Behavioral Applications of Voter Files

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Overview

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1. Voter files as is

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1. Voter files as is
2. Linked geographically

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1. Voter files as is
2. Linked geographically
3. Linked individually

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1. Voter files as is
2. Linked geographically
3. Linked individually
4. Some lessons

Voters files, as is

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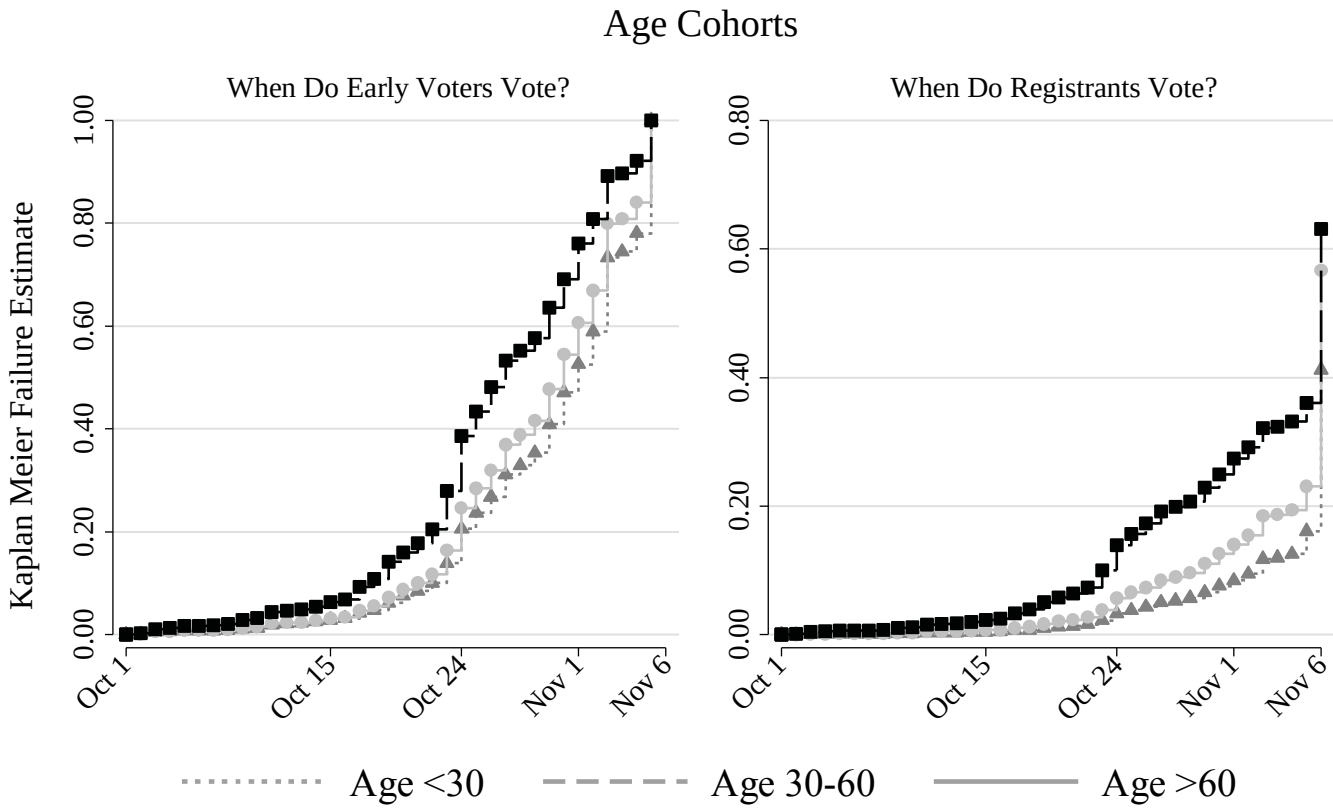

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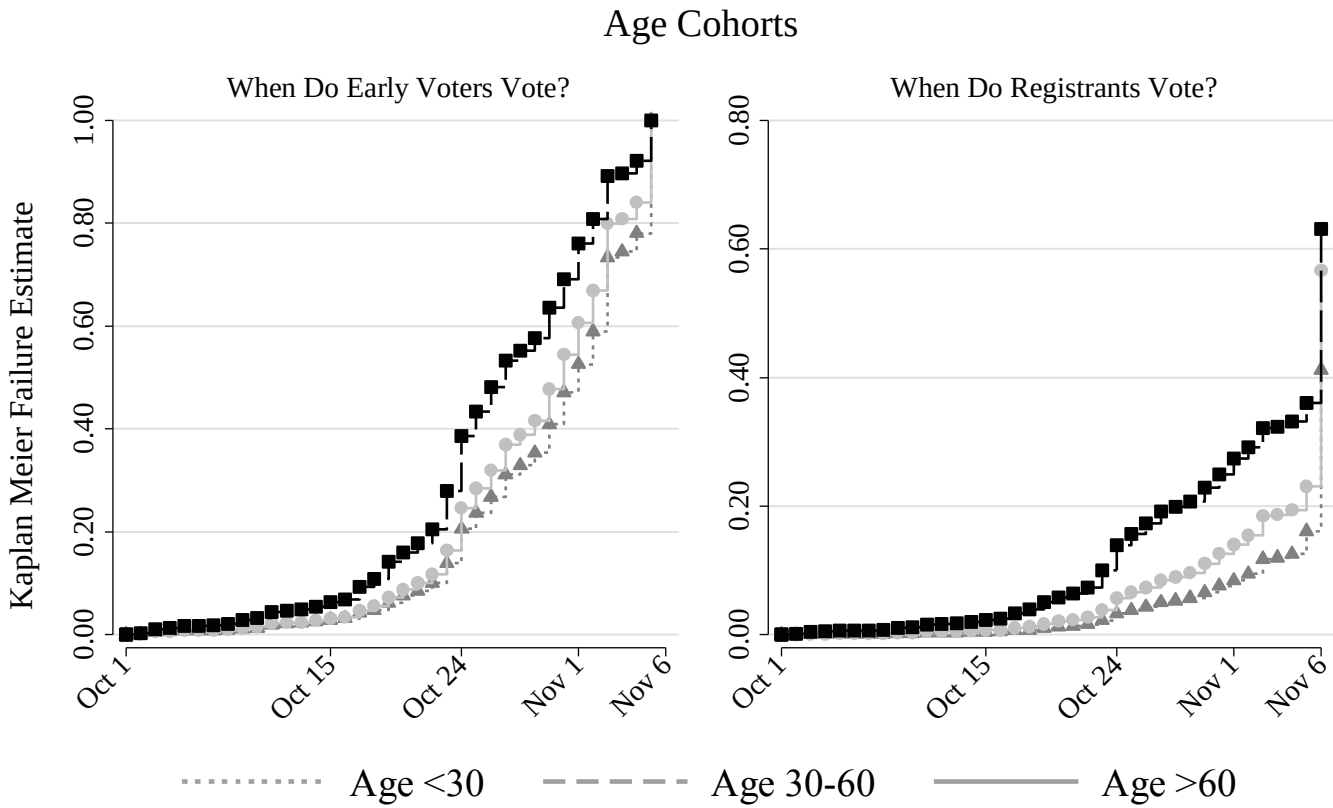

