# FLS 6415 - Causal Inference for the Political Economy of Development Week 11 - Collective Action & Comparative Cases

Jonathan Phillips

November 2017

Studies of Collective Action

### Review of Large-N Causal Inference

► How to analyze data for causal inference:

Review of Large-N Causal Inference

- How to analyze data for causal inference:
  - 1. Causal Inference logic -> Regression Structure

### Review of Large-N Causal Inference

- How to analyze data for causal inference:
  - 1. Causal Inference logic -> Regression Structure
  - 2. Outcome Type -> Regression Model

### Review of Large-N Causal Inference

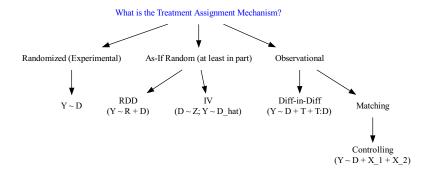
- ► How to analyze data for causal inference:
  - 1. Causal Inference logic -> Regression Structure
  - 2. Outcome Type -> Regression Model
  - 3. Treatment scale & Outcome scale -> Interpretation

### Treatment Assignment Mechanisms

#### Analysis Types and Assumptions

Week		Researcher Controls Treatment Assign- ment?	Treatment Assign- ment Inde- pendent of Potential Outcomes	SUTVA	Additional Assump- tions
	Controlled Experiments				
1	Field Experiments	1	1	1	
2	Survey and Lab Experiments	V	V	V	Controlled Environment for treatment exposure
	Natural Experiments				
3	Randomized Natural Experiments	x	1	V	Compliance with Randomization
4	Instrumental Variables	x	√	√	First stage and Exclusion Re- striction (Instrument explains treatment but not outcome)
5	Regression Discontinuity	x	√	√	Continuity of covariates; No manipulation; No compounding discontinuities
	Observational Studies				
6	Difference-in-Differences	x	x	V	No Time-varying confounders; Parallel Trends
7	Controlling for Confounding	х	х	√	Blocking all Back-door paths
8	Matching	x	x	√	Overlap in sample characteristics

### **Regression Structure**



Outcome Variable Type

Continuous -> Ordinary Least Squares

zelig(Formula, data=data, model="ls")

► Binary -> Logit

zelig(Formula, data=data, model="logit")

- Unordered categories -> Multinomial logit
  zelig(Formula, data=data, model="mlogit")
- Ordered categories -> Ordered logit

zelig(Formula, data=data, model="ologit")

# For OLS regression:

- A 1 [unit1] change in treatment [causes/is associated with] a β [unit2] change in the outcome
- unit1 : Same units as treatment variable
  - Unless treatment is log(), then unit1 is 1% and unit2 is  $\beta * ln(\frac{101}{100})$  (not %)
  - Which is almost the same as  $\frac{\beta}{100}$  (not %)
- unit2 : Same units as outcome variable
  - Unless outcome is log(), then unit2 is  $100 * (exp(\beta) 1)\%$
  - Which is almost the same as  $100 * \beta\%$

7/49

### Interpretation

zelig(mpg wt,data=mtcars,model="ls")

	Dependent variable:		
	mpg		
wt	-5.344***		
	(0.559)		
Constant	37.285***		
	(1.878)		
Observations	32		
R <sup>2</sup>	0.753		
Adjusted R <sup>2</sup>	0.745		
Decidual Ctol Error	204C(df)		

8/49

### Interpretation

zelig(mpg log(wt),data=mtcars,model="ls")

	Dependent variable:	
	mpg	
vt	-17.086***	
	(1.510)	
onstant	39.257***	
	(1.758)	
bservations	32	
<sup>2</sup>	0.810	
Adjusted R <sup>2</sup>	0.804	
Decidual Ctol Francis		

9/49

### Interpretation

zelig(log(mpg) wt,data=mtcars,model="ls")

	Dependent variable:		
-	log(mpg)		
wt	-0.272***		
	(0.025)		
Constant	3.832***		
	(0.084)		
Observations	32		
R <sup>2</sup>	0.798		
Adjusted R <sup>2</sup>	0.791		
Decidence Ctol France			

### For Logit regression:

A 1 [unit1] change in treatment [causes/is associated with]
 a β change in the log-odds of the outcome

### For Logit regression:

- A 1 [unit1] change in treatment [causes/is associated with]
  a β change in the log-odds of the outcome
- A 1 [unit1] change in treatment [causes/is associated with] a 100 \* (exp<sup>β</sup> − 1)% change in the odds (relative probability) of the outcome

zelig(am wt,data=mtcars,model="logit") mtcars

	Dependent variable:	
_	am	
wt	-0.353***	
	(0.067)	
Constant	1.542***	
	(0.226)	
Observations	32	
R <sup>2</sup>	0.480	
Adjusted R <sup>2</sup>	0.462	
Decidence Ctol Ennon		

