



computation is key

Who are these people?

An ICE Breaker

Business as Usual? Economic Responses to Political Tensions

Christina L. Davis Princeton University Sophie Meunier Princeton University

Do political tensions harm economic relations? Theories claim that trade prevents war and political relations motivate trade, but less is known about whether smaller shifts in political relations impact economic exchange. Looking at two major economies, we show that negative events have not hurt U.S. or Japanese trade or investment flows. We then examine specific incidents of tensions in U.S.-French and Sino-Japanese relations over the past decade—two case pairs that allow us to compare varying levels of political tension given high existing economic interdependence and different alliance relations. Aggregate economic flows and high salience sectors like wine and autos are unaffected by the deterioration of political relations. In an era of globalization, actors lack incentives to link political and economic relations. We argue that sunk costs in existing trade and investment make governments, firms, and consumers unlikely to change their behavior in response to political disputes.

o political tensions have economic consequences? The relationship between economic interdependence and conflict has been a central debate in international relations. Leading scholars contend that "states with good relations should have more trade than states with poor relations" and import decisions of firms will respond to "the climate of friendliness or hostility that exists between the importer and exporter" (Morrow, Siverson, and Tabares 1998, 650; Pollins 1989b, 739). Analysis of trade and conflict in a simultaneous equations model concludes that "political relations are driving commerce, not the other way around" (Keshk,

of force, and to war. While most analysis of the interdependence debate focuses on militarized disputes, we analyze the shift at the lower level from normal relations to political tensions. As noted by Pevehouse, "much of the nuance of interdependence theory has been discarded" in recent empirical studies that use dichotomous measures for conflict, and new insights may be gained by returning to the earlier approach in the literature that measured conflict and cooperation with events data (2004, 247). A large range of interactions determines the status of political relations between states. By political tensions, we mean disagreement over policy issues, hostility between

Here are some questions:

think + write + discuss

What is the key causal claim of the paper? Do they have good evidence for their causal claim? What are some descriptors for this paper? What do the authors mean by "political tensions"? How do they measure political tensions? **Let's take a closer look....**

How is this going to go?

Teaching Philosophy

Learning results from what the student does and thinks, and only from what the student does and thinks. —Herbert Simon

It is the one who does the work who does the learning.

-Terry Doyle







This is the best advice from @hadleywickham. True of learning R. True of learning anything. #rstats rposts.com/advice-to-youn...

It's easy when you start out programming to get really frustrated and think, "Oh it's me, I'm really stupid," or, "I'm not made out to program." But, that is absolutely not the case. Everyone gets frustrated. I still get frustrated occasionally when writing R code. It's just a natural part of programming. So, it happens to everyone and gets less and less over time. Don't blame yourself. Just take a break, do something fun, and then come back and try again later.

11:16 AM - 25 Aug 2018



Assignments

Weekly

- 14 conceptual homeworks (3% each; 42% total)
- 7 computational homeworks (3% each; 21% total)
- 14 reflections (1% each; 14% total)

End-of-semester

- Data assignment related to FYP (8%)
- Final exam (15%)

Orienting Ourselves

The Ten Commandments of Success in (My) POS 5737



slow your roll



thoughtful empirical analysis

p-values from regression models



first-year grad students

Journal of Economic Literature Vol. XXXIV (March 1996), pp. 97–114

(p-value) discourages The Standard Error of Regresthoughtful social

Significance testing

science.

By DEIRDRE N. MCCLOSKEY

and

STEPHEN T. ZILIAK

University of Iowa

Suggestions by two anonymous and patient referees greatly improved the paper. Our thanks also to seminars at Clark, Iowa State, Harvard, Houston, Indiana, and Kansas State universities, at Williams College, and at the universities of Virginia and Iowa. A colleague at Iowa, Calvin Siebert, was materially helpful.

THE IDEA OF statistical significance is old, as old as Cicero writing on forecasts (Cicero, *De Divinatione*, I. xiii. 23). In 1773 Laplace used it to test whether comets came from outside the solar system (Elizabeth Scott 1953, p. 20). The first use of the very word "significance" in a statistical context seems to be John Venn's, in 1888, speaking of differences expressed in units of probable error:

They inform us which of the differences in the above tables are permanent and significant for science or policy and yet be insignificant statistically, ignored by the less thoughtful researchers.