Basic Advantages: Sample size, official turnout, demographics, location data, daily updates

Voter files, linked to geographic data

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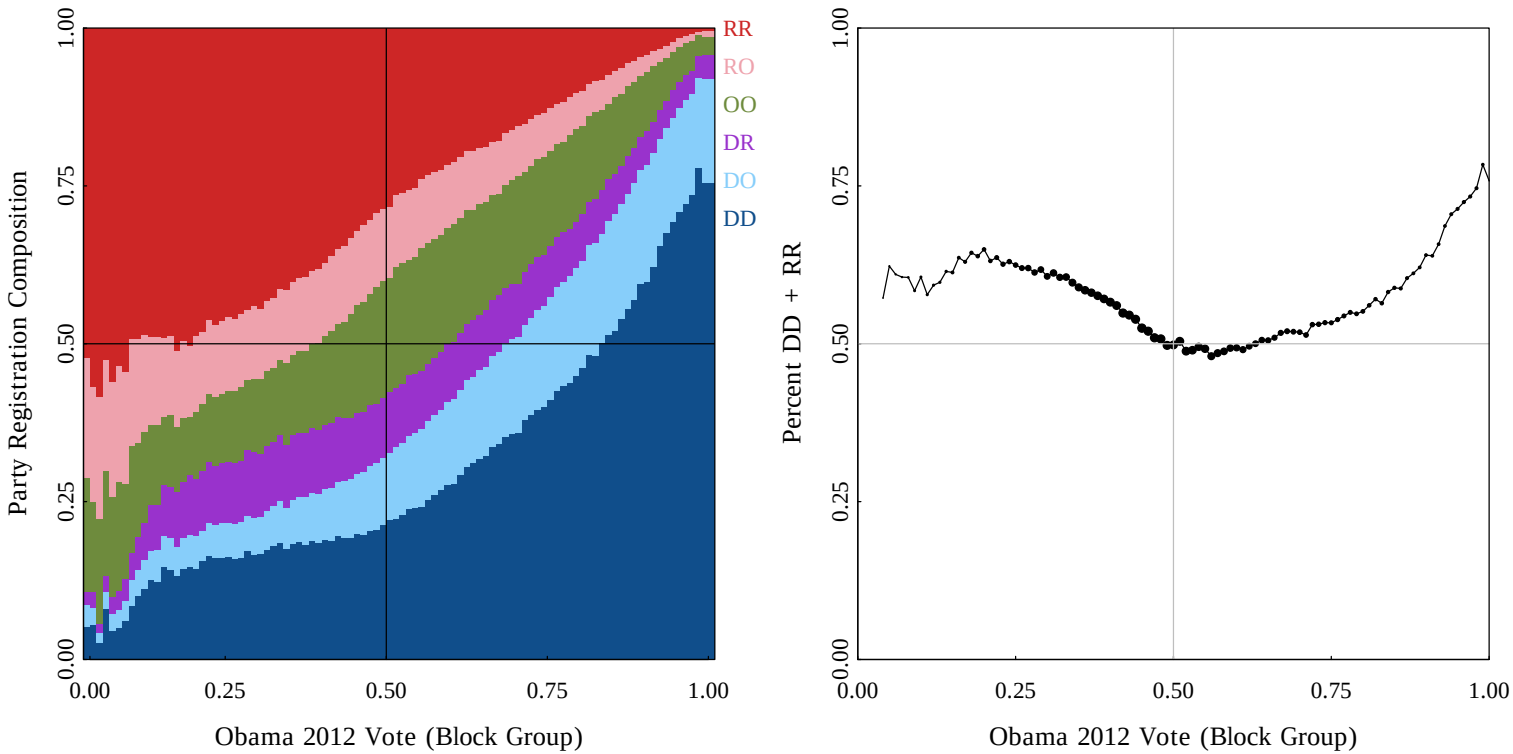