# For Ordered Logit regression:

 A 1 [unit1] change in treatment [causes/is associated with] a β change in the log-odds of moving up one unit on the outcome scale

# For Ordered Logit regression:

- A 1 [unit1] change in treatment [causes/is associated with] a β change in the log-odds of moving up one unit on the outcome scale
- A 1 [unit1] change in treatment [causes/is associated with] a 100 \* (exp<sup>β</sup> − 1)% change in the odds (relative probability) of moving up one unit on on the outcome scale

# zelig(cyl wt,data=mtcars,model="ologit")

	Dependent variable:			
	cyl			
wt	5.186***			
	(1.506)			
Observations	32			
Note:	*p<0.1; **p<0.05; ***p<0.01			

# For Unordered Logit regression:

► If there are C outcome categories, we get C - 1 coefficients on each treatment variable

# For Unordered Logit regression:

- ► If there are C outcome categories, we get C 1 coefficients on each treatment variable
- A 1 [unit1] change in treatment [causes/is associated with] a β<sub>C</sub> change in the log-odds of this outcome category compared to the base category

# For Unordered Logit regression:

- ► If there are C outcome categories, we get C 1 coefficients on each treatment variable
- A 1 [unit1] change in treatment [causes/is associated with] a β<sub>C</sub> change in the log-odds of this outcome category compared to the base category
- A 1 [unit1] change in treatment [causes/is associated with] a 100 \* (exp(β<sub>C</sub>)−1) change in the odds (relative probability) of this outcome category compared to the base category

# zelig(color wt,data=mtcars,model="mlogit")

#### [1] "Black" "Blue" "Red" "Silver"

	Estimate	Std. Error	z value	Pr(> z )
(Intercept):1	0.236	1.768	0.134	0.894
(Intercept):2	0.858	1.769	0.485	0.628
(Intercept):3	-0.834	1.800	-0.463	0.643
wt:1	-0.074	0.530	-0.139	0.889
wt:2	-0.276	0.545	-0.505	0.613
wt:3	0.249	0.517	0.482	0.630

 Necessary when there are few measurable cases of our treatment/outcome

- Necessary when there are few measurable cases of our treatment/outcome
- Exactly the same causal inference logic as Large-N

- Necessary when there are few measurable cases of our treatment/outcome
- Exactly the same causal inference logic as Large-N
- We need counterfactuals to estimate treatment effects:
  Comparative Cases

- Necessary when there are few measurable cases of our treatment/outcome
- Exactly the same causal inference logic as Large-N
- We need counterfactuals to estimate treatment effects:
  Comparative Cases
- Even if we can 'observe' the causal process, we can easily make mistakes

- Necessary when there are few measurable cases of our treatment/outcome
- Exactly the same causal inference logic as Large-N
- We need counterfactuals to estimate treatment effects:
  Comparative Cases
- Even if we can 'observe' the causal process, we can easily make mistakes
- The aim is to go beyond description

Why can't we achieve causal inference from single case studies?

- Why can't we achieve causal inference from single case studies?
- If we truly have only one 'treated' observation, we cannot know what would have happened in the absence of treatment

- Why can't we achieve causal inference from single case studies?
- If we truly have only one 'treated' observation, we cannot know what would have happened in the absence of treatment
- ► These case studies can help *generate* hypotheses...

- Why can't we achieve causal inference from single case studies?
- If we truly have only one 'treated' observation, we cannot know what would have happened in the absence of treatment
- ► These case studies can help *generate* hypotheses...
- ► And they can maybe reject or weaken a theory...

- Why can't we achieve causal inference from single case studies?
- If we truly have only one 'treated' observation, we cannot know what would have happened in the absence of treatment
- ► These case studies can help *generate* hypotheses...
- ► And they can maybe reject or weaken a theory...
- But they cannot **confirm** a theory

- Why can't we achieve causal inference from single case studies?
- If we truly have only one 'treated' observation, we cannot know what would have happened in the absence of treatment
- ► These case studies can help *generate* hypotheses...
- ► And they can maybe reject or weaken a theory...
- But they cannot **confirm** a theory
- We need variation in the dependent variable if we are to explain it

- Why can't we achieve causal inference from single case studies?
- If we truly have only one 'treated' observation, we cannot know what would have happened in the absence of treatment
- ► These case studies can help *generate* hypotheses...
- ► And they can maybe reject or weaken a theory...
- But they cannot **confirm** a theory
- We need variation in the dependent variable if we are to explain it
- Common error: "research that tries to explain the outbreak of war with studies only of wars" (KKV)

► Similarities with Large-N:

- ► Similarities with Large-N:
  - Same challenges to inference: confounding, selection, reverse causation

- Similarities with Large-N:
  - Same challenges to inference: confounding, selection, reverse causation
  - Same assumptions required: SUTVA, Balance on all confounders

- Similarities with Large-N:
  - Same challenges to inference: confounding, selection, reverse causation
  - Same assumptions required: SUTVA, Balance on all confounders
- Differences with Large-N:
  - Fewer comparisons: No uncertainty measure or confidence intervals. What's our standard of evidence?