In the 1930s Jerzy Neyman and Egon S. Pearson, and then more explicitly Abraham Wald, argued that actual investigations should depend on substantive not merely statistical significance. In 1933 Neyman and Pearson wrote of type I and type II errors:

Is it more serious to convict an innocent man or to acquit a guilty? That will depend on the

STATISTICAL MODELS don't treat them like LEATHER

Regression models

are not magic. So

David A. Freedman^{*}

Regression models have been used in the social sciences at least since 1899, when Yule published a paper on the causes of pauperism. Regression models are now used to make causal arguments in a wide variety of applications, and it is perhaps time to evaluate the results. No definitive answers can be given, but this paper takes a rather negative view. Snow's work on cholera is presented as a success story for scientific reasoning based on nonexperimental data. Failure stories are also discussed, and comparisons may provide some insight. In particular, this paper suggests that statistical technique can seldom be an adequate substitute for good design, relevant data, and testing predictions against reality in a variety of settings.

the simple tools we discuss in our first few weeks

histogram, avg, SD, scatterplot, simple linear model

ARE POWERFUL

I want you to learn to use them well.



master the simple things

GRAD STUDENT

SCATTERPLOT

HETEROSKEDASTIC Ordered probit



computation is key



change-review-commit-push



engage with me where you are

that's enough slow your roll master the simple things computation is key change-review-commit-push engage with me where you are

What should I take from this class?

Build a Foundation



What should we build a foundation for?

Where do you want to be in 10 years?

What do you need to accomplish in the next 5 years?

What do you need to take from this course to get there?







broad base of knowledge in methods that allows us to produce great research projects

broad base of knowledge in methods

- 1. **basic statistical tools**, such as a histogram, average, standard deviation, normal approximation, scatterplot, correlation, simple regression, sample surveys
- 2. **basic concepts in probability theory**, such as conditional probability, the law of averages, the expected value, the standard error.
- 3. **basic concepts in inference**, such as a point estimate, interval estimate, and hypothesis test.
- 4. **advanced concepts in probability theory** (that rely on calculus), such as a pmf or pdf, moments, and the central limit theorem.

concepts and computation

Why should I care about computation?

computation



Prices of over 50,000 round cut diamonds

Description

A dataset containing the prices and other attributes of almost 54,000 diamonds. The variables are as follows:

Usage

diamonds

Format

A data frame with 53940 rows and 10 variables:

price

price in US dollars (\\$326-\\$18,823)

carat

weight of the diamond (0.2–5.01)

cut

quality of the cut (Fair, Good, Very Good, Premium, Ideal)

color

diamond colour, from D (best) to J (worst)