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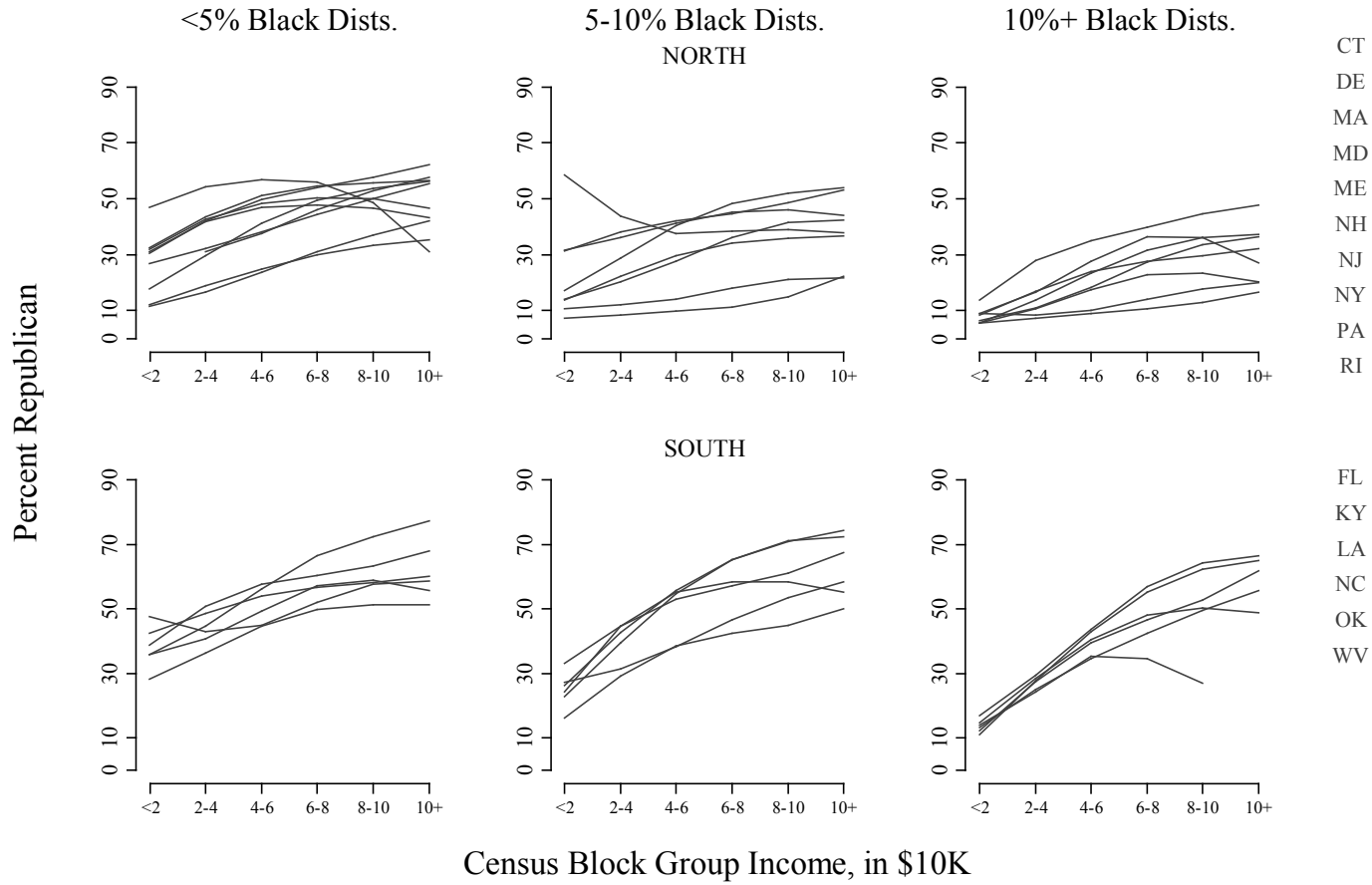

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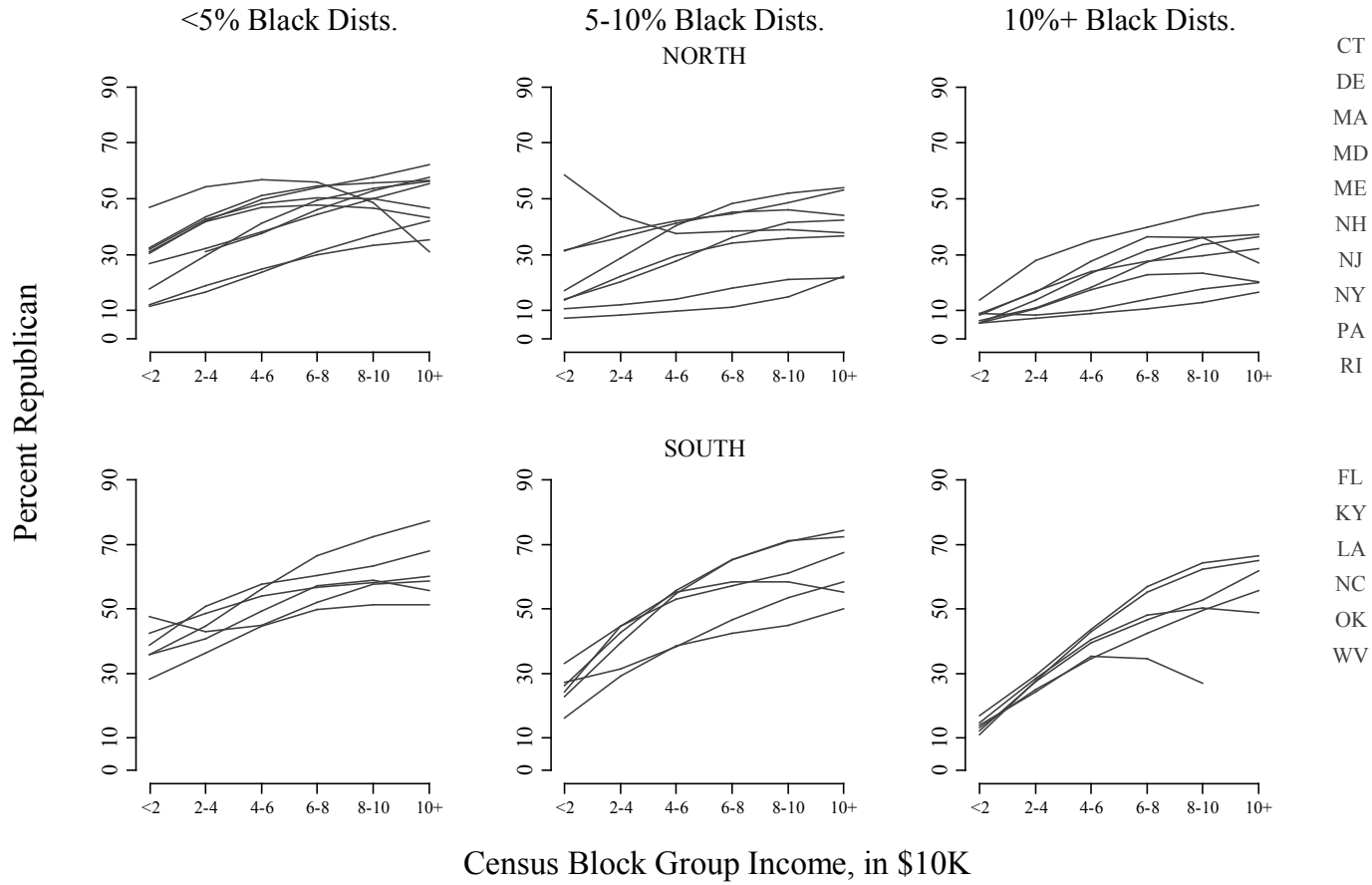

