

From Words to Actions

Testing the external validity of surveys

George Melios

London School of Economics and Political Science

As master Yoda says



As master Yoda says



- From the Bible (Mathew 1-3) to numerous cultural proverbs:
 - People appear to distinguish what they say and what they do
 - Suggest that what they say is of *"higher virtue"* than their actions
- What does this lack of congruence imply for social sciences?

Introduction

- Surveys are widely used in research to study a range of phenomena across social sciences
- Concerns about surveys' ability to accurately measure preferences, beliefs and identities
 - *Unincentivised - (Bullock et al., 2015)*
 - *Virtue Signalling - (Reisinger, 2022)*
 - *Staying in party line - (we will focus more on this later)*
- Why do we care?
- Raises questions about:
 - *External validity of a large body of research*
 - *How useful are surveys for policy design and evaluation*
 - *Whether we can improve survey designs*

Before we start



- Leverhulme Trust
- British Academy
- EC H2020
- ESRC

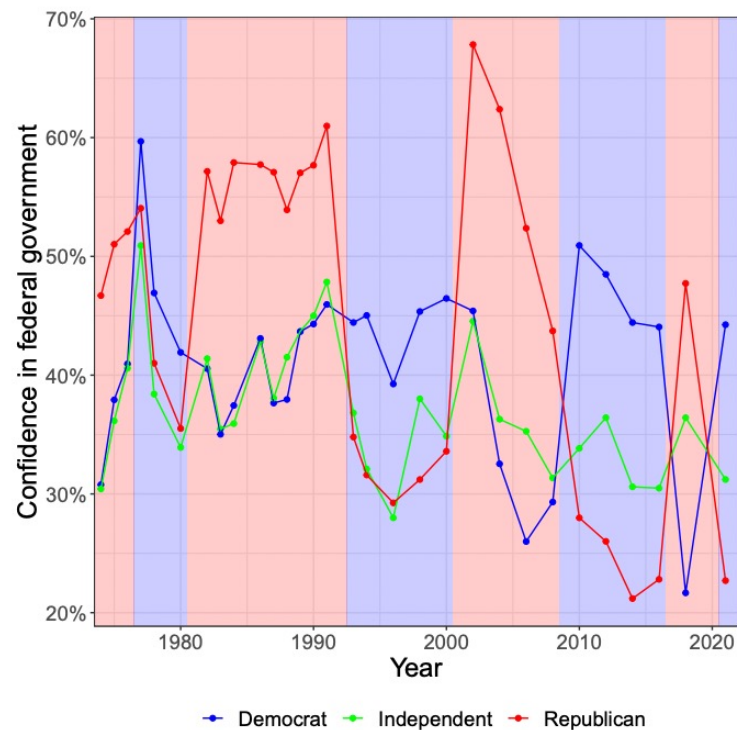
Back from commercials

- Our objective is:
 - *Not to dismiss surveys out of hand*
 - *To examine their external validity*
 - *To investigate if people's reported identities in surveys are consistent with important real-world decisions*
- We (aim) to focus on 6 projects, today we'll see 3:
 - *Are people less willing to support welfare charities when they support the incumbent government?*
 - *Are people willing to act if supporting affirmative action?*
 - *Can we test identity substitution with naturally occurring data?*

Why we study identities

- Understanding one's identity has become increasingly important
- Starting with Akerlof & Kranton (2000), Shayo (2009, 2020) suggests:
 - *Identities as preferences*
 - *Different group identities means caring about different things*
 - *Prescribed norms and behaviours*
 - *How we choose identities*
- *Alternative frameworks model identities as beliefs (see Dessi (2009), Benabou & Tirole (2011)) - stereotypes and prejudice*
 - *Social Identity, Group Behavior, and Teams (Charness and Chen, 2018 - ARE)*
 - *Identity Economics (Akerlof & Kranton, 2010)*
 - *Social Identity and Economic Policy (Shayo, 2020 - ARE)*
 - *How to Think About Social Identity (Kalin & Sambanis, 2018 - ARPS)*

Partisanship as an identity



- *Growing literature on what intensified partisan identities mean*
 - *Uncivil agreement* (Mason, 2018)
 - *Belief Disagreement and Portfolio Choice* (Meeywis et al, 2022 - JF)
 - *Political Alignment, Attitudes toward Government, and Tax Evasion* (Cullen, Turner, Washington, 2021 -AEJ:A)
- *Initial but robust evidence that some of what we say, we also do*

CHAPTER 1: Racial inequalities



Motivation

- May 26, 2020, George Floyd was killed by police officer
- BLM protests erupted across the country
- **15 to 26 million** people attended these protests
- **Largest** protests in US history
- **9 out of 10** voters said protests were “major factor in voting decision”
- How did BLM protests change the outcome of the 2020 election?

Do protests matter?

- 1960s racial justice protests:
 - Increased Democrat vote share if peaceful (Wasow, 2020)
 - Increased Republican vote share if violent (Wasow, 2020)
 - Depressed property values (Collins and Margo, 2007)
 - Lowered economic prospects African Americans (Collins and Margo, 2004)
 - Increased support for Democrats, affirmative action and racial justice 40 years later (Mazumder, 2018)
- Tea party protests increased Republican votes, donations, and policies (Madestam et al., 2013)
- Pro-immigration protests increased support for less restrictive policies (Branton et al., 2015)

Violence seems to be a key determinant



Why do protests matter?

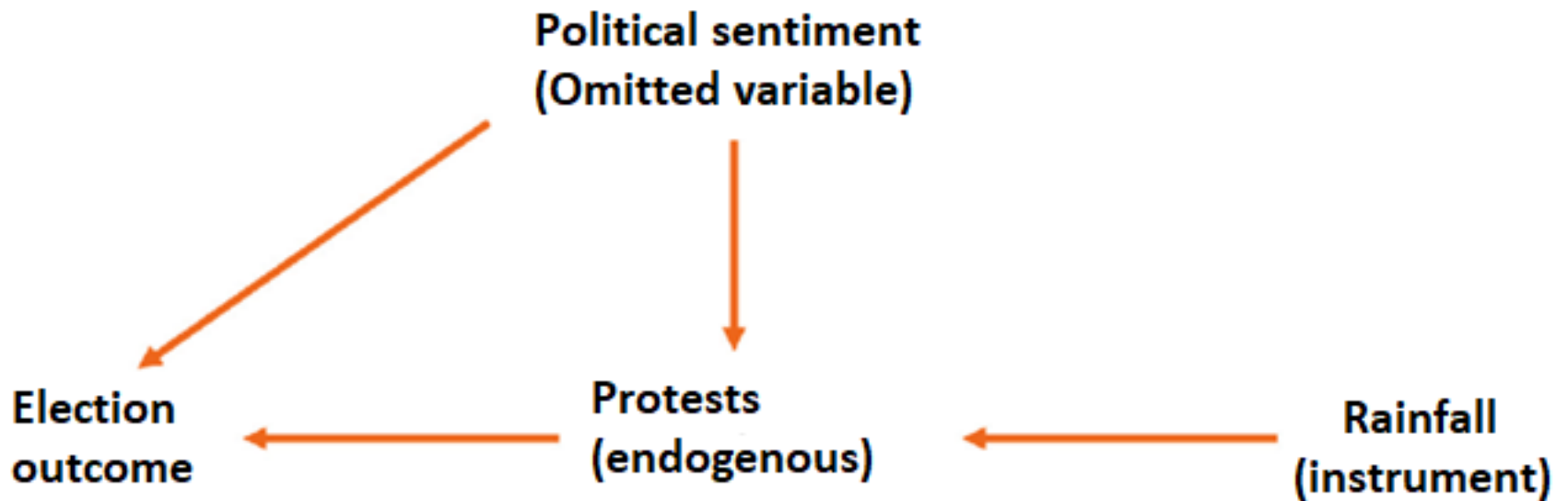
- Protests **reveal** privately held **information** to public (Lohmann, 1994)
 - Reveals extent of racial injustice
 - Shows incorrectness of status quo
- Protests push **new issues** onto news agendas (Wasow, 2020)
- Protests **reveal** political **preferences** to social network
 - People vote like their peers (Quattrone & Tversky, 1988)
 - Social norms affect voting decisions (Gerber et al., 2008)
- Protests make issues **salient**
 - Limited attention
 - Limited cognition

Protests can change both **attitudes** and **turnout**

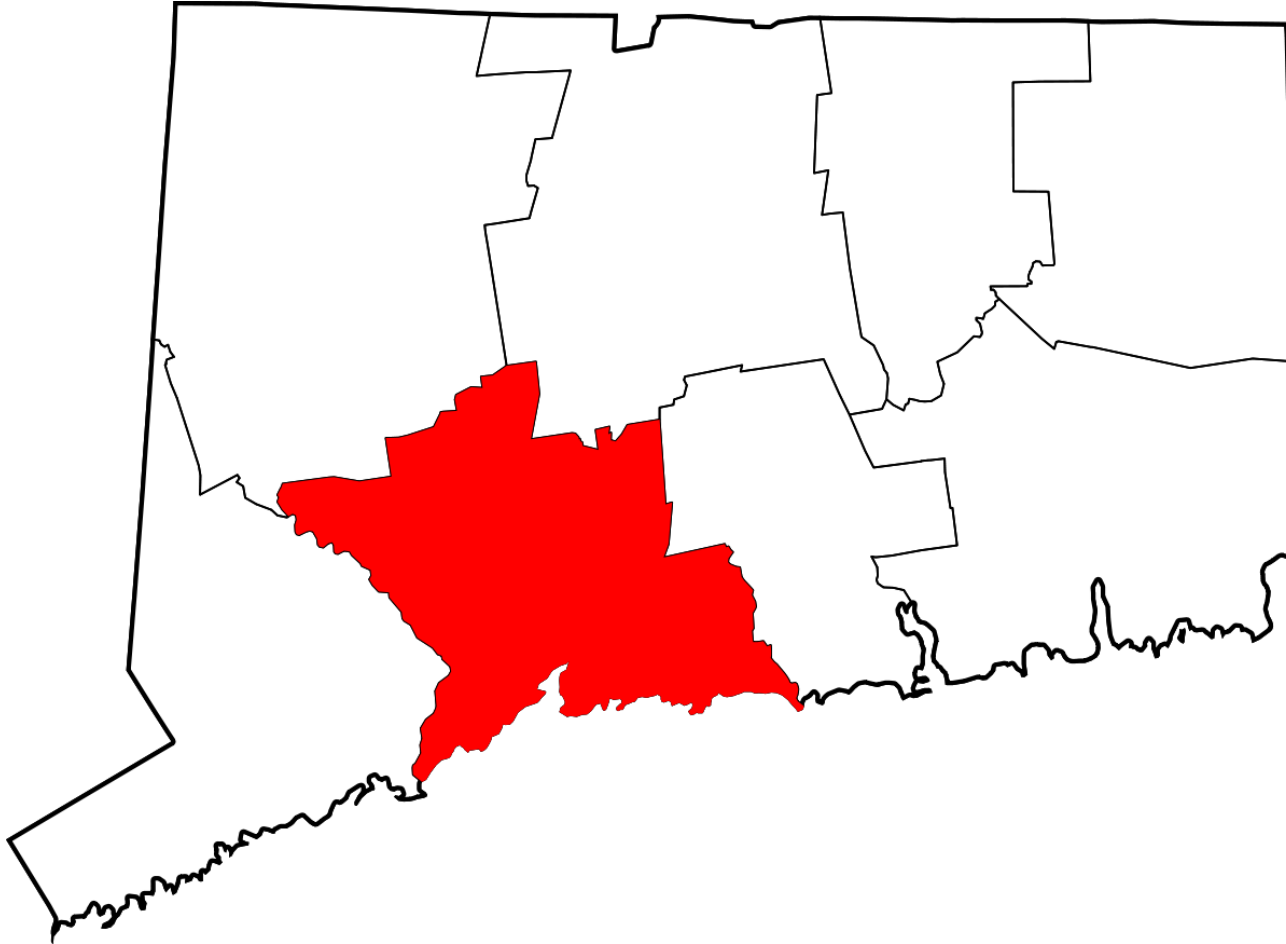
Identification Strategy

- What is the effect of BLM protests on the 2020 presidential election?
- Problem 1: Protests are **endogenous**
- Problem 2: Protests and election outcomes are **spatially correlated**
- Solution: **Spatial two-stage least squares**