clarity

a measurement of how clear the diamond is (I1 (worst), SI2, SI1, VS2, VS1, VVS2, VVS1, IF (best))


```
# load packages
 1
   library(tidyverse)
 2
 3
 4
   # loads a default data set in R
    data(diamonds)
 5
 6
 7
    # quick look at the data set
    glimpse(diamonds)
 8
 9
   # find average for each cut, color, and clarity
10
   sum_df <- diamonds %>%
11
12
   group_by(cut, color, clarity) %>%
13
   summarize(avg_price = mean(price))
14
    sum_df
15
16
   # plot averages
    ggplot(sum_df, aes(x = cut, y = avg_price, color = clarity)) +
17
    geom_point() +
18
   facet_wrap( ~ color) +
19
     theme_bw()
20
21
```





```
# load packages
 1
2 library(tidyverse)
 3
    # loads a default data set in R
 4
    data(diamonds)
 5
 6
7 # quick look at the data set
   glimpse(diamonds)
 8
 9
10 # find average for each cut, color, and clarity
11 sum_df <- diamonds %>%
      group_by(cut, color, clarity) %>%
12
      summarize(avg_price = mean(price))
13
14
    sum_df
15
    # plot averages
16
    ggplot(sum_df, aes(x = cut, y = avg_price, color = clarity)) +
17
18
      geom_point() +
19
      facet_wrap( \sim color) +
20
      theme_bw()
21
```

```
1 # load packages
2 library(tidyverse)
   library(broom)
3
 4
    # loads a default data set in R
 5
    data(diamonds)
 6
7
   # quick look at the data set
8
    glimpse(diamonds)
9
10
   # fit regression model using all predictors
11
    fit <- lm(price ~ ., data = diamonds)</pre>
12
13
   # tidy fit
14
15
   diamonds <- augment(fit, diamonds) %>%
16
      glimpse()
17
   # plot predictions
18
    ggplot(diamonds, aes(x = price, y = .fitted)) +
19
20
      geom_point()
21
```





```
# load packages
 1
 2 library(tidyverse)
 3
   # loads a default data set in R
 4
   data(diamonds)
 5
 6
   # quick look at the data set
 7
   glimpse(diamonds)
 8
 9
10 # find average for each cut, color, and clarity
11 sum_df <- diamonds %>%
      group_by(cut, color, clarity) %>%
12
      summarize(avg_price = mean(price))
13
14 sum_df
15
  # plot averages
16
  ggplot(sum_df, aes(x = cut, y = avg_price, color = clarity)) +
17
18
      geom_point() +
19
      facet_wrap( \sim color) +
20
      theme_bw()
21
```

```
# load packages
 1
 2 library(tidyverse)
 3 library(randomForest)
 4
   # loads a default data set in R
 5
6 data(diamonds)
 7
   # quick look at the data set
 8
    glimpse(diamonds)
 9
10
   # fit regression model using all predictors
11
12 fit <- randomForest(price ~ ., data = diamonds)</pre>
13
14 # tidy fit
    diamonds$.fitted <- predict(fit)</pre>
15
16
    # plot predictions
17
    ggplot(diamonds, aes(x = price, y = .fitted)) +
18
19
      geom_point()
20
```



What does a research project look like?



What are the three essential components of a great research* project?

*empirical, computational

raw data

the process

manuscript

	Contents lists available at ScienceDirect							
79 M	Electoral Studies							
ELSEVIER jou	rnal homepage: www.elsevier.com/locate/electstud							
Strategic mobilizat	ion: Why proportional representation 💦 👔 🕞							
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Carlisle Rainey Linkersty er taglika, SLIVE S20 Jack Hit A R T I C L E I N F O Article hänzy: Restvet S Jace 2014 Restvet S Jace 2014 Restvet S Jace 2014	A B S T K A C T A B S T K A C T Many scholars suggest that proportional representation increases party mobilization creating nationally competitive districts that give parties an incentive to mobilize ever where This paper provides theoretical and empirical arguments that brings its claim in question. I propage, unlike satirities scholars, that the positive offect of district competitive to mobilization for some some party mobilization for some some some some some some some some							
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Does proportional representation cause parties to mobilize more voters? Many studies of electoral systems suggest proportional electoral rules do lead to greater mobilization (and thus increased turnout). However, more recent work argues that the evidence is too limited and the recent work argues in at the evicence is too immed and the theories too under-developed to support this conclusion. In particular, Blais and Aarts (2006) suggest that political scientists cannot have confidence that proportional rules cause higher turnorat until schulars better understand the mechanism linking the two.

¹¹ Itanii john Ahipdia, William Berra, Scott Cillioti, Matt Golder, Sont Colder, Jens Grosser, Bob Jackson, John Barry Ryan, and Dave Siegel for their comments on previous drafts. The analyses presented have vere conducted with R-10 and JAC3 320. The Goldin Appendix and all distance conducted with R-10 and JAC3 320. The Goldin Appendix and all distance control and an R-10 and JAC3 320. The Goldin Appendix and all distance for the second seco

mobilization efforts under PR rules than under SMDP rules because PR rules, on average, roate more competitive districts (Cox, 1995)¹ More competitive districts, in turn, provide parties a strong incentive to mobilize voters. A large literature confirms that turnout (e.g. Rosenstone and Hansen, 1993) and mobilization (Cox and Munger, 1985; Karp et al., 2007) are higher in more competitive districts, but this relationship has only been econtined in SMDP, extends. Research environment in environment SMDP systems. Research examines the relationship ¹ Many scholars take as given that PR rules create more competitive districts, although recent work brings this common assumption inte question (Blais and Lags, 2009).