Advantages: nested geographies; households and neighborhoods, custom defined; vendors do the hard work

Voter files, individuals linked to external data

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1. Completely outsource to vendor

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2. Completely in-house linkage

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3. Hybrid outsourced/custom linkage

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   - Example 5: Survey of 2016 max-out donors (Hersh and Schaffner, in draft)
2. Completely in-house linkage

In-House Individual Link

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Research question: Did 9/11 change the politics of victims' families and neighbors?

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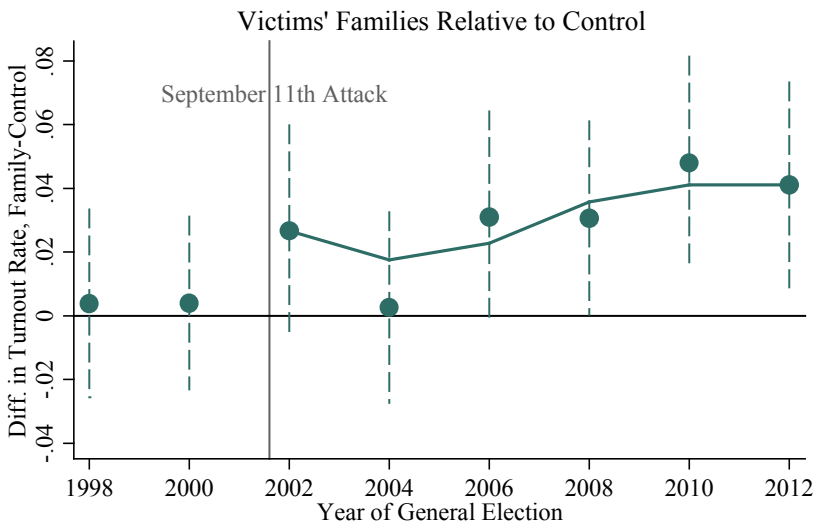
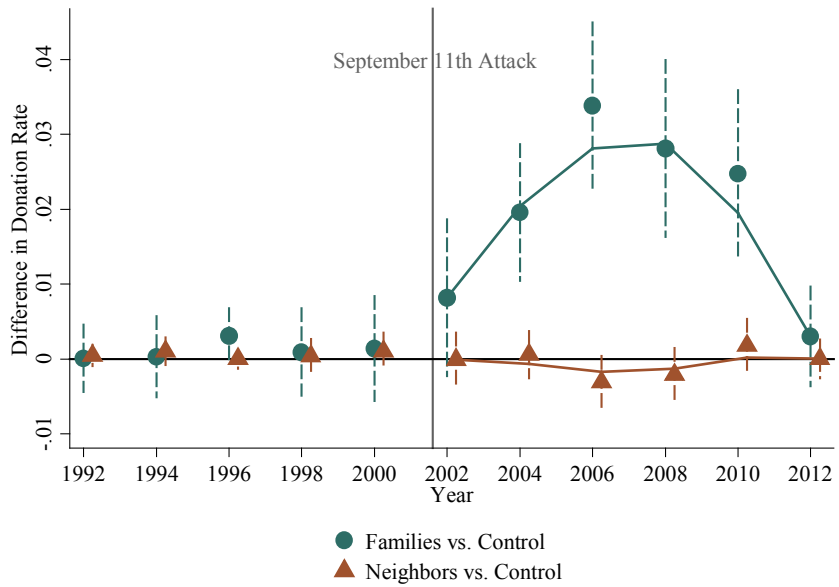
Data

- Obituary data from NYT
- Pre-9/11 NY voter file (L2)
- Year 2013 NY voter file (Catalist)

In-House Individual Link





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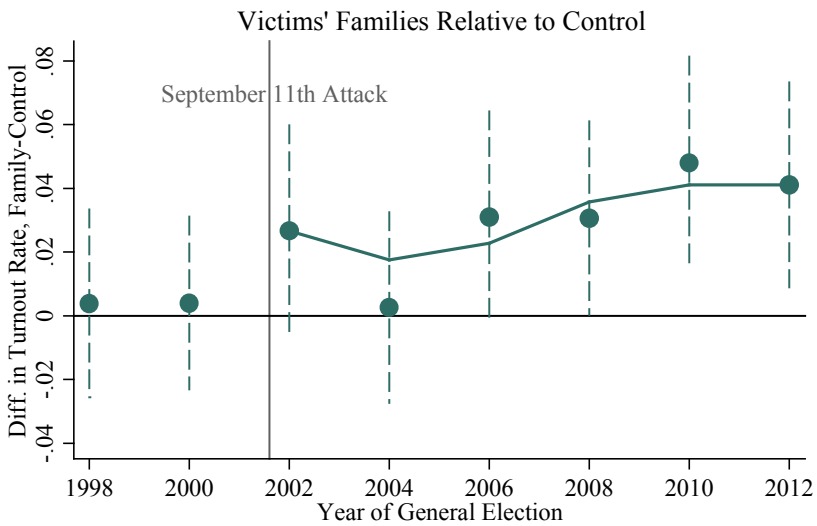