- Similarities with Large-N:
  - Same challenges to inference: confounding, selection, reverse causation
  - Same assumptions required: SUTVA, Balance on all confounders
- Differences with Large-N:
  - Fewer comparisons: No uncertainty measure or confidence intervals. What's our standard of evidence?
    - p-values aren't the only source of credibility (Slater and Ziblatt 2013)

- Similarities with Large-N:
  - Same challenges to inference: confounding, selection, reverse causation
  - Same assumptions required: SUTVA, Balance on all confounders
- Differences with Large-N:
  - Fewer comparisons: No uncertainty measure or confidence intervals. What's our standard of evidence?
    - p-values aren't the only source of credibility (Slater and Ziblatt 2013)
  - Statistical Inference: Non-random cases, so generalization is harder

- Similarities with Large-N:
  - Same challenges to inference: confounding, selection, reverse causation
  - Same assumptions required: SUTVA, Balance on all confounders
- Differences with Large-N:
  - Fewer comparisons: No uncertainty measure or confidence intervals. What's our standard of evidence?
    - p-values aren't the only source of credibility (Slater and Ziblatt 2013)
  - Statistical Inference: Non-random cases, so generalization is harder
  - Harder to balance confounders: More variables than cases!

In a small-N study, what causal inference technique is most useful?

- In a small-N study, what causal inference technique is most useful?
  - Diff-in-diff plausible if we have time-series data

- In a small-N study, what causal inference technique is most useful?
  - Diff-in-diff plausible if we have time-series data
  - IV may be possible if there is some as-if random assignment, eg. leader death from cancer

- In a small-N study, what causal inference technique is most useful?
  - Diff-in-diff plausible if we have time-series data
  - IV may be possible if there is some as-if random assignment, eg. leader death from cancer
  - Or an RDD, eg. just missing out on WB loans due to GDP measure

But most commonly, we are using a matching strategy:

- But most commonly, we are using a matching strategy:
  - Matching to ensure balance on confounders through case selection - prune unmatched cases

- But most commonly, we are using a matching strategy:
  - Matching to ensure balance on confounders through case selection - prune unmatched cases
  - Clearly we can't match on everything, so focus on getting balance on key confounders/alternative theories

- But most commonly, we are using a matching strategy:
  - Matching to ensure balance on confounders through case selection - prune unmatched cases
  - Clearly we can't match on everything, so focus on getting balance on key confounders/alternative theories
- Our Large-N dataset after matching might look very similar to a comparative case study

- ► Case Selection:
- Don't confuse two distinct considerations in choosing cases:

- ► Case Selection:
- Don't confuse two distinct considerations in choosing cases:
  - 1. Causal Inference (internal validity) can our cases tell us with confidence that *D* causes *Y*?

- ► Case Selection:
- Don't confuse two distinct considerations in choosing cases:
  - 1. Causal Inference (internal validity) can our cases tell us with confidence that *D* causes *Y*?
  - 2. Population Inference (external validity) How much can we generalize about this causal effect to a broader population?
- Ideally we want both: Control and representative variation
  - Our goal is not to explain why revolution happened in Iran, but why it happens generally

- ► Case Selection:
  - Random sampling is fine! It directly helps us generalize

- ► Case Selection:
  - Random sampling is fine! It directly helps us generalize
  - And it helps us avoid explicit bias in causal inference

- ► Case Selection:
  - Random sampling is fine! It directly helps us generalize
  - And it helps us avoid explicit bias in causal inference
  - But:

- ► Case Selection:
  - Random sampling is fine! It directly helps us generalize
  - And it helps us avoid explicit bias in causal inference
  - But:
    - Randomization does not guarantee enough variation in the treatment and outcome in small samples

- ► Case Selection:
  - Random sampling is fine! It directly helps us generalize
  - And it helps us avoid explicit bias in causal inference
  - But:
    - Randomization does not guarantee enough variation in the treatment and outcome in small samples
    - Randomization does not guarantee balance on confounders in small samples

- ► Case Selection:
  - Random sampling is fine! It directly helps us generalize
  - And it helps us avoid explicit bias in causal inference
  - But:
    - Randomization does not guarantee enough variation in the treatment and outcome in small samples
    - Randomization does not guarantee balance on confounders in small samples
    - Randomized sampling is not the same as randomized treatment
  - So even if we randomize, need to check for balance and variation

- ► Case Selection:
  - Random sampling is fine! It directly helps us generalize
  - And it helps us avoid explicit bias in causal inference
  - But:
    - Randomization does not guarantee enough variation in the treatment and outcome in small samples
    - Randomization does not guarantee balance on confounders in small samples
    - Randomized sampling is not the same as randomized treatment
  - So even if we randomize, need to check for balance and variation
  - Probably easier to 'block' on key confounders and impose variation in treatment - purposive sampling