Several explanations have emerged that attempt to explain the observation of higher turnout under propo-tional representation (PR) rules (for an overview, see Bais and Aaris, 2006). The most theoretically compelling fo-

cuses on the frequent emergence of non-competitive electoral districts in single-member district plurality

(SMDP) systems. This explanation suggests that parties (or

candidates and activists more broadly) exert greater mobilization efforts under PR rules than under SMDP rules

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raw data

the process

100s of decisions 1000s of lines of code

manuscript

lectoral Studies 37 (2015) 86-98 Contents lists available at ScienceDirect Electorol Studies Electoral Studies journal homenage: www.elsevier.com/locate/electstud Strategic mobilization: Why proportional representation decreases voter mobilization* Carlisle Rainey University or Eufficia, SUNV, 520 Park Holl, Buffals, NY 14250, USA ARTICLE INFO ABSTRACT A B S I R A C I Many scholars suggest that proportional representation increases party mobilitation by creating nationally competitive districts that give parties an incentive to mobilize every-where: This paper provides theoretical and empirical arguments that bring this claim into question. I propose, unlike earlier scholars, that the positive effect of district competi-diventors on party mobilization efforts increases as electoral districts become more disproprimal arguing that dispropotionality titlef encourges mobilizations by exag-gerating the impact of competitiveness on mobilization. Individual-level survey data from national legislative elections thew that competitiveness has a mack larger positive effect on parties' mobilization efforts in single-member districts than in proportional districts no strong incentive to mobilize anywhere. O 2014 Published by Ekevier Lid. Article historyc Received 8 June 2014 Received 8 June 2014 Received in revised form 21 October 2014 Accepted 29 October 2014 Available online 26 November 2014 Keywords: Mobilization Nonneation Turnout: Single-member districts PR SMD © 2014 Published by Elsevier Ltd.

1. Introduction

Does proportional representation cause parties to mobilize more voters? Many studies of electoral systems suggest proportional electoral rules do lead to greater mobilization (and thus increased turnout). However, more recent work argues that the evidence is too limited and the recent work argues that the evidence is too imitted and the theories too under-developed to support this conclusion. In particular, Blais and Aarts (2006) suggest that political scientists cannot have confidence that proportional rules cause higher tumorat until scholars better understand the mechanism linking the two.

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mobilization efforts under FR rules than under SMDP rules because PR rules, on average, rorete more competitive districts (Con, 1989). More competitive districts, in turn, provide parties a strong incentive to mobilize voters. A large literature confirms that turnout (e.g. Rosenstone and Hansen, 1993) and mobilization (Cox and Munger, 1989; Karg et al., 2007) are higher in more competitive districts, but this relationship has only been examined in CMDP, contexp. Remender meaning the rule timebile SMDP systems. Research examines the relationship

Several explanations have emerged that attempt to explain the observation of higher turnout under propo-tional representation (PR) rules (for an overview, see Bals and Aarts, 2006). The most theoretically compelling fo-

cuses on the frequent emergence of non-competitive electoral districts in single-member district plurality

(SMDP) systems. This explanation suggests that parties (or

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¹ Many scholars take as given that PR rules create more competitive districts, although recent work brings this common assumption inte question (Blais and Lago, 2009).

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What characteristics should the process* have?

*from raw data to published paper

raw data

(1898, 1898, 1898, 1898, 1997, 1

the process

100s of decisions 1000s of lines of code

> tidying modeling plotting

principled implemented documented

manuscript

lectoral Studies 37 (2015) 86-98 Contents lists available at ScienceDirect Electorol Studies Electoral Studies journal homenage: www.elsevier.com/locate/electstud Strategic mobilization: Why proportional representation decreases voter mobilization* Carlisle Rainey University or Eufficia, SUNV, 520 Park Holl, Buffals, NY 14250, USA ARTICLE INFO ABSTRACT A BOILE ACCI. Many scholars suggest that proportional representation increases party mobilization by creating nationally competitive districts that give parties an incentive to mobilize every-where. This paper provides theoretical and empirical arguments that bring this claim into question. I propose, unlike easilier scholars, that the positive effect of districts become mark disproportional, arguing that disproportionally itself encourages mobilization by ecag-gerating the impact of competitiveness on mobilization, individual-level survey data from national legislitave electrons thew that competitivenes has a much larger positive effect on parties' mobilization efforts in single-member districts than in proportional districts Contrary to prior illerature, these results suggest proportional decrotal rules give parties no strong incentive to mobilize anywhere. Article historyc Received 8 June 2014 Received 8 June 2014 Received in revised form 21 October 2014 Accepted 29 October 2014 Available online 26 November 2014 Keywords: Mobilization Noomzanon Turnout Propertional rules Single-member districts re © 2014 Published by Elsevier Ltd.