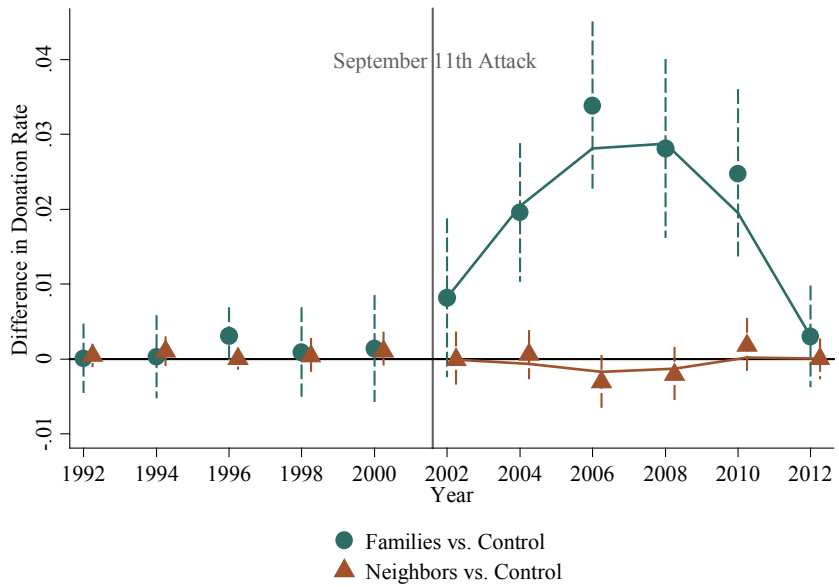

Advantages: long time frame, precise geography, pseudo control group, no misreporting, highly customized

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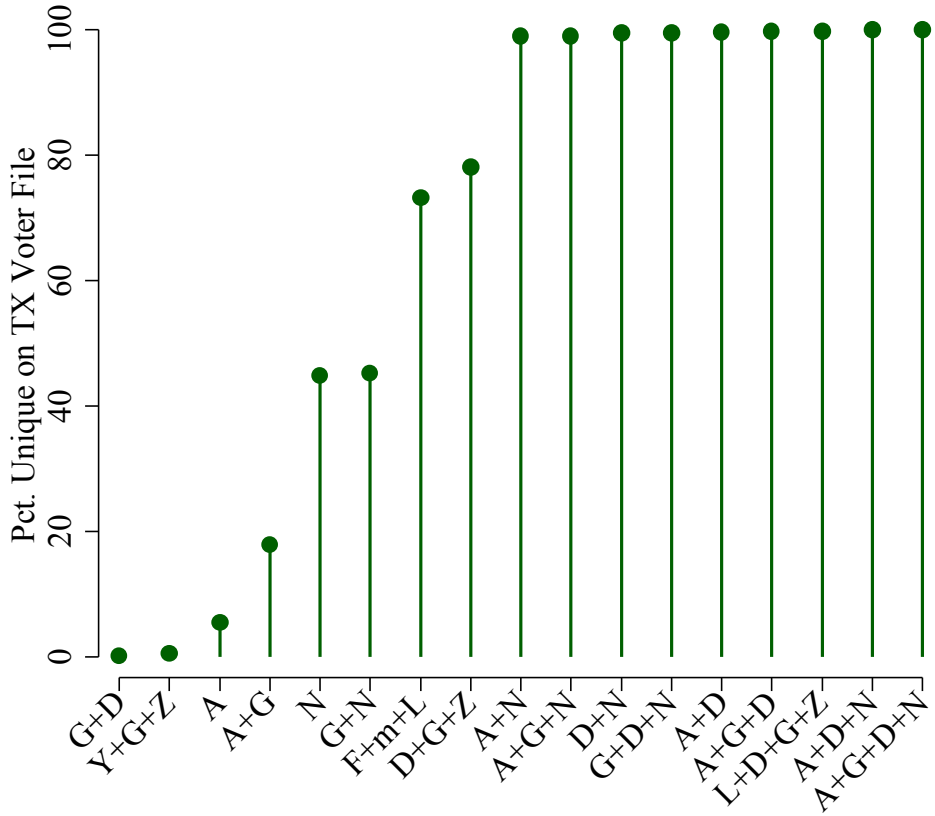
Data

- Texas voter file
- 10 ID databases (e.g. drivers, passport holders)

In-House Individual Link



A=Zip5+Street Num; G=Gender; D=MDY of Birth; N=First+Last Name
Y=Year of Birth; Z=Zip5; F=First Name; m=Middle Initial; L=Last Name

In-House Individual Link

Table: Number and Percent of instances of NO-MATCH and MATCH by Racial Group, Using Catalist Racial Classification

Race	NO-MATCH	MATCH	Total
Anglo	296,156 (3.6%)	7,949,860 (96.4%)	8,246,016
Black	127,908 (7.5%)	1,569,861 (92.5%)	1,707,769
Hispanic	174,715 (5.7%)	2,867,782 (94.2%)	3,042,497
Other	9,691 (2.0%)	481,621 (98.0%)	491,312
All	608,470 (4.5%)	12,879,124 (95.5%)	13,487,594

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Advantages: direct answer to question, customized algorithm for legal purpose

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Data

- National Provider Identification (NPI) File, CMS
- Voter file in 29 party-registration states
- Survey of primary care physicians

Targeting the Population

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Step 1 The National Provider Identification File

Targeting the Population

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1. 560,896 U.S.-based physicians

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Step 3 Target sample

Of 20,296, 13,678 when restricted to registered Ds and Rs

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Oversample doctors in mixed-partisan practices

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1. Classify practices by size and partisan composition
2. Draw 100% physicians from mid-size bipartisan stratum (754) and 6% sample of all other strata (775)
3. Survey 1,529 physicians

The Survey

...We are trying to better understand how doctors take a patient's social history and what factors may impact differences in the ways physicians approach a patient's social history...

The Survey

Nine Vignettes

A healthy-appearing, 38-year old, male patient comes to your office for a physical. This is his first appointment with you. He does not have any known prior chronic medical issues. During the patient interview, the patient...