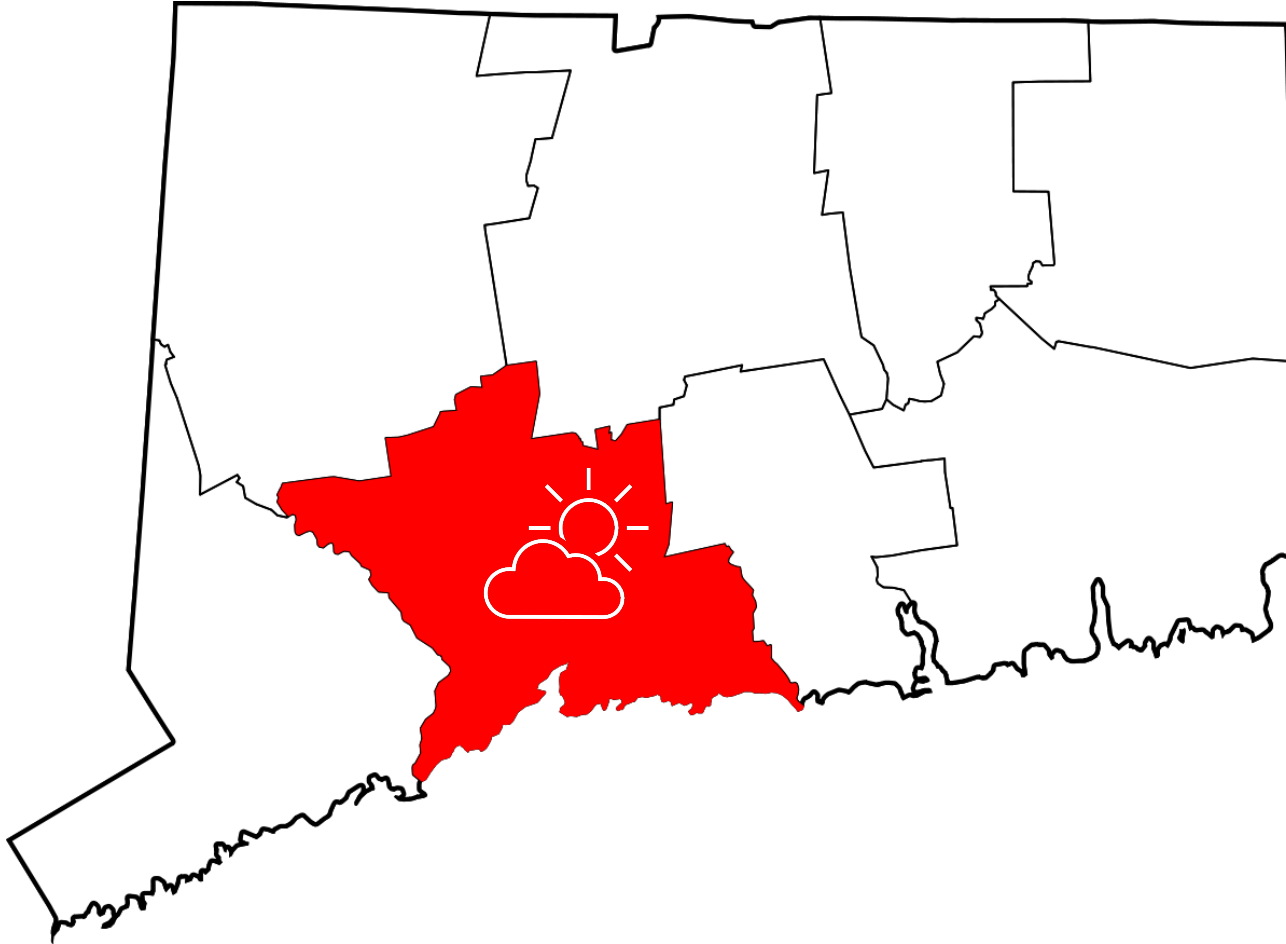
Identification Strategy



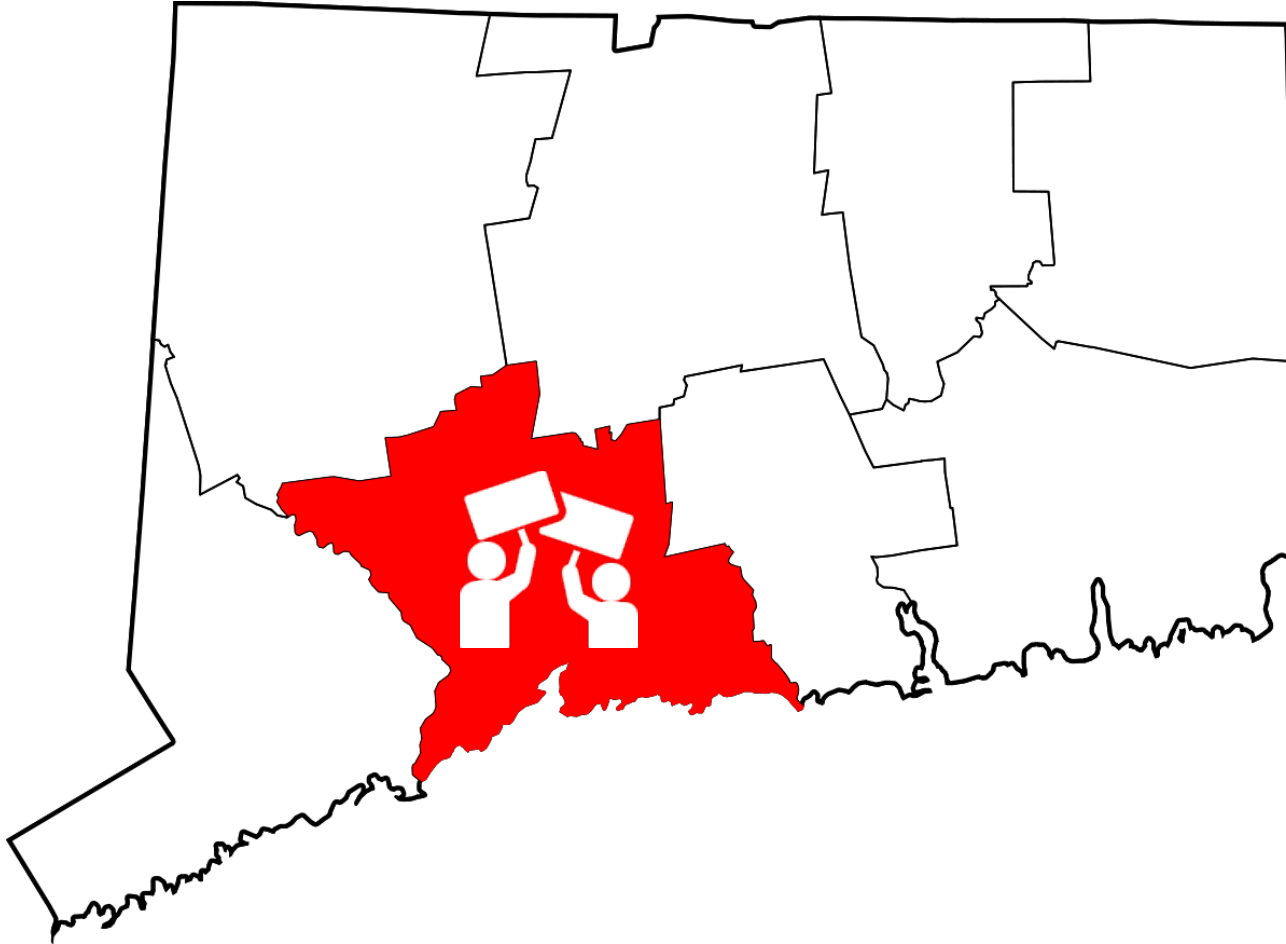
Identification: Spatial spillovers



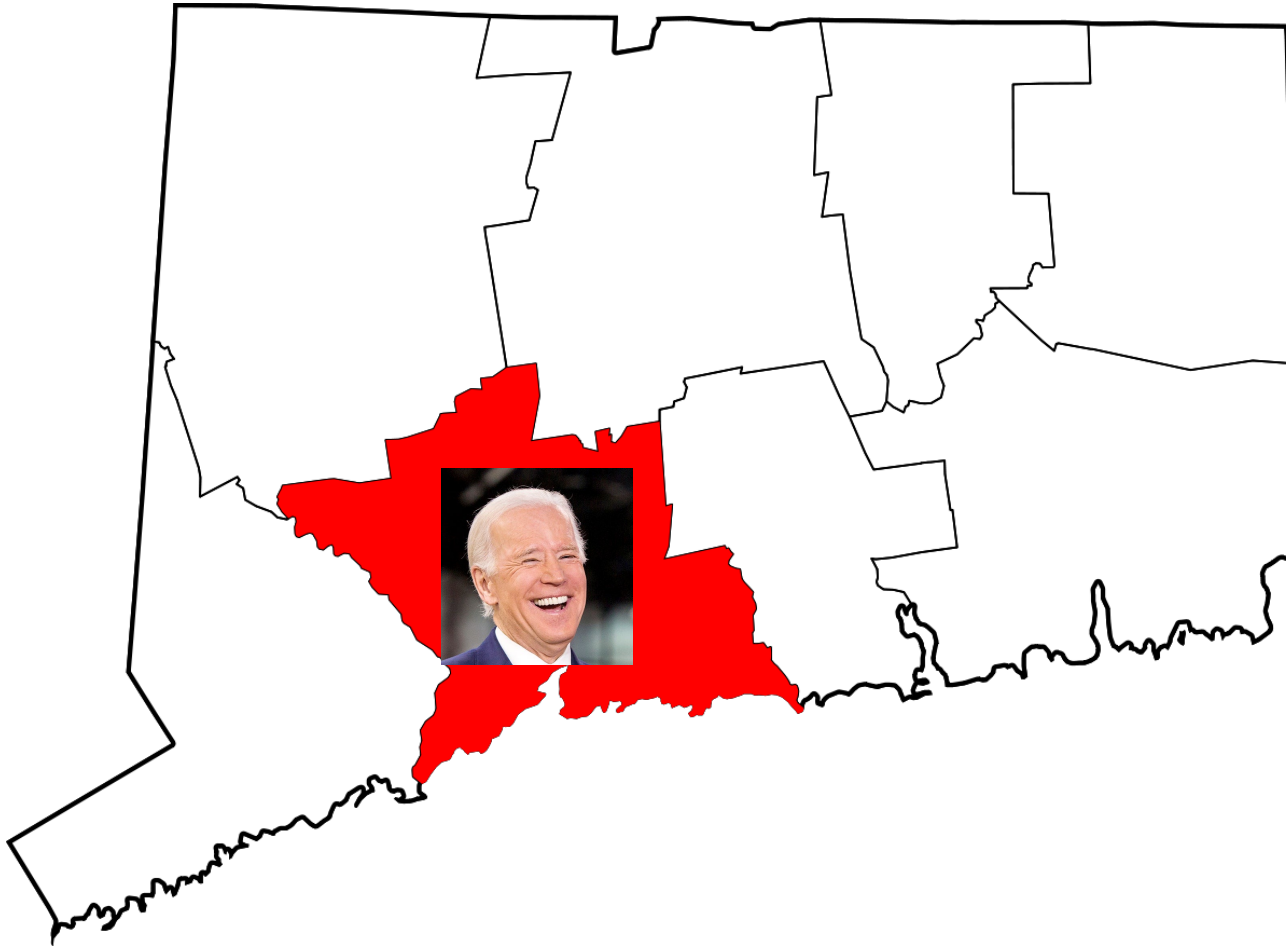
Identification: Spatial spillovers



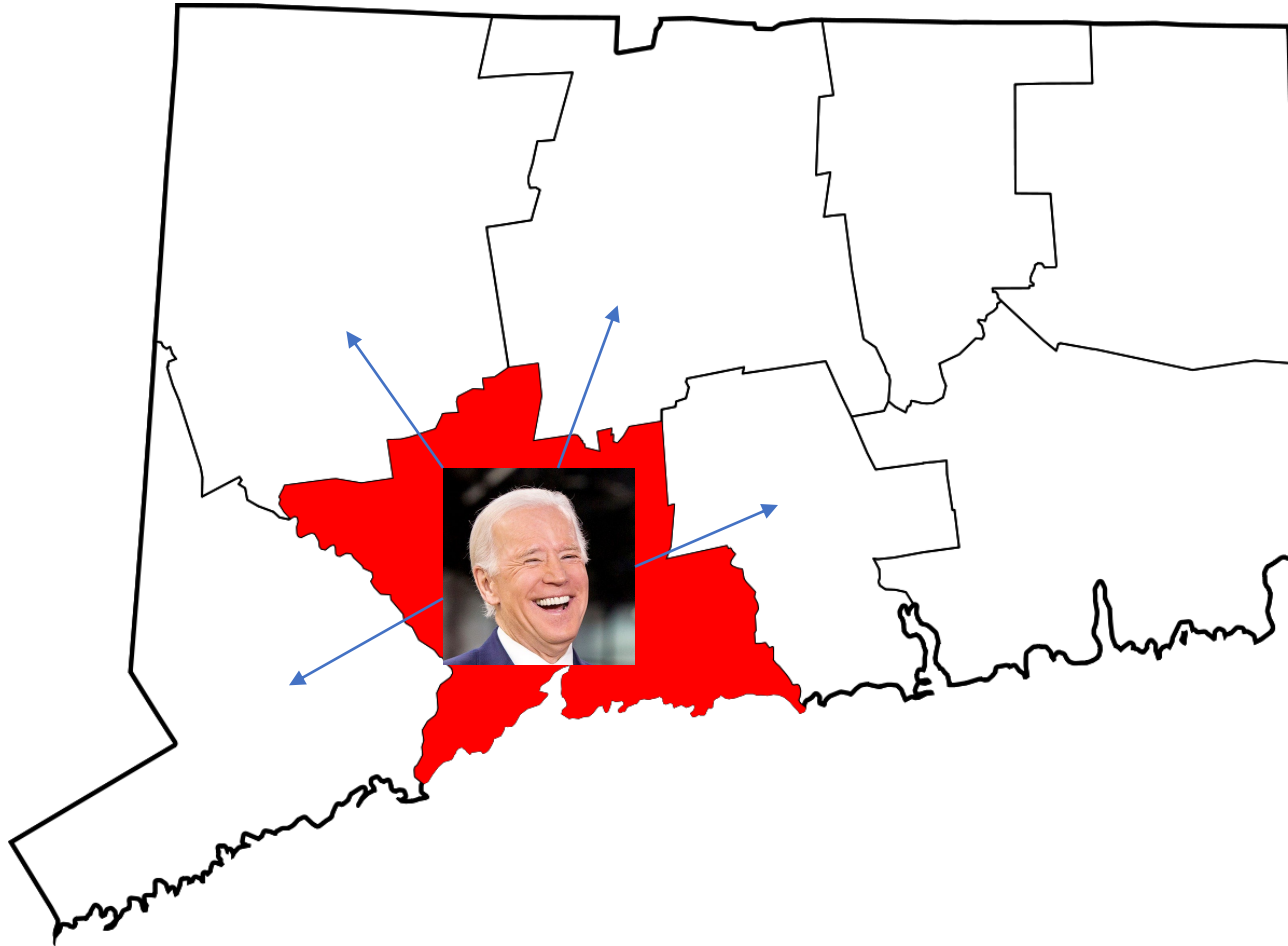
Identification: Spatial spillovers



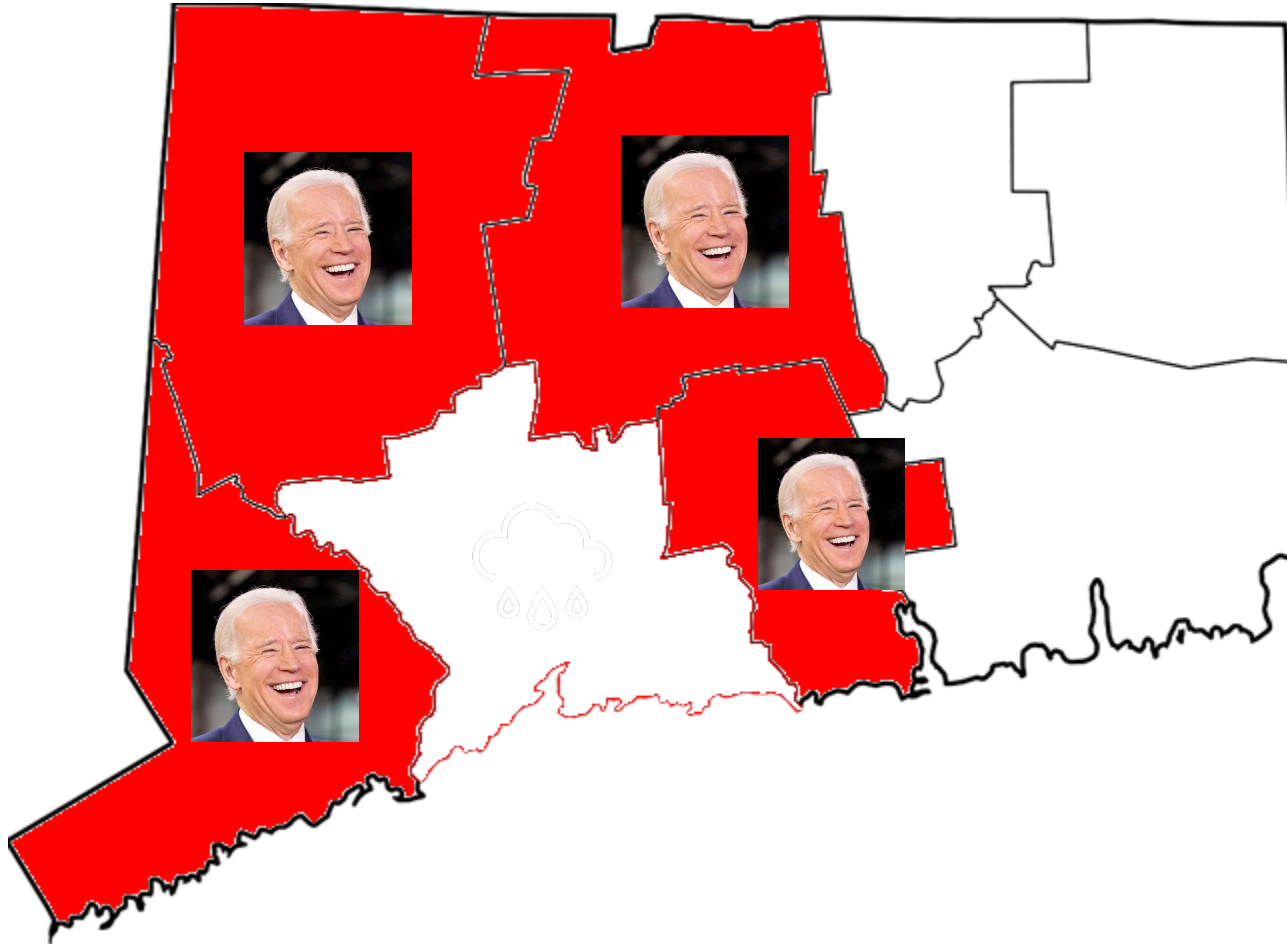
Identification: Spatial spillovers



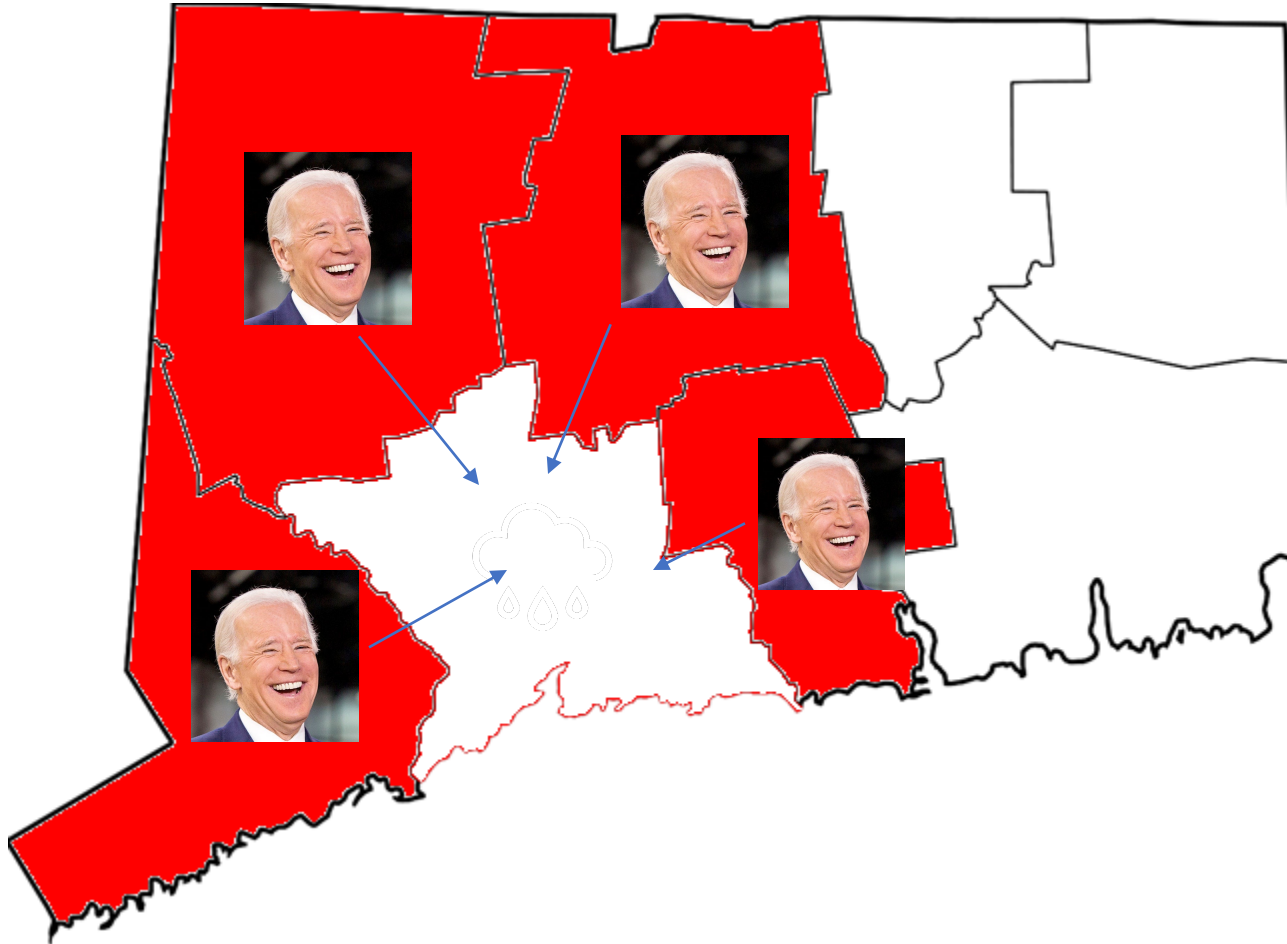
Identification: Spatial spillovers



Identification: Spatial spillovers



Identification: Spatial spillovers



Identification Strategy

- Problem 1: Protests are endogenous
- Solution: Use **rainfall** as instrument for protesting activity
 - Assumption 1.1: Rainfall discourages protests
 - Assumption 1.2: Rainfall does not otherwise affect election outcome (Mellon, 2021)
- Problem 2: Voting behavior, protests, and rainfall are spatially correlated
 - Violates assumption 1.2!
- Solution: **Spatial two-stage least squares**
 - Assumption 2.1: Outcomes and error terms are spatially correlated
 - Assumption 2.2: Spatial dependencies depend on geographical distance between counties

Methodology

$$Y_i = \beta_0 + \lambda \sum_{j=1}^N W_{ij} Y_j + \beta_1 \widehat{Protests}_i + \alpha X_i + u_i$$
$$u_i = \rho \sum_{j=1}^N W_{ij} u_j + \varepsilon_i$$

- **3 outcome variables**
 - Attitudes about discrimination and affirmative action
 - Change in Democratic vote share between 2016 and 2020
 - Change in turnout between 2016 and 2020
- **W:** Spatial weighting matrix
- **Protests:** Days of protests & Attendees/Population
- **X:** Demographic and Economic controls (racial composition, age, income, unemployment)

Data

- George Floyd's death: 25th May 2020
- Main BLM protest window: 26th May – 7th June
- **Protest data:** Crowd Counting Consortium
- **Racial attitude data:** Cooperative Election Study
- **Election data:** MIT Election Data and Science Lab
- **Weather data:** National Oceanic and Atmospheric Administration
- **County-level characteristics:** US Census

Effect of BLM protests on attitudes

Panel C: Blacks should not receive special favors

Days of protests	-0.117** (0.058)	-0.125*** (0.043)	-0.156*** (0.045)			
Attendees/Population				-0.782*** (0.274)	-0.619*** (0.148)	-0.636*** (0.136)
Rain prob.	-0.019 (0.324)	-0.468 (0.334)	-0.374 (0.344)	0.551 (0.427)	-0.331 (0.347)	-0.283 (0.338)
Population (100,000s)	0.013 (0.020)	0.029** (0.013)	0.038*** (0.013)	-0.012 (0.008)	0.001 (0.006)	0.002 (0.006)
λ	0.034 (0.054)	0.209 (0.128)	0.046 (0.049)	-0.047 (0.124)	-0.004 (0.062)	-0.026 (0.050)
ρ	2.967*** (0.893)	1.433*** (0.085)	2.082*** (0.638)	1.462* (0.801)	1.042 (0.724)	0.805 (0.704)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Economic controls	No	No	Yes	No	No	Yes
Observations	2,563	2,563	2,561	2,563	2,563	2,561

Effect of BLM protests on attitudes

Panel D: Slavery caused current disparities

Days of protests	0.142** (0.061)	0.145*** (0.050)	0.152*** (0.044)			
Attendees/Population				0.849*** (0.270)	0.688*** (0.154)	0.640*** (0.136)
Rain prob.	-0.040 (0.341)	0.330 (0.363)	0.382 (0.355)	-0.618 (0.435)	0.189 (0.371)	0.262 (0.353)
Population (100,000s)	-0.018 (0.021)	-0.030** (0.015)	-0.034** (0.013)	0.014* (0.008)	0.003 (0.006)	0.001 (0.006)
λ	-0.020 (0.070)	-0.049 (0.066)	-0.053 (0.095)	0.206 (0.143)	0.003 (0.131)	0.014 (0.060)
ρ	2.983*** (0.784)	2.032*** (0.496)	1.543* (0.857)	1.473*** (0.145)	1.214* (0.667)	0.680 (0.732)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Economic controls	No	No	Yes	No	No	Yes
Observations	2,563	2,563	2,561	2,563	2,563	2,561

Effect of BLM protests on attitudes

- BLM protests caused a shift in racial attitudes.
- People agreed **less** to the statement that *“Irish, Italians, Jewish and many other minorities overcame prejudice and worked their way up. Blacks should do the same without any special favors”*
- People agreed **more** with the statement that *“Generations of slavery and discrimination have created conditions that make it difficult for blacks to work their way out of the lower class”*
- Change in racial attitudes might explain part of the shift in voting

Effect of BLM protests on voting