- ► Case Selection:
  - DO NOT select cases by the value of the outcome (Geddes)

- ► Case Selection:
  - DO NOT select cases by the value of the outcome (Geddes)
  - If we only study success cases, we don't know the counterfactual

- ► Case Selection:
  - **DO NOT** select cases by the value of the outcome (Geddes)
  - If we only study success cases, we don't know the counterfactual
  - The 'treatment' may also have been present in the 'control' cases

- **DO NOT** select cases by the value of the outcome (Geddes)
- If we only study success cases, we don't know the counterfactual
- The 'treatment' may also have been present in the 'control' cases
- We want to explain interesting things, so we often pick 'extreme' cases, but the extremeness might reflect confounders, not the treatment

- **DO NOT** select cases by the value of the outcome (Geddes)
- If we only study success cases, we don't know the counterfactual
- The 'treatment' may also have been present in the 'control' cases
- We want to explain interesting things, so we often pick 'extreme' cases, but the extremeness might reflect confounders, not the treatment
- But: If we select cases explicitly for a range of values of the outcome, that's better

- ► Case Selection:
  - Case selection also requires properly defining our population/sample

- Case Selection:
  - Case selection also requires properly defining our population/sample
  - We risk 'survival bias' if we only look at 'active' cases

- Case Selection:
  - Case selection also requires properly defining our population/sample
  - We risk 'survival bias' if we only look at 'active' cases
    - Eg. cases where 'deterrence' fails coincide with poor communication

- ► Case Selection:
  - Case selection also requires properly defining our population/sample
  - We risk 'survival bias' if we only look at 'active' cases
    - Eg. cases where 'deterrence' fails coincide with poor communication
    - But communication is also poor every second that deterrence worked!

► Case Selection:

- ► Case Selection:
  - Achieving generalizability (population inference) depends on our cases being representative

- ► Case Selection:
  - Achieving generalizability (population inference) depends on our cases being representative
  - If we want to compare mens and womens running speeds,
    DO NOT pick Usain Bolt and Florence Griffith-Joyner

### Case Selection:

- Achieving generalizability (population inference) depends on our cases being representative
- If we want to compare mens and womens running speeds,
  DO NOT pick Usain Bolt and Florence Griffith-Joyner
- Pick units with 'median' values or a range of values on the confounding and outcome variables

- Case Selection:
  - Achieving generalizability (population inference) depends on our cases being representative
  - If we want to compare mens and womens running speeds,
    DO NOT pick Usain Bolt and Florence Griffith-Joyner
  - Pick units with 'median' values or a range of values on the confounding and outcome variables
  - Do this at the same time as balancing confounders hard!

# Most similar cases: Same covariates, different treatment value

- Most similar cases: Same covariates, different treatment value
- BUT If there are many sets of 'most similar' paired cases, which should we pick?

- Most similar cases: Same covariates, different treatment value
- BUT If there are many sets of 'most similar' paired cases, which should we pick?
  - Typical cases: Most representative paired cases on covariates, eg. Levitsky and Way

- Most similar cases: Same covariates, different treatment value
- BUT If there are many sets of 'most similar' paired cases, which should we pick?
  - Typical cases: Most representative paired cases on covariates, eg. Levitsky and Way
  - Diverse cases: Covering all values of treatment and covariates, eg. Slater

- Most similar cases: Same covariates, different treatment value
- BUT If there are many sets of 'most similar' paired cases, which should we pick?
  - Typical cases: Most representative paired cases on covariates, eg. Levitsky and Way
  - Diverse cases: Covering all values of treatment and covariates, eg. Slater
  - Extreme cases: Highest and lowest values of treatment, eg. Lieberman

Methods for alternative objectives:

- Methods for alternative objectives:
  - Deviant cases: If you want to disprove a theory or generate a new hypothesis

- Methods for alternative objectives:
  - Deviant cases: If you want to disprove a theory or generate a new hypothesis
  - Most different cases: When searching for a hypothesis to explain Y

- Methods for alternative objectives:
  - Deviant cases: If you want to disprove a theory or generate a new hypothesis
  - ► **Most different cases:** When searching for a hypothesis to explain *Y*
  - Influential cases: How sensitive is our relationship to mismeasurement of a key case?