The Survey

Nine Vignettes

A healthy-appearing, 38-year old, male patient comes to your office for a physical. This is his first appointment with you. He does not have any known prior chronic medical issues. During the patient interview, the patient...

- ... acknowledges consuming about 20 alcoholic beverages in a typical week but denies any related physical concerns.

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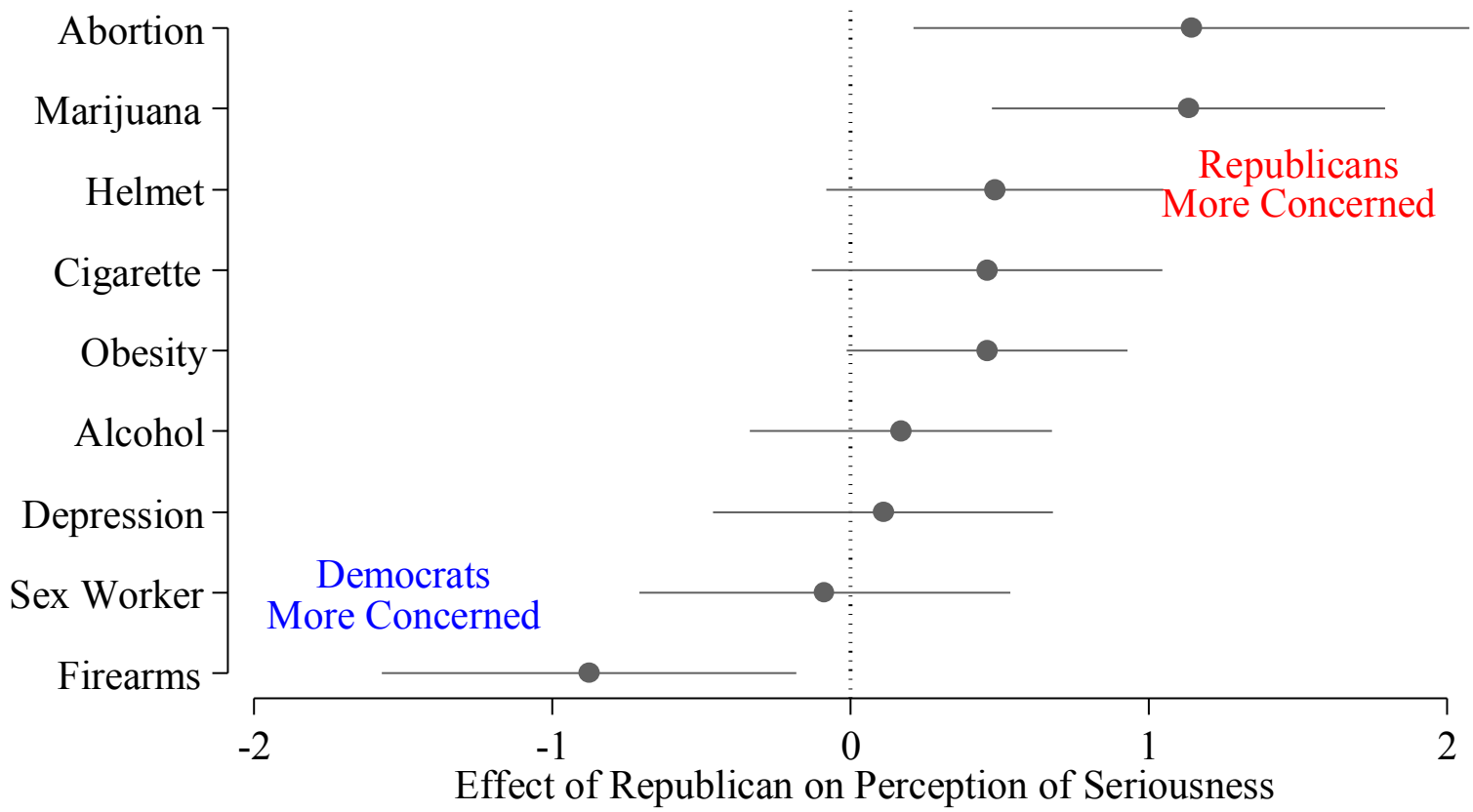
The Survey