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: Change in Democratic vote share						
Days of protests	0.012*** (0.002)	0.012*** (0.002)	0.010*** (0.002)			
Attendees/Population				0.088*** (0.017)	0.039*** (0.007)	0.034*** (0.006)
Rain prob.	0.036*** (0.011)	-0.031*** (0.010)	-0.013 (0.010)	-0.026 (0.027)	-0.035*** (0.013)	-0.015 (0.011)
Population (100,000s)	-0.003*** (0.001)	-0.003*** (0.0005)	-0.003*** (0.0004)	-0.001* (0.0004)	0.0001 (0.0002)	-0.0001 (0.0002)
λ	0.854 (0.630)	0.332 (0.446)	-0.122 (0.381)	3.358*** (1.286)	0.970** (0.492)	0.631 (0.428)
ρ	5.200*** (0.500)	5.703*** (0.764)	6.159*** (0.676)	4.972*** (1.041)	5.993*** (1.173)	6.215*** (0.994)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Economic controls	No	No	Yes	No	No	Yes
Observations	3,076	3,076	3,059	3,076	3,076	3,059

Effect of BLM protests on voting

- BLM protests **increased** Democratic vote share
- An additional day of protesting increases Democratic vote share by **1.0 to 1.2 p.p.**
- A 1 p.p. increase in attendees / population increases vote share by **3.4 to 8.8 p.p.**
- 1.7 to 4.4 p.p. increase in Dem. vote share in average protest county.
- Was progressive shift caused by **turnout** or **attitudes**?

Effect of BLM protests on turnout

Panel B: Turnout

Days of protests	0.014*** (0.003)	0.009*** (0.003)	0.007*** (0.003)			
Attendees/Population				0.073*** (0.021)	0.001 (0.011)	0.006 (0.010)
Rain prob.	-0.006 (0.020)	-0.027 (0.017)	-0.014 (0.016)	-0.046 (0.034)	-0.009 (0.017)	-0.002 (0.017)
Population (100,000s)	-0.004*** (0.001)	-0.002** (0.001)	-0.001* (0.001)	-0.001** (0.001)	0.001** (0.0003)	0.0004 (0.0003)
λ	-0.862*** (0.228)	-0.598*** (0.200)	-0.646*** (0.192)	-0.417 (0.288)	-0.916*** (0.233)	-0.820*** (0.223)
ρ	5.360*** (0.430)	4.452*** (0.322)	4.376*** (0.322)	5.703*** (0.698)	4.224*** (0.252)	4.255*** (0.275)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Economic controls	No	No	Yes	No	No	Yes
Observations	3,076	3,076	3,059	3,076	3,076	3,059

Effect of BLM protests on turnout

- BLM protests had mixed effect on turnout
- An additional day of protesting increases turnout by **0.7 to 1.4 p.p.**
- Number of attendees has **no significant effect**
- Turnout does not seem to explain the full progressive shift
- Protests seem to have swayed some voters'

Robustness checks

Rain, Rain, Go Away: 176 potential exclusion-restriction violations for studies using weather as an instrumental variable

Jonathan Mellon (University of Manchester)

2021-04-21

Abstract

Instrumental variable (IV) analysis assumes that the instrument only affects the dependent variable via its relationship with the independent variable. Other possible causal routes from the IV to the dependent variable are exclusion-restriction violations and make the instrument invalid. Weather has been widely used as an instrumental variable in social science to predict many different variables. The use of weather to instrument different independent variables represents strong prima facie evidence of exclusion violations for all studies using weather as an IV. A review of 217 social science studies reveals 176 variables which have been linked to weather, all of which represent potential exclusion violations. I conclude with practical steps to systematically review existing literature to identify possible exclusion violations when using IV designs. I demonstrate how sensitivity analysis can quantify the vulnerability of a particular IV estimate to exclusion restriction violations in the literature.

Robustness checks

- 100s of papers use rainfall as an instrument
- Many of these papers provide potential exclusion restriction violations for ours
 - Crime
 - Mood
 - Productivity
- Compare reduced form estimates during protest window to same-length windows prior to George Floyd's death
- Effect of rainfall on voting 100 times larger during BLM protest window
- Additional placebo tests show no effect on previous elections

Robustness checks

- Did we omit election-relevant factors?
- Estimate additional placebo regressions of rainfall on previous elections
- We find no effect

Robustness checks

- What happens when we ignore spatial autocorrelation?