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Several explanations have emerged that attempt to explain the observation of higher turnout under propo-tional representation (RP) rules (for an overview, see Bais and Aaris, 2006). The most theoretically compelling fo-

principled if you made correct decisions

implemented

if you did what you decided to do

documented

if you can check that you did what you decided to do





principled implemented documented

Rank these from least to most challenging.

What makes a research project compelling?

The Process

"The process never ends until we die. And the choices we make are ultimately our own responsibility."

-Eleanor Roosevelt

principled if you made correct decisions

implemented

if you did what you decided to do

documented

if you can check that you did what you decided to do

principled

sharp intuition

some math

implemented

two sources of errors

errors in a script

software errors

user errors

```
# Make sure that working directory is set properly
# setwd("~/Dropbox/projects/strategic-mobilization/")
# Clear workspace
rm(list = ls())
# Read in the raw data from the CSES Module 2 data set
cses2 <- read.csv("data/cses2 rawdata.txt")</pre>
# Pull out variables of interest
mycses2 <- c("B1004", "B2001", "B2002", "B2003", "B2004", "B2005", "B2020", "B2023", "B2030", "B2031", "B3001_2", "B3002_2",
"B3003", "B3004 1", "B3014", "B3016", "B3028", "B3045", "B3047 1", "B3047 2", "B3047 3", "B4001", "B4002", "B4003", "B4004 A",
"B4004 B", "B4004 C", "B4004 D", "B4004 E", "B4004 F", "B4005", "B5043 1")
cses2 <- cses2[, mycses2]</pre>
#
     Change the variable names
names(cses2) <- c("Alpha.Polity", "Age", "Male", "Education", "Married", "Union.Member", "Household.Income",</pre>
"Religious.Attendance", "Urban", "District", "Campaign.Activities", "Freq.Campaign", "Contacted", "Cast.Ballot", "Vote.Matters",
"Cast.Ballot.Previous", "Close.To.Party", "Ideology", "Know1", "Know2", "Know3", "Number.Seats", "Number.Candidates",
"Number.Lists", "VoteA", "VoteB", "VoteC", "VoteD", "VoteE", "VoteF", "District.Turnout", "Electoral.Formula")
# Drop countries for which there is not information about the electoral district
cses2 <- cses2[cses2$District!= 99999, ]</pre>
cses2 <- cses2[cses2$Number.Seats != 999, ]</pre>
#### Recode and Create Variables
# Alpha.Polity
cses2$Alpha.Polity <- as.character(cses2$Alpha.Polity)</pre>
cses2$Alpha.Polity[cses2$Alpha.Polity=="CAN 2004"] <- "Canada"
cses2$Alpha.Polity[cses2$Alpha.Polity=="FIN 2003"] <- "Finland"</pre>
cses2$Alpha.Polity[cses2$Alpha.Polity=="GBR 2005"] <- "Great Britain"</pre>
cses2$Alpha.Polity[cses2$Alpha.Polity=="PRT 2002"] <- "Portugal 2002"</pre>
cses2$Alpha.Polity[cses2$Alpha.Polity=="PRT 2005"] <- "Portugal 2005"</pre>
cses2 <- cses2[cses2$Alpha.Polity == "Canada" |</pre>
                 cses2$Alpha.Polity == "Finland"
                 cses2$Alpha.Polity == "Great Britain"
                 cses2$Alpha.Polity == "Portugal 2002"|
                 cses2$Alpha.Polity == "Portugal 2005", ]
cses2$Alpha.Polity <- as.factor(cses2$Alpha.Polity)</pre>
```

```
cses2$District.Country <- paste(cses2$Alpha.Polity, cses2$District, sep = "")</pre>
cses2$District.Country <- as.factor(cses2$District.Country)</pre>
District.Names <- sort(unique(cses2$District.Country))</pre>
for (i in 1:length(District.Names)) {
  cses2$District[cses2$District.Country == District.Names[i]] <- i</pre>
## Save datasets as .csv files
cses2$District <- as.numeric(as.character(cses2$District))</pre>
cses2$Country <- as.numeric(cses2$Alpha.Polity)</pre>
# Save a listwise-deleted data set.
ld.vars <- c("Contacted", "Age", "Male", "Education", "Married", "Union.Member", "Household.Income", "Urban", "Close.To.Party",</pre>
"District.Competitiveness", "ENEP", "PR", "Alpha.Polity", "District", "Country", "District.Country")
ld.data <- cses2[, ld.vars]</pre>
ld.data <- na.omit(ld.data)</pre>
write.csv(ld.data, "output/ld-data.csv")
# Save a data set
                               ng val as for multiple imputation.
                      Pol. " "Je "Mol", "Election", "Merried" "Union Wender", usehold.Income", "F ious.Attendance",

pa n.Ad iv: es, ".eq m gn" Co act 1" Ca .F .lot "Vote Cers", "Ca .Ballot.Previous",

deology "K w1 "Know, "K w , "I strice.compe tivenes ', " ", "N Ser.Seats", "EP", "Country",
mi.vars <- c("Alpł</pre>
"Urban", "District
"Close.To.Party",
"District")
mi.data <- cses2[, mi.vars]</pre>
write.csv(mi.data, "output/mi-data.csv")
# Create the district-level data
get.first <- function(x) {</pre>
 return(x[1])
district.data <- cses2[, c("Alpha.Polity", "Country", "District", "District.Competitiveness", "PR")]</pre>
district.data <- aggregate(district.data, by = list(cses2$District), FUN = get.first)</pre>
district.data$SMDP <- 1 - district.data$PR</pre>
write.csv(district.data, "output/district-data.csv")
# Create the country-level data
country.data <- cses2[, c("Alpha.Polity", "Country", "PR")]</pre>
country.data <- aggregate(country.data, by = list(cses2$Country), FUN = get.first)</pre>
country.data$SMDP <- 1 - country.data$PR</pre>
write.csv(country.data, "output/country_data.csv")
```