Nine Vignettes

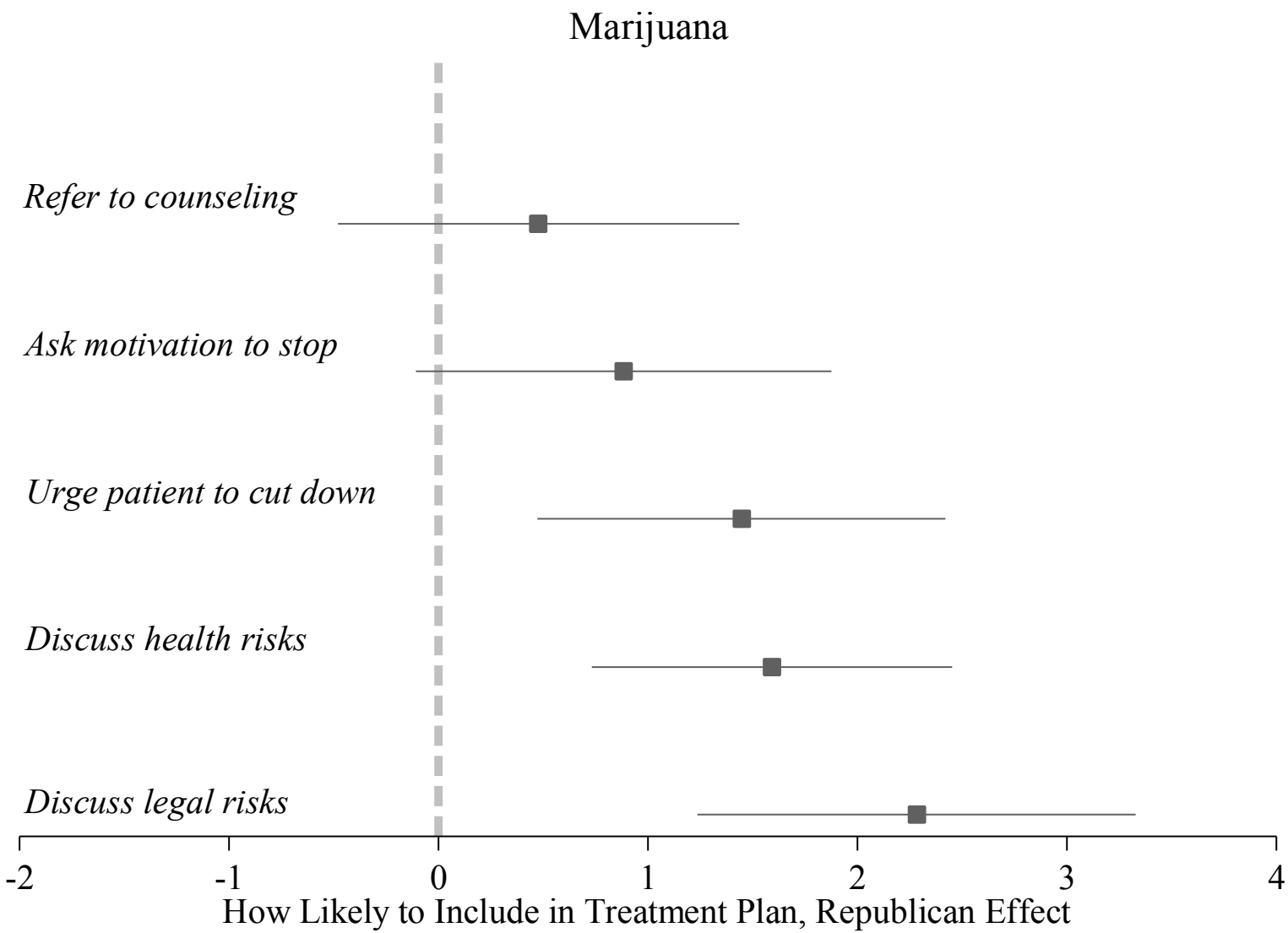
A healthy-appearing, 38-year old, male patient comes to your office for a physical. This is his first appointment with you. He does not have any known prior chronic medical issues. During the patient interview, the patient...

- ... acknowledges using recreational marijuana approximately three times per week but denies any related physical concerns.

Results


Abortion
Marijuana
Helmet
Cigarette
Obesity
Alcohol
Depression
Sex Worker
Firearms
Republicans
More Concerned
Democrats
More Concerned
-2
-1
0
1
2
Effect of Republican on Perception of Seriousness

Results


Marijuana
Refer to counseling
Ask motivation to stop
Urge patient to cut down
Discuss health risks
Discuss legal risks
-2
-1
0
1
2
3
4
How Likely to Include in Treatment Plan, Republican Effect

Hybrid Individual Link

Example 9: Eitan Hersh and Gabrielle Malina, "Partisan Pastor" In Progress

Research questions: Do pastors reflect the political views of their congregants? Do Democratic and Republican pastors lead differently?

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Data

- 41 find-a-church websites, scraped (Upwork)
- Additional pastors added (MTurk)
- Voter file link (Catalist)
- link to survey data

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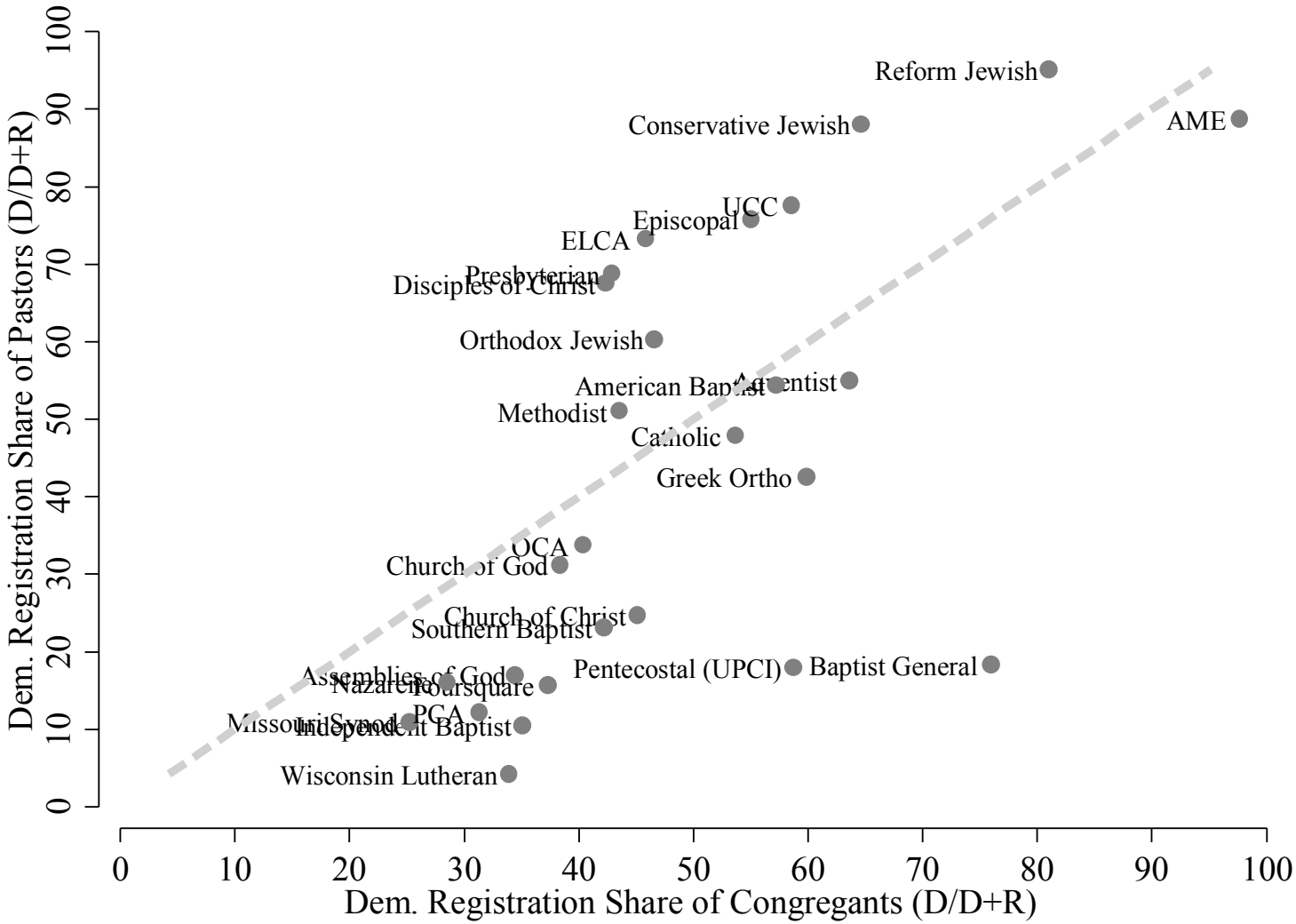