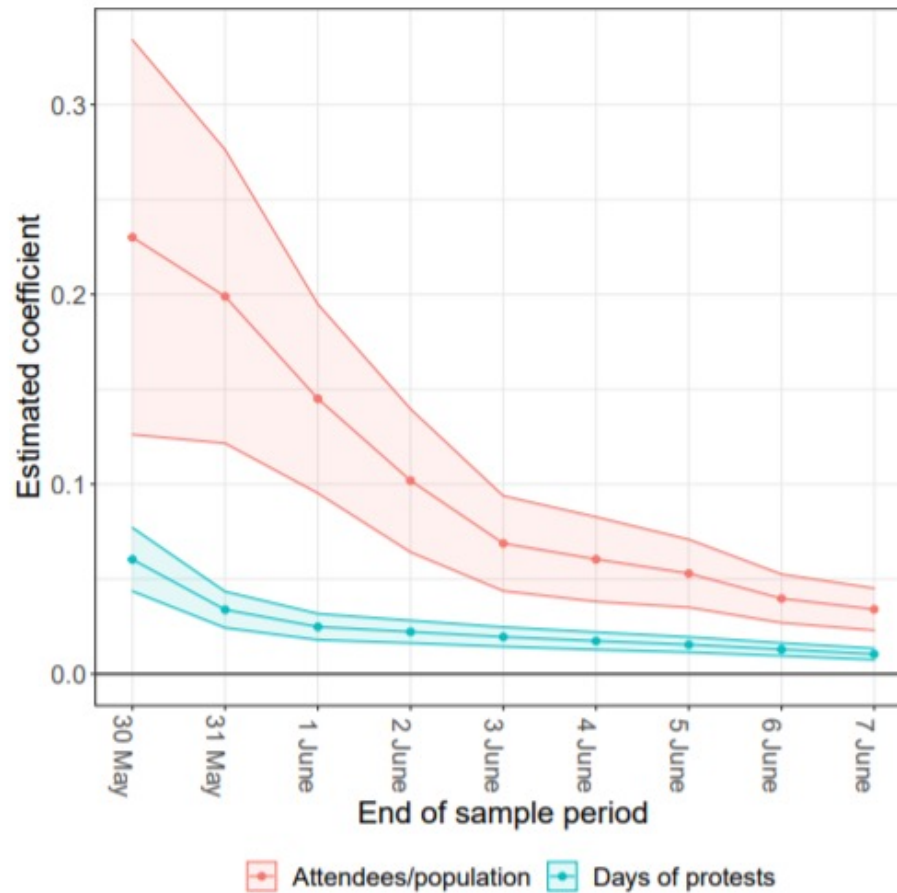
Panel B: Ignoring spatial autocorrelation

Days of Protests	0.072*** (0.020)	0.059*** (0.018)	0.054*** (0.019)			
Attendees/Population				0.151*** (0.035)	0.120*** (0.031)	0.102*** (0.029)
Rain prob.	-0.102** (0.050)	-0.205*** (0.063)	-0.188*** (0.066)	-0.062* (0.033)	-0.115*** (0.034)	-0.100*** (0.030)
Population (100,000s)	-0.027*** (0.008)	-0.017*** (0.005)	-0.015*** (0.006)	-0.003*** (0.001)	-0.001* (0.001)	-0.001** (0.001)
Observations	3076	3076	3061	3076	3076	3061
Demographic controls	No	Yes	Yes	No	Yes	Yes
Economic controls	No	No	Yes	No	No	Yes

- Effect sizes grow by factor 6!
- Raises questions about prior protest research

Robustness checks

- Choice of protest window



Conclusion

- BLM protests largest collective action ever in the US
- Protests caused a progressive shift in the 2020 election
- Only part can be explained by increased turnout
- Protests caused a shift in racial attitudes
- Protests can engender change!

Pause

Download the paper here:



Questions?
Suggestions?

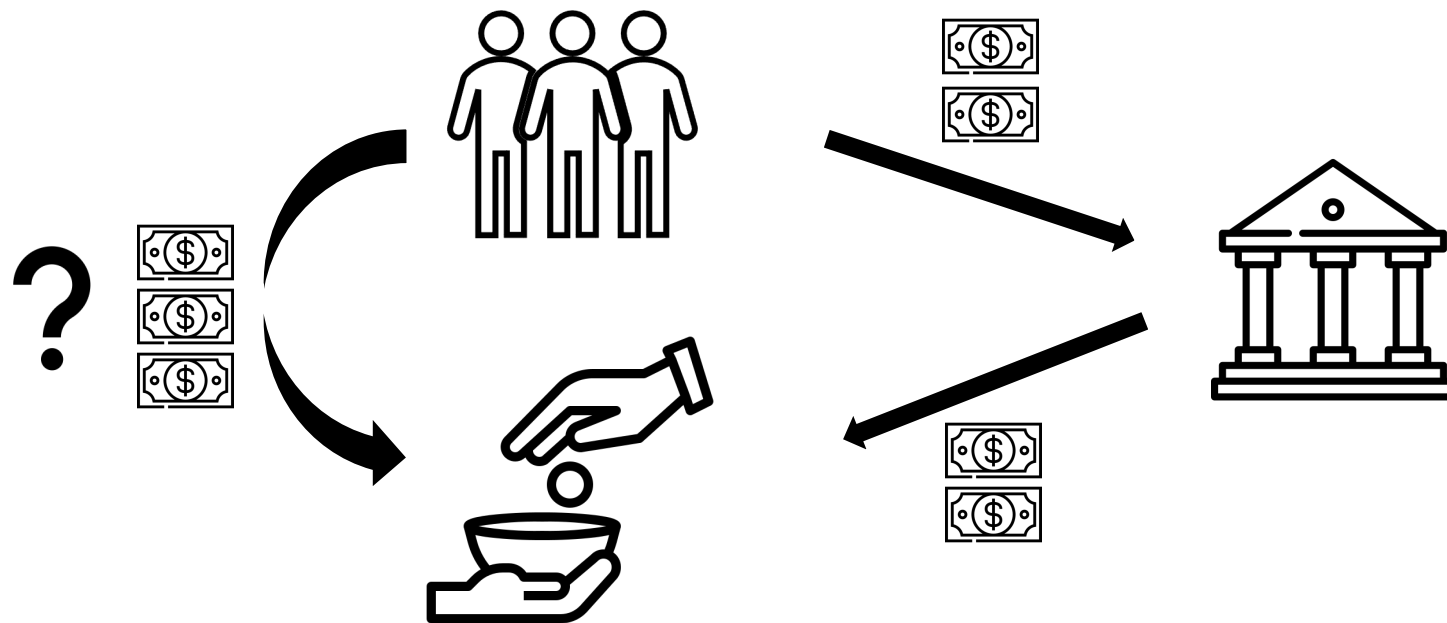




CHAPTER 2: Charitable Donations

Background: Charitable Donations

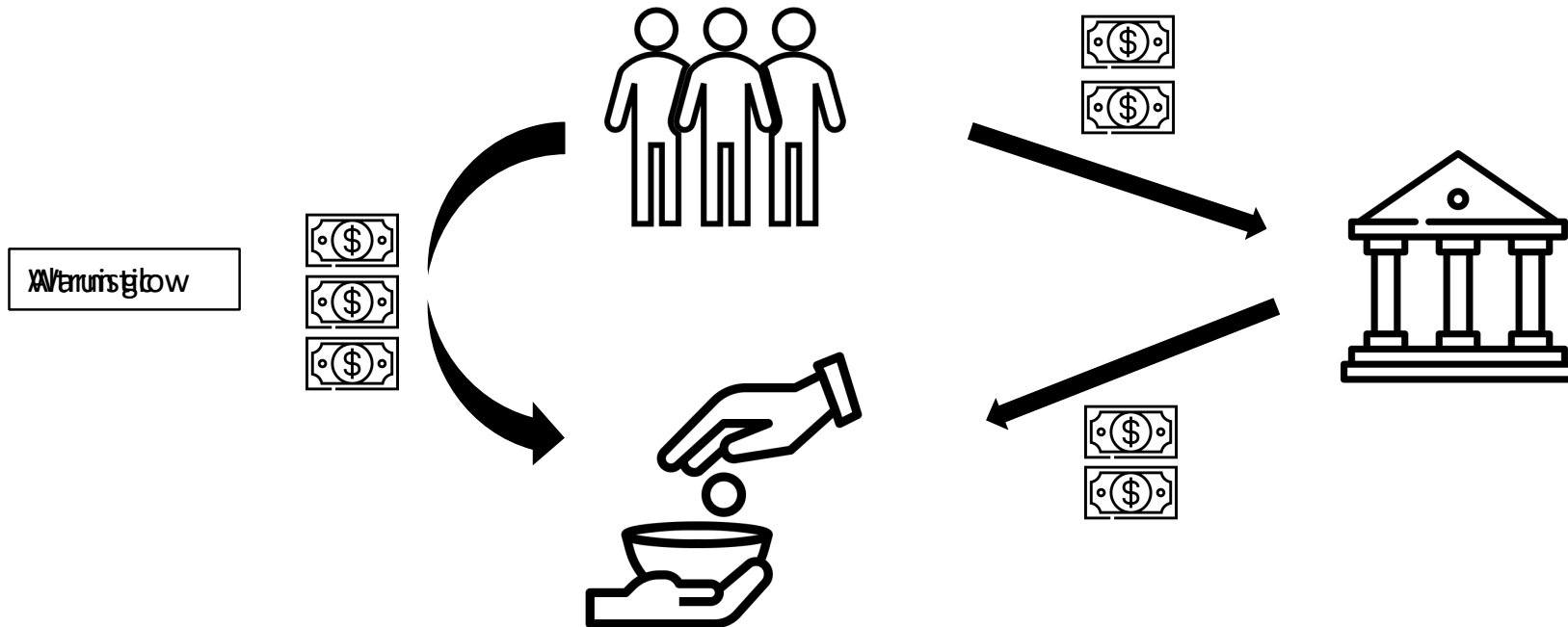
- We examine the relationship between **alignment with government** and **charitable donations**
- Relates to whether **government spending** crowds out **charitable donations**



Background: Charitable Donations

- Important policy question for provision of **welfare** and **public goods**
 - Links government spending to total welfare provision
 - Informs optimal policy-making
 - Potentially explains why so little charity goes to the poor
- Theoretical research:
 - **One-for-one crowding out** if people have altruistic preferences (e.g. Warr, 1982; Roberts, 1984)
 - **Partial crowding out** if donations yield a warm-glow effect (e.g. Andreoni 1990)

Background: Charitable Donations

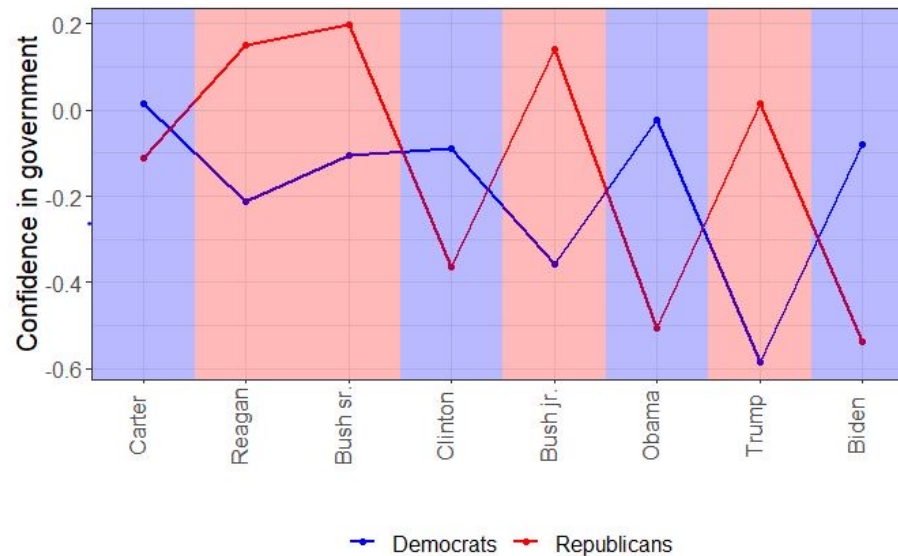


Background: Charitable Donations

- How about the empirics?
- Evidence is **mixed**:
 - Large crowding out (e.g. Hungerman and Gruber, 2007)
 - Small crowding out (e.g. Kingma, 1989)
 - Neither crowding out nor crowding in (e.g. Khanna et al., 1995)
 - Crowding in (e.g. Okten and Weisbrod, 2000)
- How can we explain this?

Background: Political Beliefs

- **Political beliefs** often depend on people's **alignment** with the government



Background: Political Beliefs

- **Partisans** engage in **politically motivated reasoning** (e.g. Nye, 1997; Taber and Lodge, 2006; Newton, 2020; Rieger and Wang, 2021)
- Partisans likely believe that their own party is better at solving problems
- Questions whether stated beliefs reflect true beliefs (e.g. Herber & Gruber, 2008)
 - Party cheerleading
 - Social desirability bias
 - Misreporting
- Partisans are incentivized to seek **alternative solutions** to problems during **other-party** presidencies
- We examine whether **alignment** with the government changes people's perceptions on the role of gov
- **Whether subsequently affects charitable giving**

Methodology

- Classify zip codes as Republican, Democrat, and Independent
 - **Republican/Democrat:** Vote share >50% each election between 2000 and 2016
 - **Independent:** both vote shares <60% and both parties won at least once between 2000 and 2016
- **Turnover elections** move **partisan** zip codes in and out of alignment
- We use **non-partisan** zips as a control group

Methodology

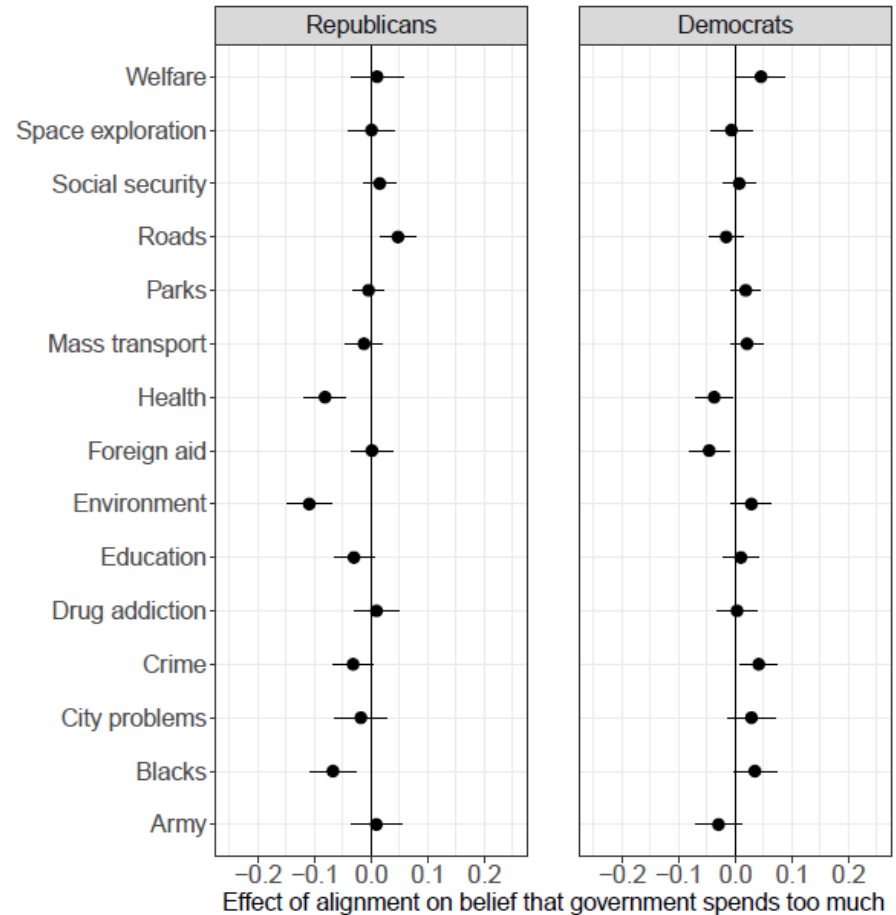
$$\mathbf{Beliefs}_{it} = \beta_1 \times (\mathbf{Zip} = \mathbf{Rep})_i \times (\mathbf{Pres} = \mathbf{Rep})_t + \beta_2 \times (\mathbf{Zip} = \mathbf{Dem})_i \times (\mathbf{Pres} = \mathbf{Dem})_t + X_{it}\boldsymbol{\Omega} + \alpha_i + \delta_t + \epsilon_{it}$$