## Three forms of mixed methods:

### Three forms of mixed methods:

1. Large-N measurement supports case selection for Small-N analysis (Seawright and Gerring)

## Three forms of mixed methods:

- 1. Large-N measurement supports case selection for Small-N analysis (Seawright and Gerring)
- 2. Small-N study to identify relationship, then tested for generalizability in Large-N sample (Lieberman)

## Three forms of mixed methods:

- 1. Large-N measurement supports case selection for Small-N analysis (Seawright and Gerring)
- 2. Small-N study to identify relationship, then tested for generalizability in Large-N sample (Lieberman)
- Large-N analysis to show causal mechanism within-case, then generalized using comparative case studies (Ziblatt and Slater)

Strategies for increasing the number of observations:

- Strategies for increasing the number of observations:
  - 1. Additional measurable implications of the causal theory

- Strategies for increasing the number of observations:
  - 1. Additional measurable implications of the causal theory
  - 2. Subnational units

- Strategies for increasing the number of observations:
  - 1. Additional measurable implications of the causal theory
  - 2. Subnational units
  - 3. Time-series

- Strategies for increasing the number of observations:
  - 1. Additional measurable implications of the causal theory
  - 2. Subnational units
  - 3. Time-series
  - 4. Alternative mesaures

How do individuals organize to achieve shared goals?

- How do individuals organize to achieve shared goals?
- When do they succeed in achieving those goals?

- How do individuals organize to achieve shared goals?
- When do they succeed in achieving those goals?
- Many processes of collective action are national in scope and have few cases

- How do individuals organize to achieve shared goals?
- When do they succeed in achieving those goals?
- Many processes of collective action are national in scope and have few cases
  - Elite loyalty

- How do individuals organize to achieve shared goals?
- When do they succeed in achieving those goals?
- Many processes of collective action are national in scope and have few cases
  - Elite loyalty
  - Protest

- How do individuals organize to achieve shared goals?
- When do they succeed in achieving those goals?
- Many processes of collective action are national in scope and have few cases
  - Elite loyalty
  - Protest
  - Tax compliance

- Levitsky and Way (2003)
  - What is their theory?

- Levitsky and Way (2003)
  - What is their theory?
  - How do the comparative cases provide supportive evidence?

- Levitsky and Way (2003)
  - What is their theory?
  - How do the comparative cases provide supportive evidence?
  - How generalizable are the findings?

- Levitsky and Way (2003)
  - What is their theory?
  - How do the comparative cases provide supportive evidence?
  - How generalizable are the findings?
  - How did they select their cases?

- Levitsky and Way (2003)
  - When do authoritarian parties collapse? (No specific treatment variable)

- Levitsky and Way (2003)
  - When do authoritarian parties collapse? (No specific treatment variable)
  - Does a ruling party that emerged from violent revolution cause a lower risk of authoritarian party collapse? (Specific treatment variable)

- Levitsky and Way (2003)
  - When do authoritarian parties collapse? (No specific treatment variable)
  - Does a ruling party that emerged from violent revolution cause a lower risk of authoritarian party collapse? (Specific treatment variable)
  - Does a [ruling party that emerged from violent revolution] cause a [lower risk of authoritarian party collapse]?

- Levitsky and Way (2003)
- Causal theory/mechanisms that affect collective action:

- Levitsky and Way (2003)
- Causal theory/mechanisms that affect collective action:
  - Clearer group boundaries and solidarity

- Levitsky and Way (2003)
- Causal theory/mechanisms that affect collective action:
  - Clearer group boundaries and solidarity
  - Leader legitimacy

- Levitsky and Way (2003)
- Causal theory/mechanisms that affect collective action:
  - Clearer group boundaries and solidarity
  - Leader legitimacy
  - Raising the moral and social costs of defection

- Levitsky and Way (2003)
- Causal theory/mechanisms that affect collective action:
  - Clearer group boundaries and solidarity
  - Leader legitimacy
  - Raising the moral and social costs of defection
  - Greater 'stomach' for repression

- Levitsky and Way (2003)
  - Population:

- Levitsky and Way (2003)
  - Population: One-Party Competitive Authoritarian regimes during economic crisis (scope condition)

- Levitsky and Way (2003)
  - Population: One-Party Competitive Authoritarian regimes during economic crisis (scope condition)
  - Sample:

- Levitsky and Way (2003)
  - Population: One-Party Competitive Authoritarian regimes during economic crisis (scope condition)
  - Sample: Kenya, Mozambique, Zimbabwe, Zambia

- Levitsky and Way (2003)
  - Population: One-Party Competitive Authoritarian regimes during economic crisis (scope condition)
  - Sample: Kenya, Mozambique, Zimbabwe, Zambia
  - Treatment:

- Levitsky and Way (2003)
  - Population: One-Party Competitive Authoritarian regimes during economic crisis (scope condition)
  - Sample: Kenya, Mozambique, Zimbabwe, Zambia
  - Treatment: Party formed by violent conflict

- Levitsky and Way (2003)
  - Population: One-Party Competitive Authoritarian regimes during economic crisis (scope condition)
  - Sample: Kenya, Mozambique, Zimbabwe, Zambia
  - Treatment: Party formed by violent conflict
  - Control:

- Levitsky and Way (2003)
  - Population: One-Party Competitive Authoritarian regimes during economic crisis (scope condition)
  - Sample: Kenya, Mozambique, Zimbabwe, Zambia
  - Treatment: Party formed by violent conflict
  - Control: Party not formed by violent conflict

- Levitsky and Way (2003)
  - Population: One-Party Competitive Authoritarian regimes during economic crisis (scope condition)
  - Sample: Kenya, Mozambique, Zimbabwe, Zambia
  - Treatment: Party formed by violent conflict
  - Control: Party not formed by violent conflict
  - Treatment Assignment:

- Levitsky and Way (2003)
  - Population: One-Party Competitive Authoritarian regimes during economic crisis (scope condition)
  - Sample: Kenya, Mozambique, Zimbabwe, Zambia
  - Treatment: Party formed by violent conflict
  - Control: Party not formed by violent conflict
  - Treatment Assignment: Complex historical processes

- Levitsky and Way (2003)
  - Population: One-Party Competitive Authoritarian regimes during economic crisis (scope condition)
  - Sample: Kenya, Mozambique, Zimbabwe, Zambia
  - Treatment: Party formed by violent conflict
  - Control: Party not formed by violent conflict
  - Treatment Assignment: Complex historical processes
  - Outcome:

- Levitsky and Way (2003)
  - Population: One-Party Competitive Authoritarian regimes during economic crisis (scope condition)
  - Sample: Kenya, Mozambique, Zimbabwe, Zambia
  - Treatment: Party formed by violent conflict
  - Control: Party not formed by violent conflict
  - Treatment Assignment: Complex historical processes
  - Outcome: Regime survival

- Levitsky and Way (2003)
- Estimating the causal effect is easy:

	Control	Treated
Regime collapse	Kenya, Zambia	
Regime survival		Mozambique, Zimbabwe

- Levitsky and Way (2003)
  - The 'work' is in measuring the variables and controlling for alternative explanations

- The 'work' is in measuring the variables and controlling for alternative explanations
- Is self-selection a concern? Not so much hard for a leader to choose their party origins

- The 'work' is in measuring the variables and controlling for alternative explanations
- Is self-selection a concern? Not so much hard for a leader to choose their party origins
- Confounders are identified from alternative theories that explain the outcome

- The 'work' is in measuring the variables and controlling for alternative explanations
- Is self-selection a concern? Not so much hard for a leader to choose their party origins
- Confounders are identified from alternative theories that explain the outcome
- Our cases must be balanced on these variables

- The 'work' is in measuring the variables and controlling for alternative explanations
- Is self-selection a concern? Not so much hard for a leader to choose their party origins
- Confounders are identified from alternative theories that explain the outcome
- Our cases must be balanced on these variables
  - Duration in power

- The 'work' is in measuring the variables and controlling for alternative explanations
- Is self-selection a concern? Not so much hard for a leader to choose their party origins
- Confounders are identified from alternative theories that explain the outcome
- Our cases must be balanced on these variables
  - Duration in power
  - Strength of opposition

- The 'work' is in measuring the variables and controlling for alternative explanations
- Is self-selection a concern? Not so much hard for a leader to choose their party origins
- Confounders are identified from alternative theories that explain the outcome
- Our cases must be balanced on these variables
  - Duration in power
  - Strength of opposition
  - All experienced fiscal crisis

- The 'work' is in measuring the variables and controlling for alternative explanations
- Is self-selection a concern? Not so much hard for a leader to choose their party origins
- Confounders are identified from alternative theories that explain the outcome
- Our cases must be balanced on these variables
  - Duration in power
  - Strength of opposition
  - All experienced fiscal crisis

 OR the expected bias from the imbalance must make it less likely for us to find a treatment effect

- OR the expected bias from the imbalance must make it less likely for us to find a treatment effect
  - Eg. Zimbabwe had higher income than Zambia and Kenya so modernization theory would predict regime collapse is more likely

- OR the expected bias from the imbalance must make it less likely for us to find a treatment effect
  - Eg. Zimbabwe had higher income than Zambia and Kenya so modernization theory would predict regime collapse is more likely
  - And a worse economic crisis also suggests regime collapse more likely...

- OR the expected bias from the imbalance must make it less likely for us to find a treatment effect
  - Eg. Zimbabwe had higher income than Zambia and Kenya so modernization theory would predict regime collapse is more likely
  - And a worse economic crisis also suggests regime collapse more likely...
  - So if the Zimbabwe regime survives, that can't be due to these confounders

- OR the expected bias from the imbalance must make it less likely for us to find a treatment effect
  - Eg. Zimbabwe had higher income than Zambia and Kenya so modernization theory would predict regime collapse is more likely
  - And a worse economic crisis also suggests regime collapse more likely...
  - So if the Zimbabwe regime survives, that can't be due to these confounders

- Levitsky and Way (2003)
- Case Selection?