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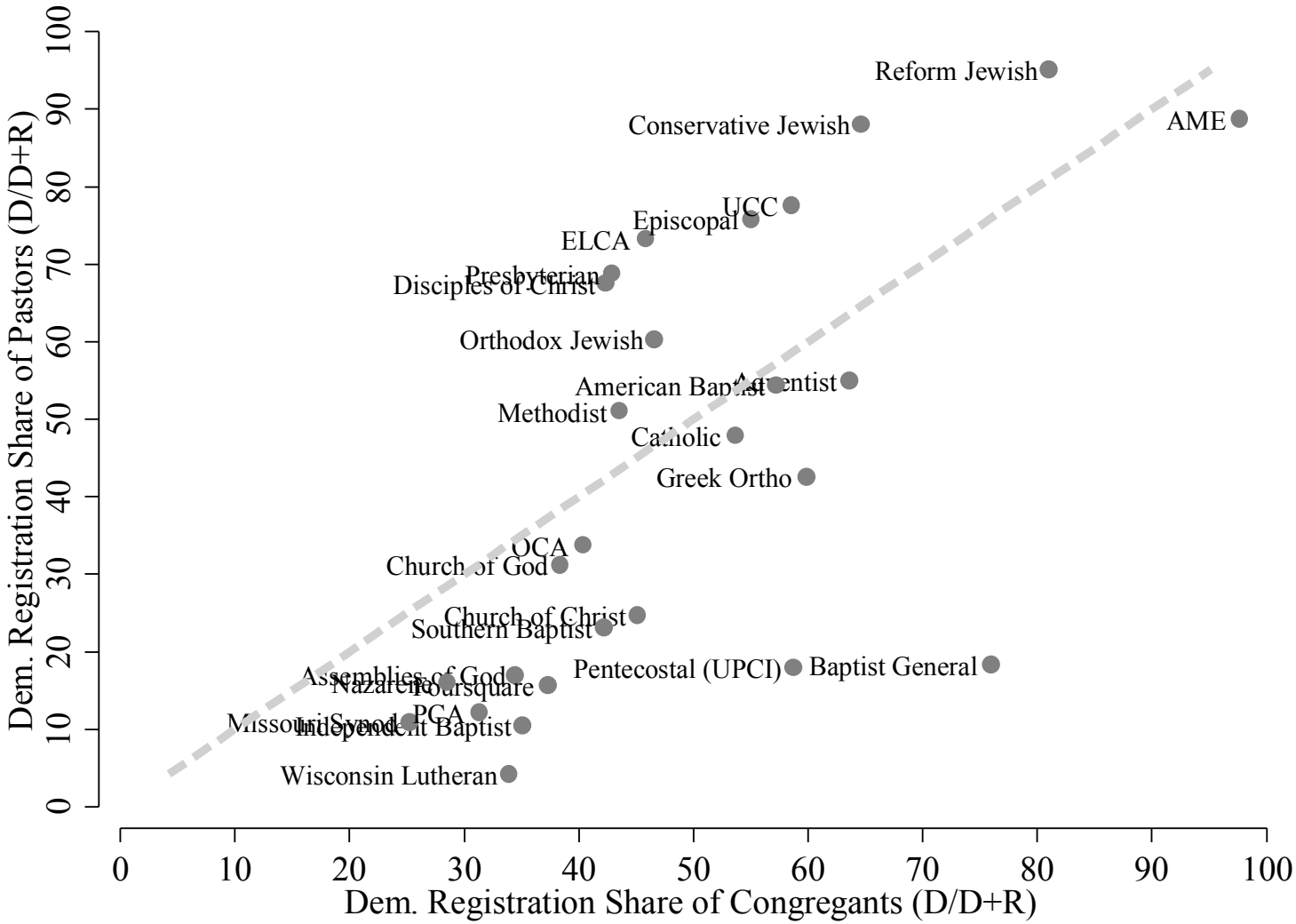

Advantages: comprehensive data on small but important population, within- and cross-denominational variation

Some Lessons

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Match rate to registered voters

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	Doctors	Pastors	9/11	Donors
First Pass	43%	44		

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Second Pass	57	63		

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Second Pass	57	63		
Only Pass			68	79*

Some Lessons

Mail survey response rates

Some Lessons

Mail survey response rates

Doctors: 20%

Donors: 17%

Some Lessons

Some Lessons

False positives

Some Lessons

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3. False positives in Texas case:

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False positives

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2. 21/6,500 “donors” (0.3%) said they weren’t the donor
3. False positives in Texas case:

ADGN Match	SSN9 Match		
	No SSN Match	SSN Match	Total
No ADGN Match	1,207,739 [TN]	135,686 [FN]	1,343,425
ADGN Match	119,601 [FP]	5,249,230 [TP]	5,368,831
Total	1,327,340	5,384,916	6,712,256

Behavioral Applications of Voter Files

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