- $(\mathbf{Zip} = \mathbf{Rep})_i$: Zip leans Republican
- $(\mathbf{Pres} = \mathbf{Rep})_t$: President is Republican
- $(\mathbf{Zip} = \mathbf{Dem})_i$: Zip leans Democrat
- $(\mathbf{Pres} = \mathbf{Dem})_t$: President is Democrat
- X_{it} : Additional controls (income and unemployment)
- α_i : Zip fixed effects
- δ_t : Year fixed effects

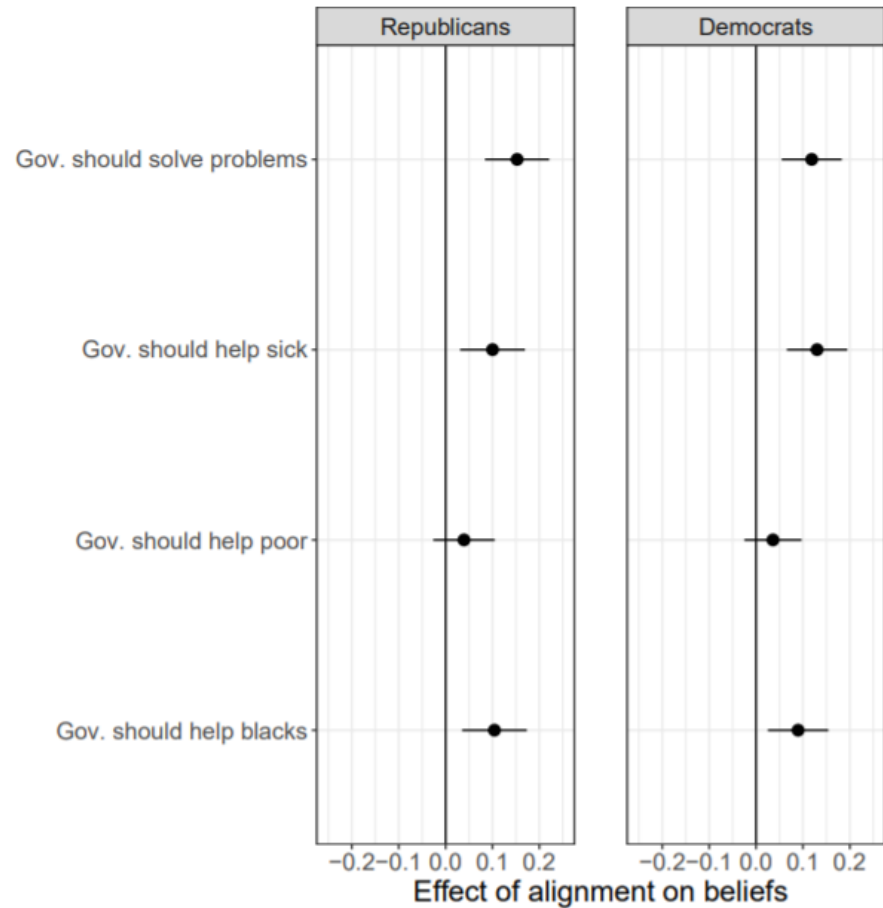
Political Beliefs

- Use GSS data to examine the effect of alignment on following questions:
- Does the government **spend too much/too little/enough** on 15 categories (crime, health, army, etc.)
- Is the government **responsible** for:
 - Solving the country's problems
 - Helping the sick
 - Helping the poor
 - Helping African Americans

Political Beliefs



Political Beliefs on role of government



Political Beliefs on role of government

- **Beliefs** about government spending **do not change**
 - Very little effect of alignment on beliefs about spending
 - If anything, people believe that other party spends **too much**
- **Normative Beliefs** about the role of government **do!**
 - **In-party** partisans believe that the **government** is responsible for solving problems
 - **Out-party** partisans believe that **private parties** are responsible for solving problems
- Well, does that make aligned partisans less probable to donate to charities?

Data

- Zip-level donation data from 2002 to 2018 (IRS tax returns)
 - Number of tax-paying individuals
 - Total income
 - Total deductions for charitable donations
 - Number of people with deductions
- County-level election results from 2000 to 2016 (MIT Election lab)
- Individuals' beliefs about government from 1983 to 2018 (GSS)
- Charity-level donation receipts from 1990 to 2018 (NCCS)
- Political donations from 2002 to 2018 (DIME)

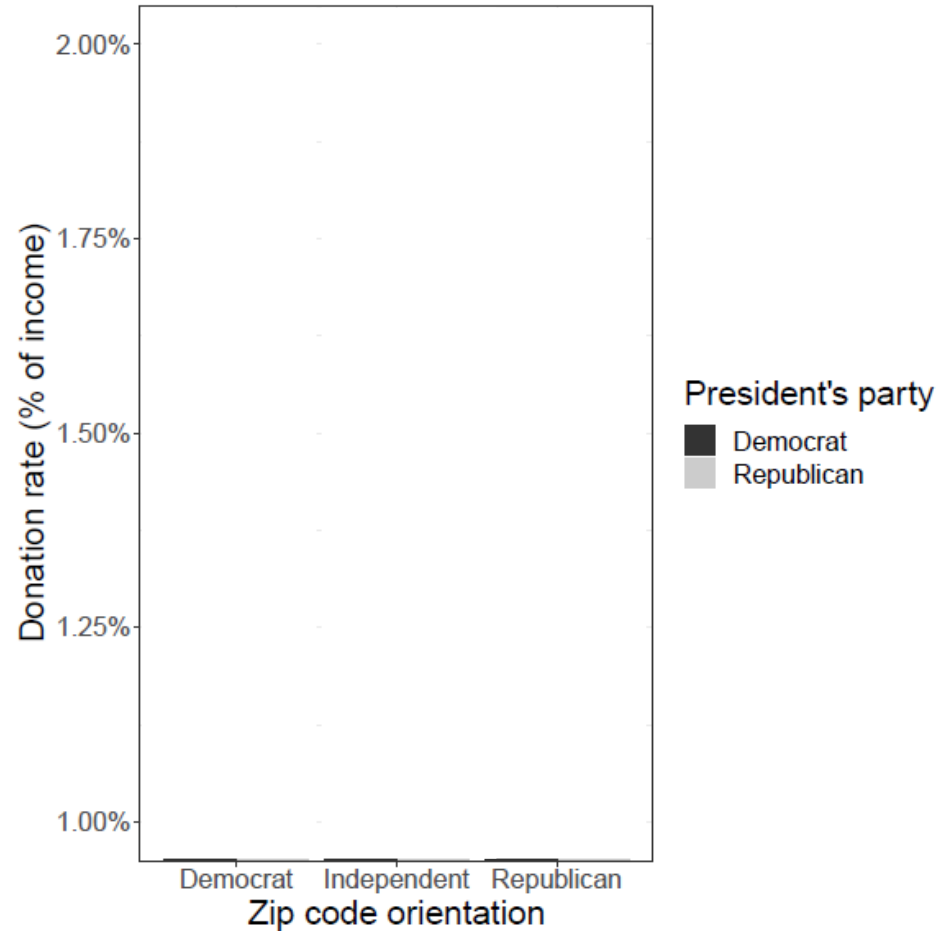
Methodology

- Do partisans donate **less** when they **support** the president?
- Classify zip codes as Republican, Democrat, and Independent
 - **Republican/Democrat**: Vote share >50% each election between 2000 and 2016
 - **Independent**: both vote shares <60% and both parties won at least once between 2000 and 2016
- **Turnover elections** move **partisan** zip codes in and out of alignment
- We use **non-partisan** zips as a control group

Methodology

$$\mathit{Donations}_{it} = \beta_1 \times (\mathit{Zip} = \mathit{Rep})_i \times (\mathit{Pres} = \mathit{Rep})_t + \beta_2 \times (\mathit{Zip} = \mathit{Dem})_i \times (\mathit{Pres} = \mathit{Dem})_t + X_{it}\Omega + \alpha_i + \delta_t + \epsilon_{it}$$

- $\mathit{Donations}_{it}$: Zip-level donations as % of income
- $(\mathit{Zip} = \mathit{Rep})_i$: Zip leans Republican
- $(\mathit{Pres} = \mathit{Rep})_t$: President is Republican
- $(\mathit{Zip} = \mathit{Dem})_i$: Zip leans Democrat
- $(\mathit{Pres} = \mathit{Dem})_t$: President is Democrat
- X_{it} : Additional controls (income and unemployment)
- α_i : Zip fixed effects
- δ_t : Year fixed effects



Results

	Model 1	Model 2	Model 3	Model 4
Republican zip x Republican pres.				
Democrat zip x Democrat pres.				
Zip fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	No	No
State-year fixed-effects	No	No	Yes	Yes
Controls	No	Yes	No	Yes
Observations	248,256	248,126	248,256	248,126
Adjusted R ²	0.825	0.826	0.834	0.835

Results

- **Democrats:** alignment reduces donations by 59-78 cents per \$1000 earned
- **Republicans:** alignment reduces donations by 49-71 cents per \$1000 earned
- In relative terms, both groups donate approximately **4% less** during own-party presidencies

Alternative Explanations

- Differences in **government spending** between Rep/Dem presidencies
 - Year fixed effects
 - State-year fixed effects
 - Gov. spending x partisanship
- Differences in **government grants** to charities between Rep/Dem presidencies
 - Panel of charity-level funding data from 1990 to 2018
 - Consider charities registered in Dem/Rep zip codes
 - Consider charities focused on Dem. issues (civil rights, environment, foreign aid) vs. Rep. issues (crime and religion)
 - Use log(grants) as outcome variable
- Differences in **Fundraising** activity between Rep/Dem presidencies
 - Same methodology, use log(fundraising) as outcome variable

	Model 1	Model 2	Model 3	Model 4
Republican zip x Republican pres.	-0.073*** (0.004)	-0.071*** (0.004)	-0.058*** (0.004)	-0.056*** (0.004)
Democrat zip x Democrat pres.	-0.077*** (0.005)	-0.071*** (0.005)	-0.058*** (0.005)	-0.052*** (0.005)
Republican zip x Government spending	-0.007 (0.005)	0.001 (0.005)	-0.021*** (0.006)	-0.018*** (0.006)
Democrat zip x Government spending	-0.003 (0.007)	-0.012* (0.007)	-0.012 (0.007)	-0.018** (0.008)
Zip fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	No	No
State-year fixed-effects	No	No	Yes	Yes
Controls	No	Yes	No	Yes
Observations	248,256	248,126	248,256	248,126
Adjusted R ²	0.825	0.826	0.834	0.835

Table A1: Effect of alignment on grants and fundraising, charity location

	Model 1	Model 2	Model 3	Model 4
Panel A: Government grants				
Republican county x Republican Pres.	-0.034 (0.056)	-0.027 (0.055)	-0.037 (0.058)	-0.037 (0.059)
Democrat county x Democrat pres.	0.030 (0.031)	0.042 (0.031)	0.041 (0.036)	0.041 (0.036)
Charity fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	No	No
State-year fixed-effects	No	No	Yes	Yes
Controls	No	Yes	No	Yes
Observations	45,997	45,946	45,997	45,946
Adjusted R ²	0.847	0.847	0.848	0.849
Panel B: Fundraising expenses				
Republican county x Republican Pres.	-0.007 (0.035)	-0.010 (0.035)	-0.003 (0.039)	-0.003 (0.039)
Democrat county x Democrat pres.	-0.007 (0.023)	-0.008 (0.022)	-0.009 (0.027)	-0.005 (0.027)
Charity fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	No	No
State-year fixed-effects	No	No	Yes	Yes
Controls	No	Yes	No	Yes
Observations	55,478	55,428	55,478	55,428
Adjusted R ²	0.874	0.874	0.875	0.876

Table A2: Effect of alignment on grants and fundraising, charity cause

	Model 1	Model 2	Model 3	Model 4
Panel A: Government grants				
Republican cause x Republican Pres.	-0.089 (0.080)	-0.090 (0.079)	-0.095 (0.081)	-0.095 (0.081)
Democrat cause x Democrat pres.	-0.068 (0.070)	-0.065 (0.069)	-0.078 (0.068)	-0.078 (0.067)
Charity fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	No	No
State-year fixed-effects	No	No	Yes	Yes
Controls	No	Yes	No	Yes
Observations	73,562	73,511	73,562	73,511
Adjusted R ²	0.840	0.840	0.841	0.841
Panel B: Fundraising expenses				
Republican cause x Republican Pres.	-0.041 (0.062)	-0.040 (0.061)	-0.043 (0.062)	-0.041 (0.062)
Democrat cause x Democrat pres.	0.033 (0.038)	0.035 (0.038)	0.034 (0.040)	0.039 (0.040)
Charity fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	No	No
State-year fixed-effects	No	No	Yes	Yes
Controls	No	Yes	No	Yes
Observations	88,236	88,186	88,236	88,186
Adjusted R ²	0.871	0.871	0.872	0.872

Alternative explanations

- Differences in government spending **cannot** explain our results
- Republican/Democrat-leaning charities do **not receive more grants** from Rep/Dem governments
- Rep/Dem leaning charities do **not spend less on fundraising** during Rep/Dem governments
- Results seem to be driven by partisans' alignment with the president

Ancillary Analysis

We examine four additional questions:

- Are results driven by **intensive** or **extensive margin** of giving?
- Does the **composition** of charitable donations change?
- Do people **substitute** between **charitable** donations and **political** donations?