two sources of errors

errors in a script

software errors

user errors

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two sources of errors

errors in a script

software errors

user errors

mismanage your files mismanage versions mismanage dependencies



documented share your work

Carlisle's Fundamental Theorem of Implementation (CFTI) The same strategies that allow others to easily check your work (1) allow you to easily check your work and (2) ensure that you implement your decisions correctly in the first place.

What tools allow me to execute a compelling research project?

Our Tools



statistical computing




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6	options(mc.cores = parallel::detectCores())	000		List	t of 10			Q
7	library(loo)	<pre> mf mm obs_df rep_df </pre>			4 obs. of a	2 variab	les	
9	(tordry(bdyesptoc)				[1:1204, 3	1:2] 1 1	1111	1 1 1 1 🔲
10	# load simulated data				4 obs. of 4	4 variab	les	
11	rsw_df <- read_csv("rsw/budget.csv") %>%				440 obs. o	f 5 vari	ables	
12	glimpse()	🜔 rep_df_i		1204	4 obs. of !	5 variab	les	
14	# format data for stan	🜔 rsw_d	df	1204	4 obs. of 4	42 varia	bles	
15	f <- leg_total ~ gov_total	📀 stan	_data_lis	: List	t of 4			Q
16	<pre>mf <- model.frame(f, data = rsw_df)</pre>	💿 y_rep			Large matrix (2408000 elements, 18.4 M… 🗔			
17	mm <- model.matrix(f, mf) stap data list <- list(y = mf\$lea total	Values						
19	$\begin{aligned} x &= mm, \\ N &= nrow(mm), \end{aligned}$			leg_	leg_total ~ gov_total			
20				100L				
21	K = ncol(mm))	Files	Plots Pa	ackages Help Viewer				
22	# simple linear model fit with least squares	(ا ا	🔎 Zoom	- 🎦 Ex	kport 🚽 😳	1		-2 - C
24	fit_lm <- lm(f, data = rsw_df)							
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+ 10	<pre>ep_df <- bind_rows(rep_df, rep_df_i)</pre>							
+ }				•				
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creating documents



Templates

144 % Abstract

Typeset

145 {\centerline{\textbf{Abstract}}}

LaTeX

- 146 \begin{quote}\noindent
- Political scientists commonly focus on quantities of interest computed from model coefficients rather than on the coefficients themselves.