- Levitsky and Way (2003)
- Case Selection?
  - Not ex ante explicit

- Levitsky and Way (2003)
- Case Selection?
  - Not ex ante explicit
  - But designed to achieve balance

- Levitsky and Way (2003)
- Case Selection?
  - Not ex ante explicit
  - But designed to achieve balance
- Generalizability?
  - How unusual are Zimbabwe and Mozambique?

- Levitsky and Way (2003)
- Case Selection?
  - Not ex ante explicit
  - But designed to achieve balance
- Generalizability?
  - How unusual are Zimbabwe and Mozambique?
  - Can't say much outside of Africa

- Lieberman (2003)
  - What is his theory?

- Lieberman (2003)
  - What is his theory?
  - How do the comparative cases provide supportive evidence?

- Lieberman (2003)
  - What is his theory?
  - How do the comparative cases provide supportive evidence?
  - How generalizable are the findings?

- Lieberman (2003)
  - What is his theory?
  - How do the comparative cases provide supportive evidence?
  - How generalizable are the findings?
  - How did he select his cases?

- ► Lieberman (2003)
  - Why is it so much harder to collect taxes in Brazil than South Africa?

- ► Lieberman (2003)
  - Why is it so much harder to collect taxes in Brazil than South Africa?
  - Do salient racial cleavages increase willingness to pay taxes?

- Lieberman (2003)
  - Population:

- Lieberman (2003)
  - Population: Developing countries

- Lieberman (2003)
  - Population: Developing countries
  - Sample:

- Lieberman (2003)
  - Population: Developing countries
  - Sample: Brazil and South Africa

- Lieberman (2003)
  - Population: Developing countries
  - Sample: Brazil and South Africa
  - Treatment:

- ► Lieberman (2003)
  - Population: Developing countries
  - Sample: Brazil and South Africa
  - Treatment: Cross-class racial cleavage

- Lieberman (2003)
  - Population: Developing countries
  - Sample: Brazil and South Africa
  - Treatment: Cross-class racial cleavage
  - Control:

- Lieberman (2003)
  - Population: Developing countries
  - Sample: Brazil and South Africa
  - Treatment: Cross-class racial cleavage
  - Control: Non-racial class cleavage

- Lieberman (2003)
  - Population: Developing countries
  - Sample: Brazil and South Africa
  - Treatment: Cross-class racial cleavage
  - Control: Non-racial class cleavage
  - Treatment Assignment:

- Lieberman (2003)
  - Population: Developing countries
  - Sample: Brazil and South Africa
  - Treatment: Cross-class racial cleavage
  - Control: Non-racial class cleavage
  - Treatment Assignment: History of social relations, constitutional conventions, policies

- Lieberman (2003)
  - Population: Developing countries
  - Sample: Brazil and South Africa
  - Treatment: Cross-class racial cleavage
  - Control: Non-racial class cleavage
  - Treatment Assignment: History of social relations, constitutional conventions, policies
  - Outcome:

- Lieberman (2003)
  - Population: Developing countries
  - Sample: Brazil and South Africa
  - Treatment: Cross-class racial cleavage
  - Control: Non-racial class cleavage
  - Treatment Assignment: History of social relations, constitutional conventions, policies
  - Outcome: Compliance of the rich with direct taxation

- Lieberman (2003)
- Balancing on Confounders

- Lieberman (2003)
- Balancing on Confounders
  - Authoritarian history/democratization

- Lieberman (2003)
- Balancing on Confounders
  - Authoritarian history/democratization
  - Development Strategy

- Lieberman (2003)
- Balancing on Confounders
  - Authoritarian history/democratization
  - Development Strategy
  - Income levels

- Lieberman (2003)
- Balancing on Confounders
  - Authoritarian history/democratization
  - Development Strategy
  - Income levels
  - Income inequality

- Lieberman (2003)
- Balancing on Confounders
  - Authoritarian history/democratization
  - Development Strategy
  - Income levels
  - Income inequality
  - Ethnic diversity

- Lieberman (2003)
- Balancing on Confounders
  - Authoritarian history/democratization
  - Development Strategy
  - Income levels
  - Income inequality
  - Ethnic diversity
  - Wars/International context

- Lieberman (2003)
  - Brazil and South Africa might be imbalanced on the amount of fish they catch

- Brazil and South Africa might be imbalanced on the amount of fish they catch
- And there's always a chance that this might matter

- Brazil and South Africa might be imbalanced on the amount of fish they catch
- And there's always a chance that this might matter
- But if we have balanced all theoretically-relevant confounders, that's pretty good

- Brazil and South Africa might be imbalanced on the amount of fish they catch
- And there's always a chance that this might matter
- But if we have balanced all theoretically-relevant confounders, that's pretty good
- Don't balance on recent indiciators of trust, corruption or culture. Why?