Extensive vs Intensive Margin

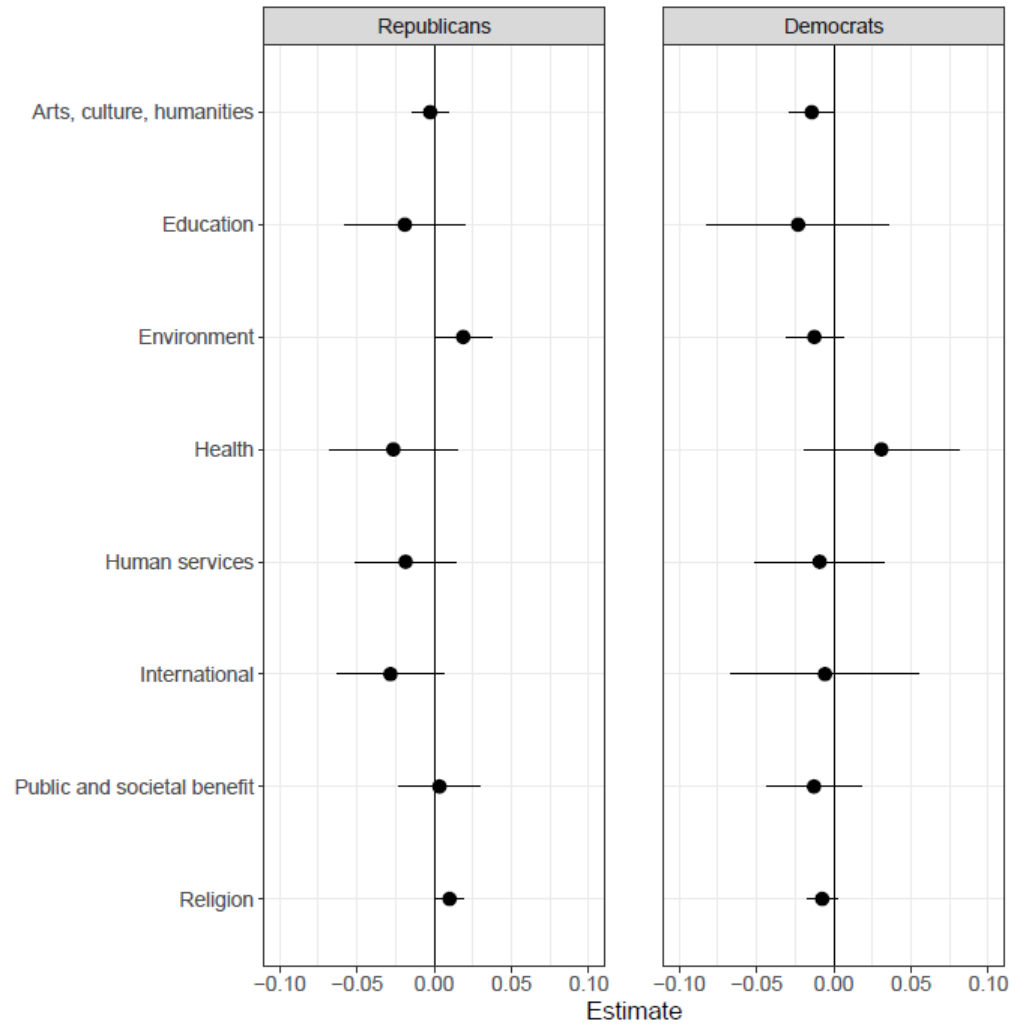
- Do **fewer** people give, or does the same number of donors give **less**?
- Use same data as before
- We consider two additional outcome variables:
 - Fraction of people that donate (extensive margin)
 - Average amount given per donor (intensive margin)
- Use same methodology as before

Extensive vs Intensive Margin

	Model 1	Model 2	Model 3	Model 4
Panel A: Intensive margin				
Republican zip x Republican pres.	-0.082*** (0.032)	0.087* (0.048)	-0.062* (0.034)	0.076* (0.044)
Democrat zip x Democrat pres.	-0.243*** (0.048)	-0.090* (0.046)	-0.296*** (0.057)	-0.157*** (0.052)
Zip fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	No	No
State-year fixed-effects	No	No	Yes	Yes
Controls	No	Yes	No	Yes
Observations	242,430	242,300	242,430	242,300
Adjusted R ²	0.579	0.666	0.583	0.675
Panel B: Extensive margin				
Republican zip x Republican pres.	-0.245*** (0.032)	-0.188*** (0.032)	-0.323*** (0.033)	-0.198*** (0.032)
Democrat zip x Democrat pres.	-0.022 (0.043)	0.012 (0.042)	-0.111*** (0.042)	-0.116*** (0.042)
Zip fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	No	No
State-year fixed-effects	No	No	Yes	Yes
Controls	No	Yes	No	Yes
Observations	248,256	248,126	248,256	248,126
Adjusted R ²	0.954	0.954	0.965	0.966

Composition

- Does alignment affect the **composition** of charitable donations?
- Use charity-level donation receipts from 1990 to 2018 (NCCS)
- NCCS classifies charities by 8 main **activity codes** (education, environment, health, etc.)
- Aggregate donation receipts for all charities registered in a county
- Local donation receipts proxy for local donations
- **Outcome variable:** donations per activity code as fraction of total donations in a county



Political Donations

- Do people shift donations from **charities** to **political parties**?
- Use political donation data from 2002 to 2015 (DIME)
- Aggregate donations at the zip-level of contributors
- **Outcome variable:** Political donations as a fraction of zip-level income

Political Donations

	Model 1	Model 2	Model 3	Model 4
Republican zip x Republican pres.				
Democrat zip x Democrat pres.				
Zip fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	No	No
State-year fixed-effects	No	No	Yes	Yes
Controls	No	Yes	No	Yes
Observations	38,783	38,781	38,783	38,781
Adjusted R ²	0.499	0.499	0.521	0.522

Political Donations

- **Alignment** with the president's party **crowds out** private charitable donations
- Results **cannot** be explained by:
 - Government spending
 - Beliefs about government spending
 - Government grants to charities
 - Charity fundraising activity
 - Shift towards political donations
- Results **are consistent with** changing **beliefs** about government responsibilities
- Possible explanation for inconsistent results in crowding out literature

Pause



Download the paper here:



**Questions?
Suggestions?**

Validating Identity choice out of surveys

- How Do We Choose Our Identity? (Atkin, Colson-Sihra, Shayo (2021) JPE)
 - Are identities fungible?
 - How do we come to identify with specific social groups?
 - How can we measure identities?

How Do We Choose Our Identity?

- How Do We Choose Our Identity? (Atkin, Colson-Sihra, Shayo (2021) JPE)
 - Are identities fungible? -> **Yes**
 - How do we come to identify with specific social groups? -> **Group Salience and Status**
 - How can we measure identities? -> **Well, not just with surveys**

How Do We Choose Our Identity?

- Authors build on a growing literature to study (out of the lab) how social identities:
 - Affect the behavior of judges (Shayo and Zussman, 2011)
 - Team production (Hjort, 2014)
 - Female labor supply (Bertrand, Kamenica, and Pan, 2015)
 - Grading decisions (Lavy, Sand, and Shayo 2018)
 - Charitable donations (Klein Teeselink and Melios, 2022)
 - Conflict (Depetris-Chauvin and Durante, 2019)
- Novelty:
 - Consumption data are widely available (and accurate)
 - Largely affected by identity prescribed behaviours
 - Use policy changes and tensions in 1990s as cost shocks

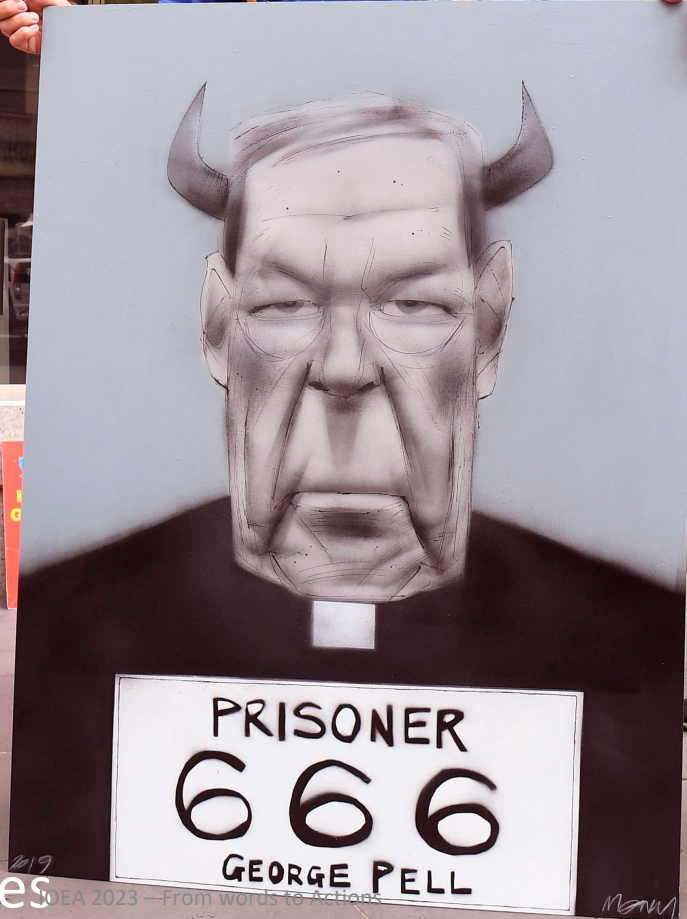
How Do We Choose Our Identity?

- Different groups have different norms
 - Consumption can be used as revealed preference approach
 - For example, a Muslim who consumes pork identifies less with his religion than one who abstains
 - Conditional on income and prices
- Focus on food consumption in India:
 - India is characterised by deep ethnic and linguistic divisions
 - Religiously diverse
 - Provides well-defined sets of identities from which individuals can choose
- Food consumption in India is associated with strong norms and taboos

How Do We Choose Our Identity?

- Results:
- Group salience, status, and economic costs influence consumption of "identity goods" (foods associated with specific groups)
- Food consumption was a better predictor of identity changes than:
 - Not just survey responses
 - voting patterns
- Identity choices also responded to the cost of following prescribed behaviors

**YOU'RE NEVER
TOO OLD TO BE
ARRESTED
FOR RAPING
CHILDREN**



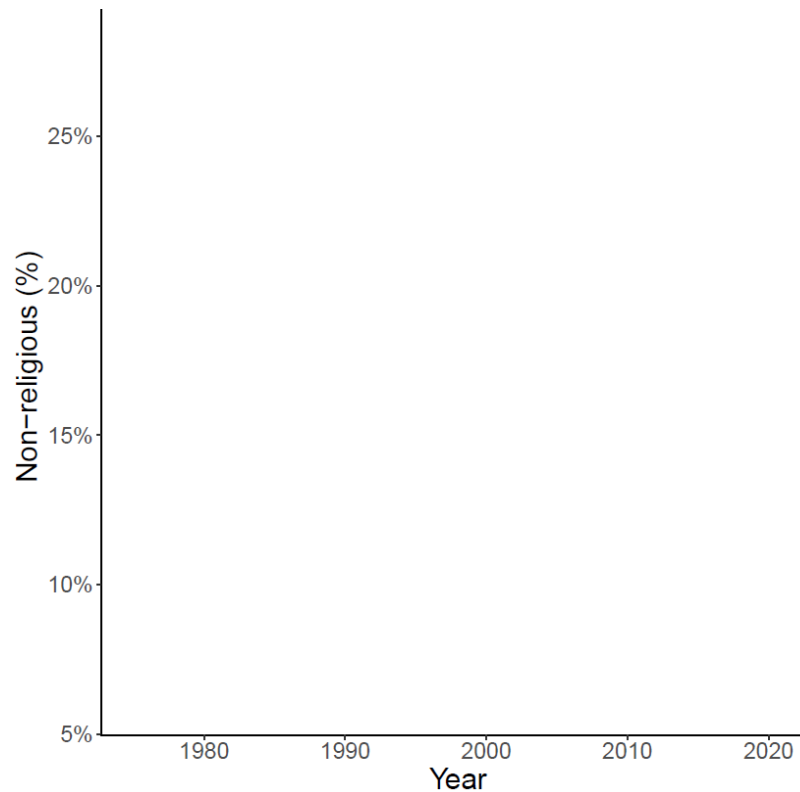
**PRISONER
666
GEORGE PELL**

How Do We Choose Our Identity?

- Results:
- Group salience, status, and economic costs influence consumption of "identity goods" (foods associated with specific groups)
- Food consumption was a better predictor of identity changes than:
 - Not just survey responses
 - voting patterns
- Identity choices also responded to the cost of following prescribed behaviors

Shifting identities?

- Religion is disappearing from people's lives



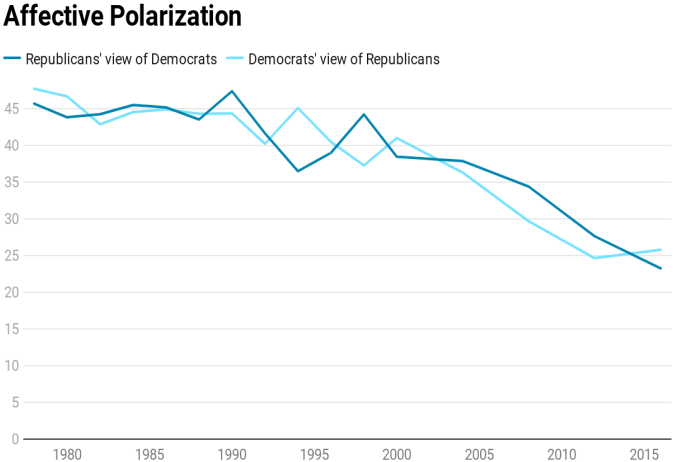
Previous literature: Religion

- Religions is associated with many **positive** outcomes
 - Lower suicide rates (Gearing & Lizardi, 2008)
 - Stronger social ties (Putnam, 2000)
 - Lower crime (Evans et al, 1995; Lipford et al., 1993, Hull & Bold, 1995)
 - Higher subjective well-being (Helliwell, 2006; Campante and Yanagizawa-Drott, 2015)
 - Better education (Gruber, 2005)
 - Less substance abuse (Gruber & Hungerman, 2008)
 - Social preferences (Bottan and Perez-Truglia, 2015)
- Effect on **income** is **ambiguous** (Weber, 1904)
 - Positive (Gruber, 2005; Bryan, 2021)
 - Negative (Barro and McCleary, 2003)

Shifting Identities

- For most of history, religion acted as guarantor of **group identity**
- Secularization leaves an 'identity void'
- Commentators suggest that **political** identity replaced **religious identity** (e.g. Hamid, 2021)

- Mostly correlator



- Prior literature shows


- Country vs. class
- Race vs. nationalit
- Religion vs. region

r identities (Shayo, 2009;

- We examine **identit**

i and politics

Chart: Peter Levine • Source: American National Election Studies



Everybody worships. The only
choice we get is what to worship.

