presidents) exiting the**

office are more likely to grant clemencies and mass clemencies compared to when they are up for re-election.

Thank You for taking the time to read this document!

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