Macros 🗸

Tags

However, the quantities of interest, such as predicted probabilities, first differences, and marginal effects, do necessarily not inherit the small sample properties of the coefficient estimates.

- Indeed, unbiased coefficients estimates are neither necessary nor sufficient for unbiased estimates of the quantities of interest.
- I characterize this transformation-induced bias, calculate an approximation, illustrate its importance with two simulation studies, and discuss its relevance to methodological research.
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- 167 %\section*{Introduction}
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- Political scientists use a wide range of statistical models $y_i \le f(\theta_i)$, where $i \le 1, ..., N$ and f represents a probability distribution.
- The parameter \hat{s} is connected to a design matrix X of k explanatory variables and a column of ones by a link function g, so that $g(\underline{theta_i}) = X_i$.
- In the binary logit, for example, \$f\$ represents the Bernoulli probability mass function and \$g\$ represents the logit function, so that \$y_i \sim \text{Bernoulli}(\pi_i)\$ and \$\pi_i = \text{logit} \\ ^{-1}(X_i\beta)\$.

- The researcher usually estimates **\beta** with maximum likelihood (ML), and, depending on the choice of \$g\$ and \$f\$, the estimate \$\hat{\beta}\$ might have desirable small sample properties.
- 174 However, ML does not produce unbiased estimates in general.
- For this reason, methodologists frequently use Monte Carlo simulations to assess the small sample properties of estimators and provide users with rules of thumb about appropriate sample sizes.
- 176 For example, the ML estimates of \$\beta\$ for the binary logit are biased away from zero,

Transformation-Induced Bias

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Unbiased Coefficients Do Not Imply Unbiased Quantities of Interest*

Carlisle Rainey[†]

Abstract

Political scientists commonly focus on quantities of interest computed from model coefficients rather than on the coefficients themselves. However, the quantities of interest, such as predicted probabilities, first differences, and marginal effects, do necessarily not inherit the small sample properties of the coefficient estimates. Indeed, unbiased coefficients estimates are neither necessary nor sufficient for unbiased estimates of the quantities of interest. I characterize this transformation-induced bias, calculate an approximation, illustrate its importance with two simulation studies, and discuss its relevance to methodological research.

Political scientists use a wide range of statistical models $y_i \sim f(\theta_i)$, where $i \in \{1, ..., N\}$ and f represents a probability distribution. The parameter θ_i is connected to a design matrix X of k explanatory variables and a column of ones by a link function g, so that $g(\theta_i) = X_i \beta$. In the binary logit, for example, f represents the Bernoulli probability mass function and g represents the logit function, so that $y_i \sim \text{Bernoulli}(\pi_i)$ and $\pi_i = \text{logit}^{-1}(X_i\beta)$.

The researcher usually estimates β with maximum likelihood (ML), and, depending on the choice of g and f, the estimate $\hat{\beta}$ might have desirable small sample properties. However, ML does not produce unbiased estimates in general. For this reason, methodologists frequently use Monte Carlo simulations to assess the small sample properties of estimators and provide users with rules of thumb about appropriate sample sizes. For example, the ML estimates of β for the binary logit are biased away from zero, leading **?**, p. 54 to suggest that "it is risky to use ML with samples smaller than 100, while samples larger than 500 seem adequate."

Although methodologists tend to focus on estimating model coefficients, substantive re-

searchers tend to focus on some other quantity of interest. A quantity of interest is simply a

¹⁷²

^{*}All computer code necessary for replication is available at github.com/carlislerainey/transformation-inducedbias and dx.doi.org/10.7910/DVN/CYXFB8 (?).

[†]Carlisle Rainey is Assistant Professor of Political Science, Texas A&M University, 2010 Allen Building, College Station, TX, 77843 (crainey@tamu.edu).



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Alright, what's the first homework?

Homework 1: Intro

Conceptual Homework: Several readings and exercises; data sets, research design, computational research

Computational Homework

- Part 1: Installing and testing software (long and tedious) At some point, come to my At some point, come stion. At some point a guestion
- Part 2: Practice making a data set
- Part 3: Practice loading a data set
- **Reflection:** What did you learn?