David Foster Wallace

 quote fancy

Shifting Involvements

- Hirschman (1982) argues that societies often go through cycles of **public** and **private involvements**
- Public involvements include **collective action, community participation, and religious affiliation**
- Private involvements include **consumption, monetary pursuits, and career**
- When people get **disappointed** with one, they shift attention towards the other
- Hence, **secularization** might coincide with increased focus on **private affairs**
- We examine the effect of **religious de-identification** on **economic behavior**

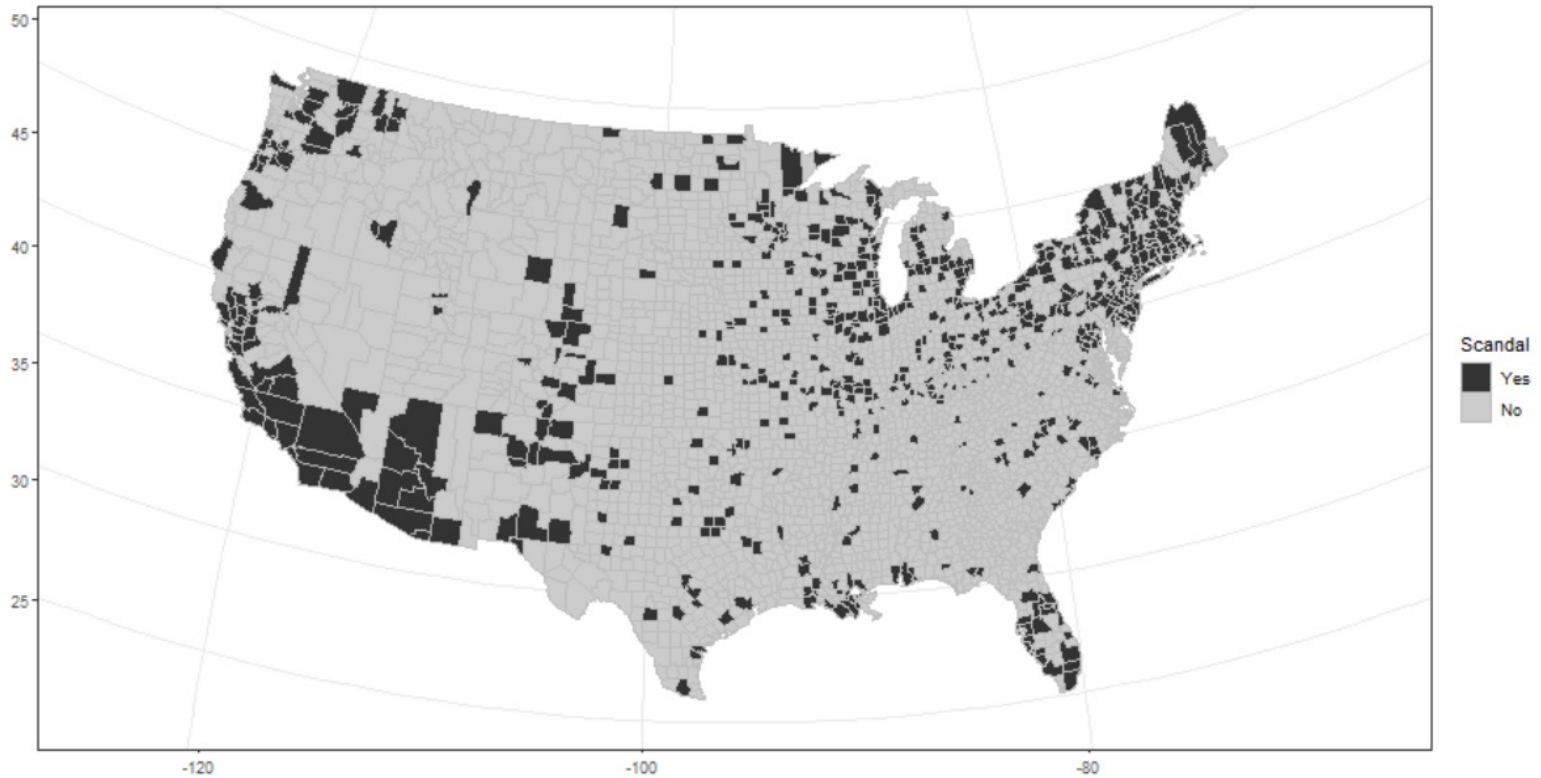
Overview



Background & Identification

- Religion is **non-random** (people choose their religion)
 - Likely correlated with unobserved factors such as ability, culture, etc.
- Since mid-80s, repeated allegations of sexual abuse in Catholic Church
- More than 5000 allegations between 1950 and 2009
- Consequence: People de-identify with their religion (Bottan & Perez-Truglia, 2015)
- We use **clergy scandals** as source of exogenous variation in **religious participation**

Background & Identification



Methodology

- To estimate the effect of scandals, we use a **difference-in-differences** methodology:

$$Y_{it} = \sum_{k=-L}^{-2} \tau^k D_{it}^k + \sum_{k=0}^K \tau^k D_{it}^k + \alpha_i + \delta_t + \varepsilon_{it}$$

- Unit of analysis: Zip code or county
- D_{it}^k : Zip/county has experienced church scandal
- Y_{it} :
 - Religious (religious schools, religious students, religious census)
 - Political (turnout, political donations, voting patterns)
 - Economic (GDP per capita, ...)
- Control group: Zips/counties without scandals
- Remove control zips/counties within 50km from scandal zips/counties to avoid **spillovers**
- Methodology: **Two-stage difference-in-differences** (Gardner, 2021)

Data

- Church Scandals

- Number of church scandals (Bottan & Perez-Truglia 2015, zip/county, 1980-2012)

- Religious identification

- Religious identification (American Census of Religion, county level, decennial, 1980-2010)
- Number of Catholic/non-Catholic schools/students (Private School Universe Survey, zip level, bi-annual, 1989-2019)

- Political identification

- Vote shares and turnout (David Leip's Election Atlas, county level, 1980-2020)
- Political donations (Database on Ideology, Money in Politics, and Elections, county level, 1980-2010)

- Economic behaviour

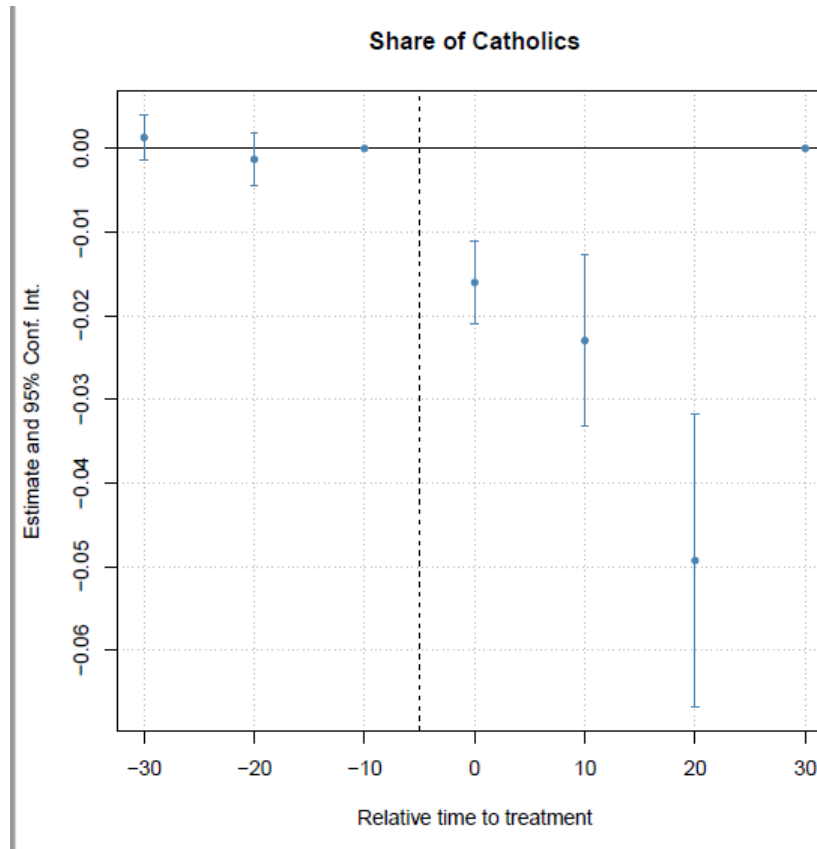
- GDP per capita (Zip Codes Business Patterns, zip level, 1994-2019)

- Still to come:

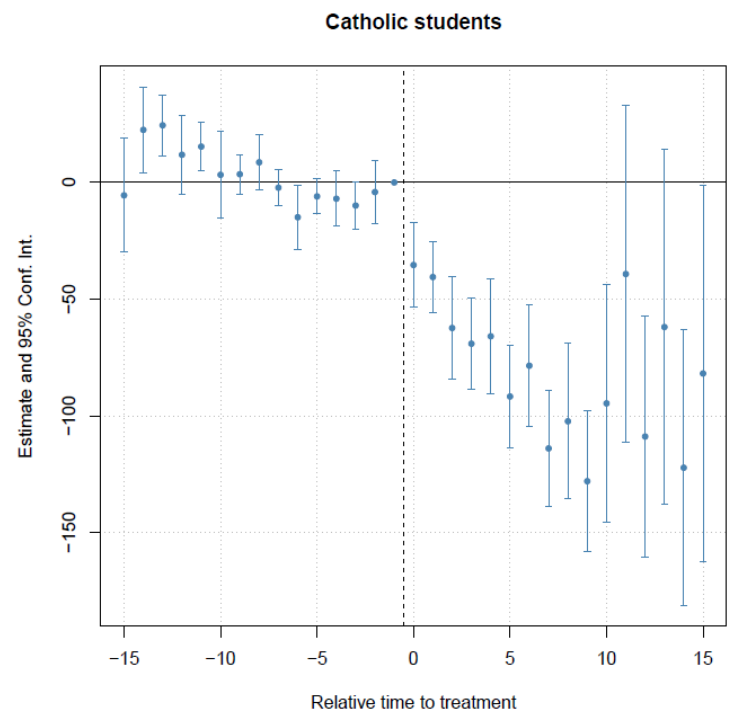
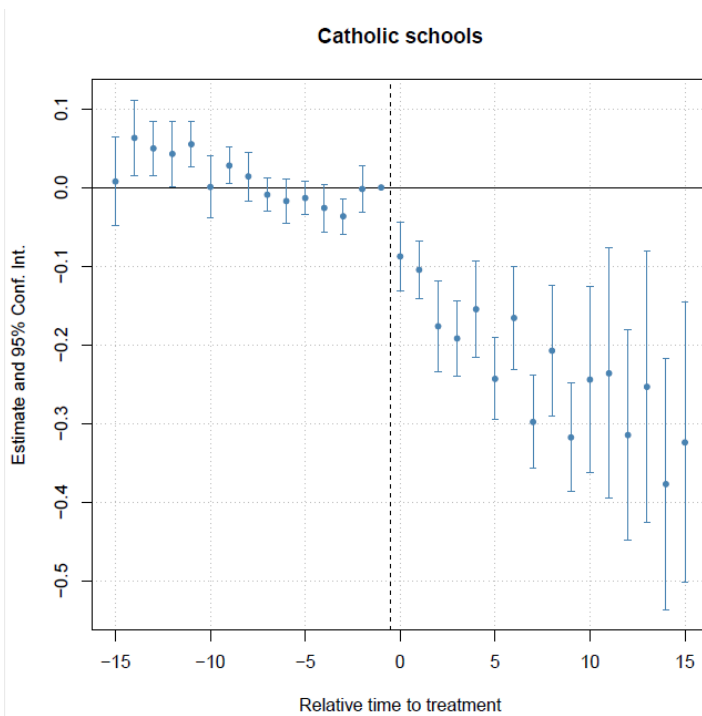
- Beliefs and values (General Social Survey, 1980-2021)
- Consumption and savings (Panel Study of Income Dynamics, 1980-2021)

Do scandals reduce religiosity?

Religious Identification

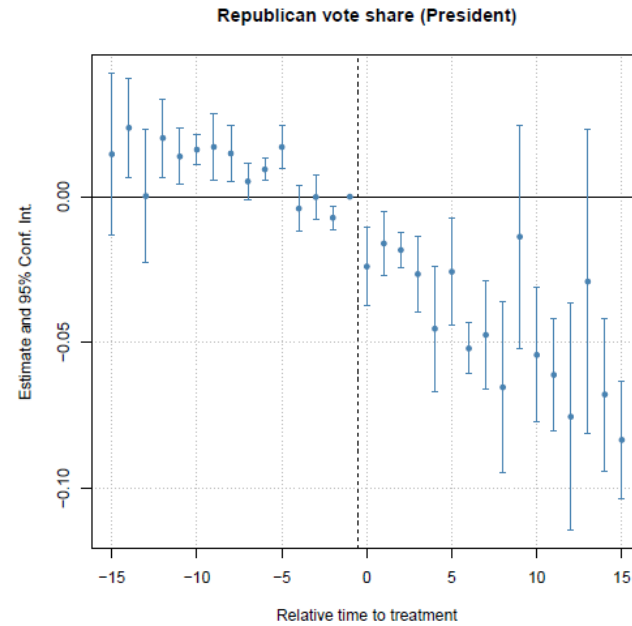
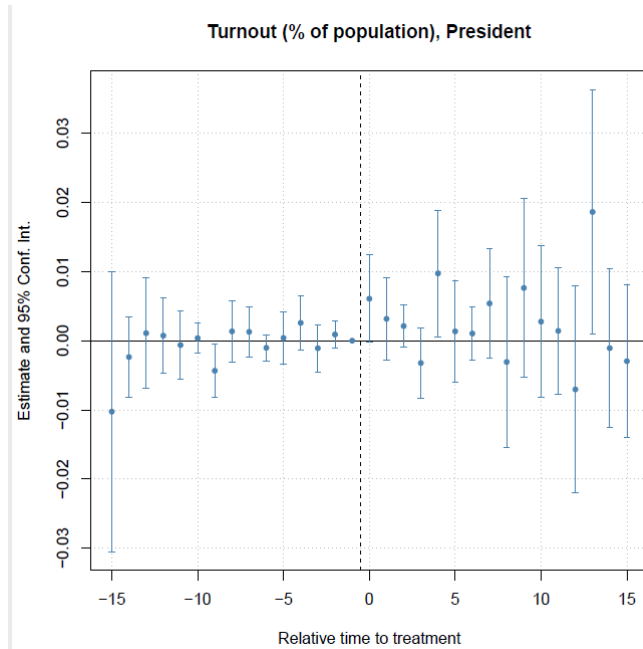


Religious Schooling

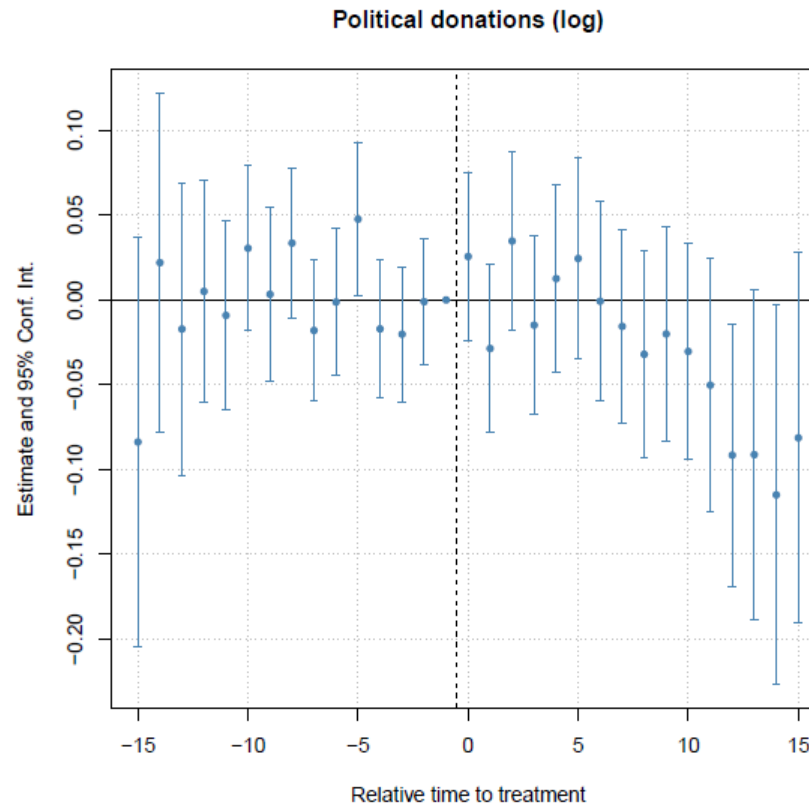


Do scandals increase political identification?