- Brazil and South Africa might be imbalanced on the amount of fish they catch
- And there's always a chance that this might matter
- But if we have balanced all theoretically-relevant confounders, that's pretty good
- Don't balance on recent indiciators of trust, corruption or culture. Why?
  - These variables are post-treatment affected by the national political community

- ► Lieberman (2003)
  - Complements the comparative case study with a cross-national regression

- ► Lieberman (2003)
  - Complements the comparative case study with a cross-national regression
  - Measurement accuracy vs generalizability

- ► Slater (2009)
  - What is his theory?

- Slater (2009)
  - What is his theory?
  - How do the comparative cases provide supportive evidence?

- Slater (2009)
  - What is his theory?
  - How do the comparative cases provide supportive evidence?
  - How generalizable are the findings?

- Slater (2009)
  - What is his theory?
  - How do the comparative cases provide supportive evidence?
  - How generalizable are the findings?
  - How did he select his cases?

- ► Slater (2009)
  - When does protest occur?

## Slater (2009)

- When does protest occur?
- When does protest succeed?

## Slater (2009)

- When does protest occur?
- When does protest succeed?
- Theory: Economic crisis or modernization or a stronger middle-class is not enough: Democrats also have to overcome the collective action problem

# Slater (2009)

- When does protest occur?
- When does protest succeed?
- Theory: Economic crisis or modernization or a stronger middle-class is not enough: Democrats also have to overcome the collective action problem
- Does the support of communal elites make mass protest more likely, and more likely to succeed?

- ► Slater (2009)
  - Holding region constant

- ► Slater (2009)
  - Holding region constant
  - Balance cases on income / material interests (alternative theory)

- ► Slater (2009)
  - Holding region constant
  - Balance cases on income / material interests (alternative theory)
  - Tries to correct a selection bias in the literature: Scholars measure protest but not the **absence of protest**

Population:

# Population: Authoritarian regimes

- Population: Authoritarian regimes
- ► Sample:

- Population: Authoritarian regimes
- ► Sample: 10 country-years in Southeast Asia

- Population: Authoritarian regimes
- ► Sample: 10 country-years in Southeast Asia
- Treatment:

- **Population:** Authoritarian regimes
- **Sample:** 10 country-years in Southeast Asia
- ► Treatment: Communal elites support the opposition

- Population: Authoritarian regimes
- **Sample:** 10 country-years in Southeast Asia
- ► **Treatment:** Communal elites support the opposition
- Control:

- **Population:** Authoritarian regimes
- ► Sample: 10 country-years in Southeast Asia
- ► Treatment: Communal elites support the opposition
- ► **Control:** Communal elites support the regime/split

- Population: Authoritarian regimes
- ► Sample: 10 country-years in Southeast Asia
- ► Treatment: Communal elites support the opposition
- ► **Control:** Communal elites support the regime/split
- Treatment Assignment:

- **Population:** Authoritarian regimes
- ► Sample: 10 country-years in Southeast Asia
- ► **Treatment:** Communal elites support the opposition
- ► **Control:** Communal elites support the regime/split
- Treatment Assignment: Historical processes of colonialism, decolonisation, and authoritarianism

- Population: Authoritarian regimes
- ► Sample: 10 country-years in Southeast Asia
- ► **Treatment:** Communal elites support the opposition
- ► **Control:** Communal elites support the regime/split
- Treatment Assignment: Historical processes of colonialism, decolonisation, and authoritarianism
- Outcome:

- Population: Authoritarian regimes
- **Sample:** 10 country-years in Southeast Asia
- ► **Treatment:** Communal elites support the opposition
- ► **Control:** Communal elites support the regime/split
- Treatment Assignment: Historical processes of colonialism, decolonisation, and authoritarianism
- Outcome: No protests, failed protests or protest success

TABLE 1										
COMMUNAL ELITES VERSUS RIVAL EXPLANATIONS FOR DEMOCRATIC MOBILIZATION IN SOUTHEAST ASIA										

	Philippines (1986)	Thailand (1973)	Thailand (1992)	Indonesia (1998)	Indonesia (1978)	Malaysia (1998)	Burma (1988–90)	Burma (2007)	Singapore	Vietnam
Economic										
development	Low- medium	Low- medium	Medium- high	Medium	Low- medium	Medium- high	Low	Low	High	Low- medium
Economic										
downturn	Yes	Yes	No	Yes	No	Yes	Yes	Yes	No	Yes
Stolen election	Yes	No	No	No	No	No	Yes	No	No	No
International										
diffusion	No	No	Yes	No	No	Yes	No	Yes	No	Yes
Politically autonomous communal										
elites	Yes	Yes	Yes	Split	Split	Split	Split	Split	No	No
Communal elites' predominant										
posture	Opposition	Opposition	Opposition	Opposition	Regime	Regime	Deadlock	Deadlock	Regime	Regime
Mobilization										
outcome	Revolution	Revolution	Revolution	Revolution	Crackdown	Crackdown	Crackdown	Crackdown	Quiescence	Quiesceno