Political Identification: Voting

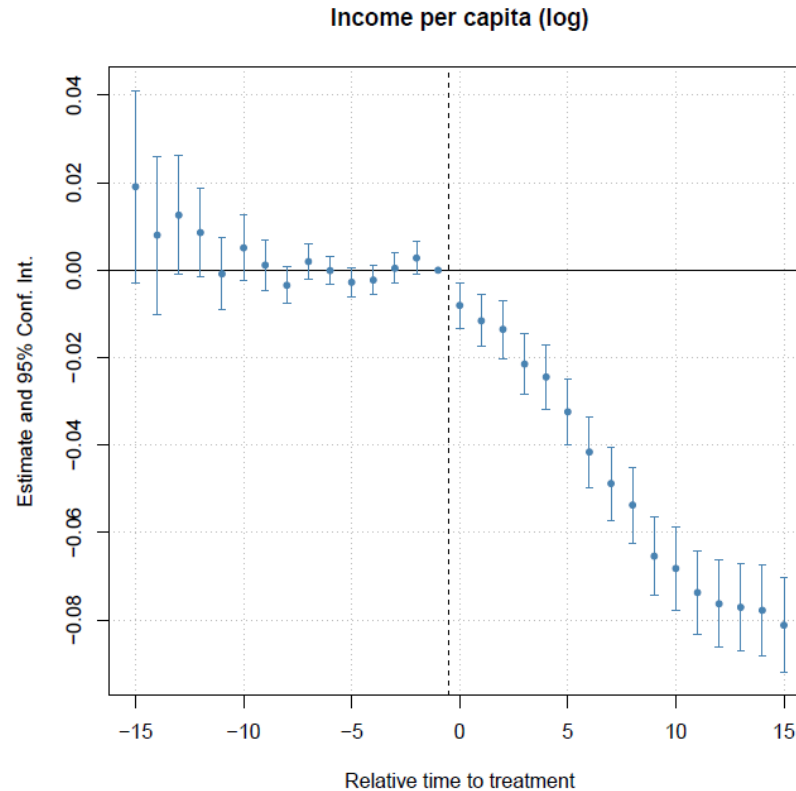


Political Identification: Political Donations



Do scandals affect economic behaviour?

Economic Behaviour: Income per capita



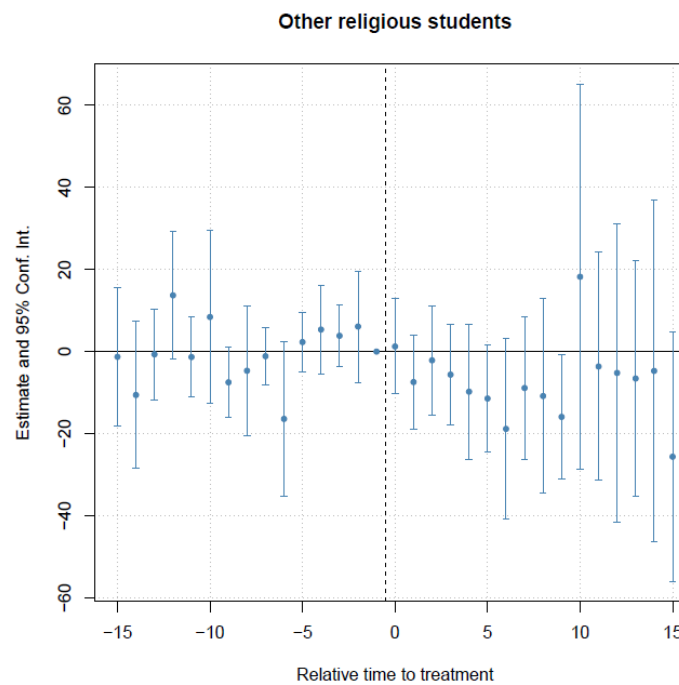
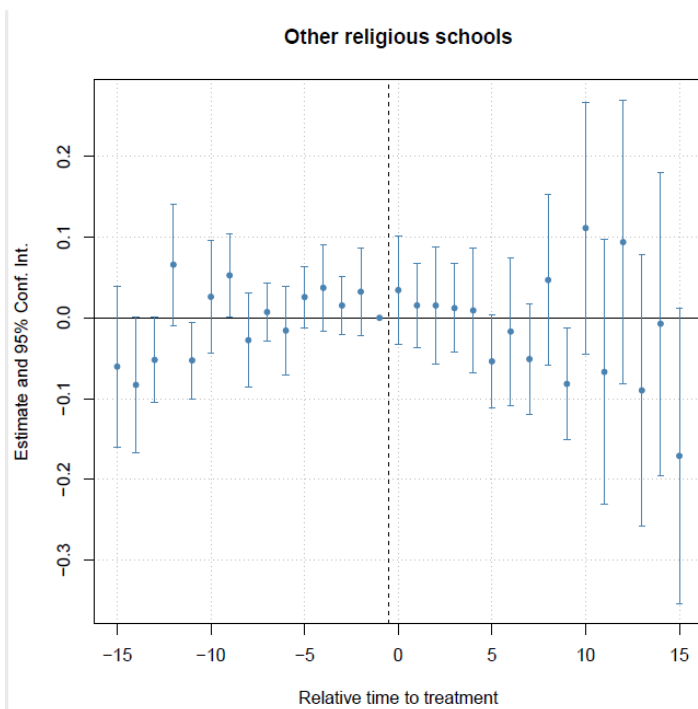
Robustness checks (to do)

- Different diff-in-diff methodologies (Roth et al., 2021)
- Explicitly consider spatial spillovers (Butts, 2021)
- Examine sensitivity of results to parallel trend violations (Rambachan & Roth, 2022)

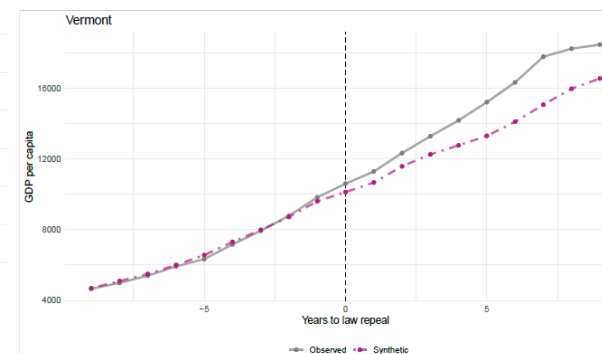
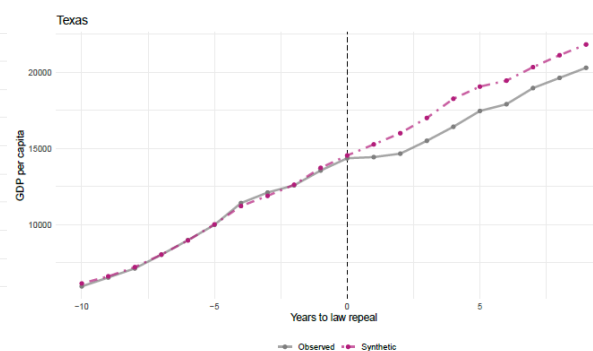
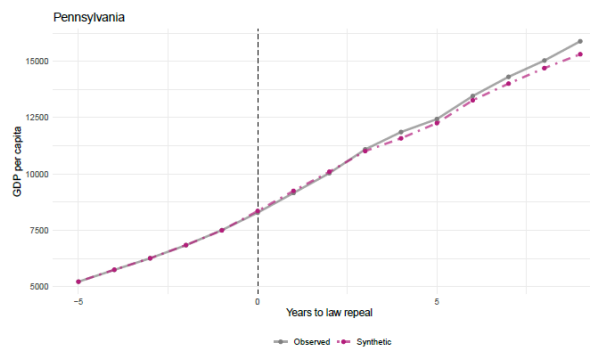
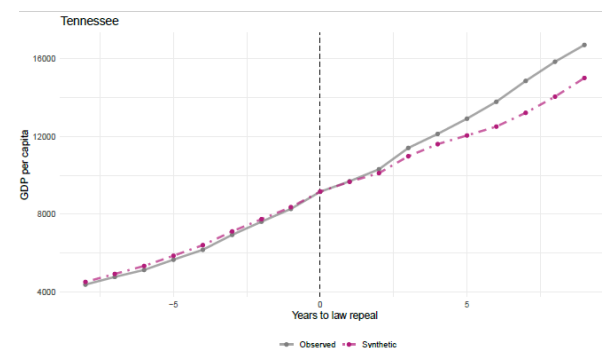
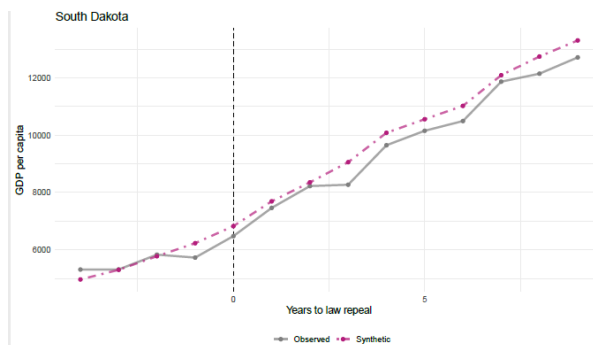
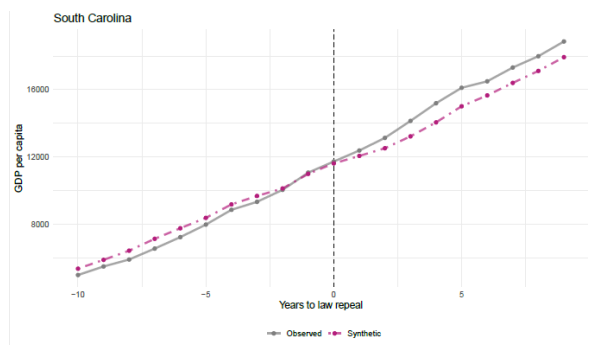
Ancillary Analyses

- Do people switch between religious affiliations?
- Do blue law repeals have the same effect as scandals?

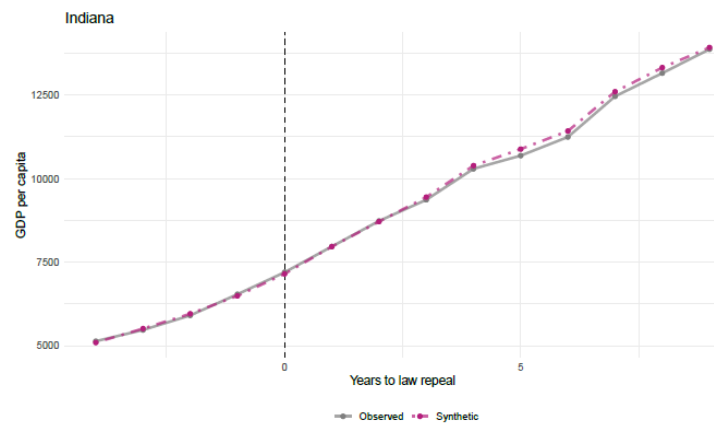
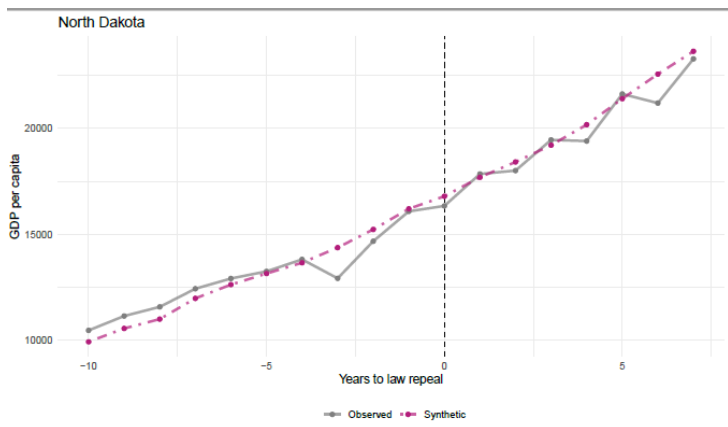
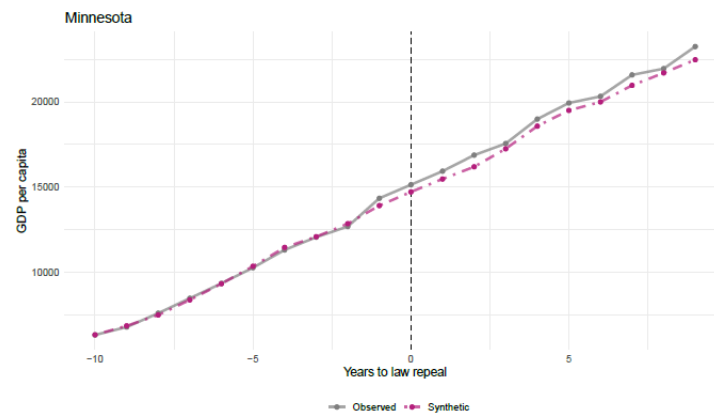
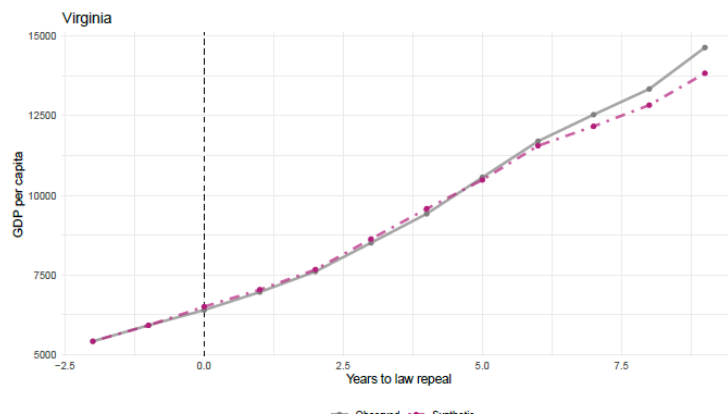
Ancillary analyses: Religious Substitution



Ancillary analyses: Blue law repeals



Ancillary analyses: Blue law repeals



Conclusion

- Church scandals lead to a significant **decline in religiosity**
- No apparent change in degree of **political identification**
- (Potential) shift from Republican to **Democrat**
- Clear **reduction** in GDP per capita
- Open questions/extensions:
 - What's driving the decrease in GDP?
 - Other outcomes: Deaths of despair, health, life expectancy, etc.
 - Shift towards other identities (national, regional, race, etc.)
 - Other sources of secularization
 - Other countries