Immigration, Political Ideologies and the Polarization of American Politics 1992-2016

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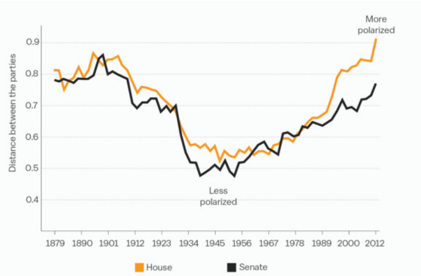
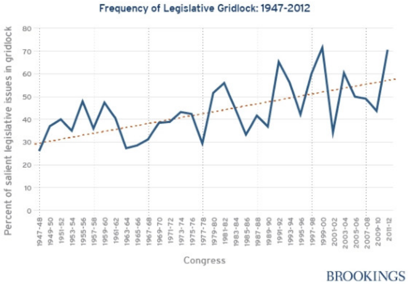
Long-Run Trends in Polarization and Gridlock in Congress



Source: Voteview



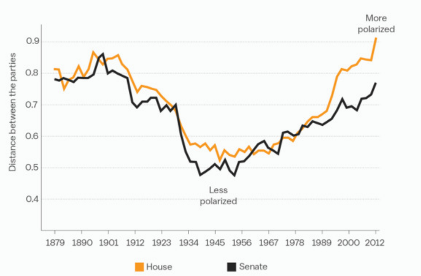
Source: Binder, 2014

Motivation

"The frequency of extremists on immigration rises over time and almost doubles between 1998 and 2016. This happens because both extreme opponents and supporters of immigration have risen."

(Gennaioli & Tabellini, 2019, p.33) based on ANES.

Long-Run Trends in Polarization and Immigration



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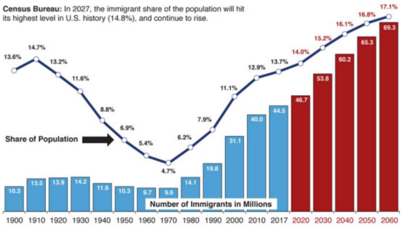


Source: Census Bureau

Research Question

Does immigration influence polarization & political ideology?

- unit of analysis: county
- period: 1992 - 2016
- context: House of Representatives
  - candidate ideology, ideological composition of campaign contributions, vote share
- variable of interest: immigrants and refugees

Contribution

First to consider immigration and polarisation

- Migrants and vote shares: Mayda et al. (2020, *AEJ: Applied*), Edo et al. (2020, *EER*), Dustmann et al. (2020, *REStud*), Steinmayr (2020, *REStat*), Tabellini (2020, *REStud*), Giuliano & Tabellini (2020, *WP*)
- Drivers of polarisation: Autor et al. (2020, *AER*), Canen et al. (2020, *Econometrica*), Boxell et al. (2017, *PNAS*)

First to consider the political impact of US refugees

- Refugees: Dustmann et al. (2020, *REStud*), Steinmayr (2020, *REStat*)

New data: geocoded refugee data (1975-2008; -2016)

- universe of refugees
- individual level
- basic characteristics

Theory

Social Psychology

- Contact Theory (Allport, 1954)
- Group Threat Theory (Campbell, 1965)

$\Rightarrow$ quality of contact, endogeneity of contact

Social Identity & Beliefs

- prior beliefs (Dixit & Weibull, 2007)
- salience, ethnic identity & group stereotypes (Gennaioli & Tabellini, 2019)

Data

Migration

- Immigration (Census, ACS, CPS)
- Refugees (ORR, PRM)
  - universe
  - individual level
  - education

Political Outcomes

- Candidate ideology (Bonica, 2019)
  - incl. first-time candidates and
  - failed candidates
- Campaign contributions (Bonica, 2019)
  - 16 million
  - gender & occupation of donors
- Vote shares (Election Data Services, 2019)
  - county-district-candidate level

Measuring Ideology

Calculation

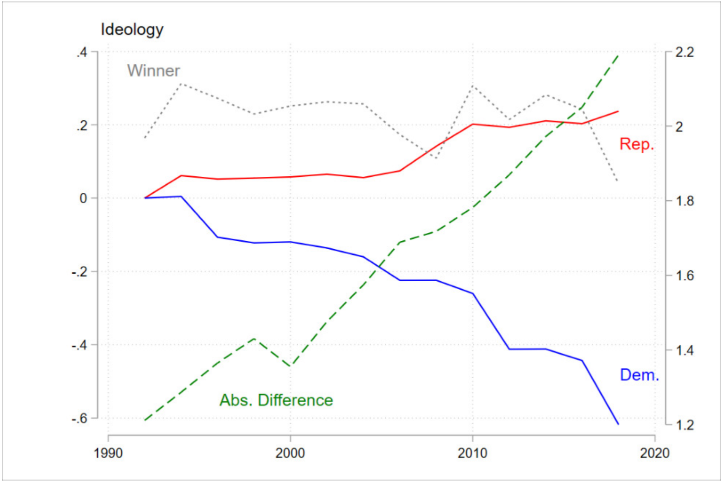
- Contributors will on average prefer ideologically proximate candidates to those that are more distant
- Who contributes to whom? (correspondance analysis)
- Validation

Examples:

- Alexandria Ocasio-Cortez (-1.69), Nancy Pelosi (-0.83)
- Michele Bachmann (1.36), Paul Ryan (1.16)

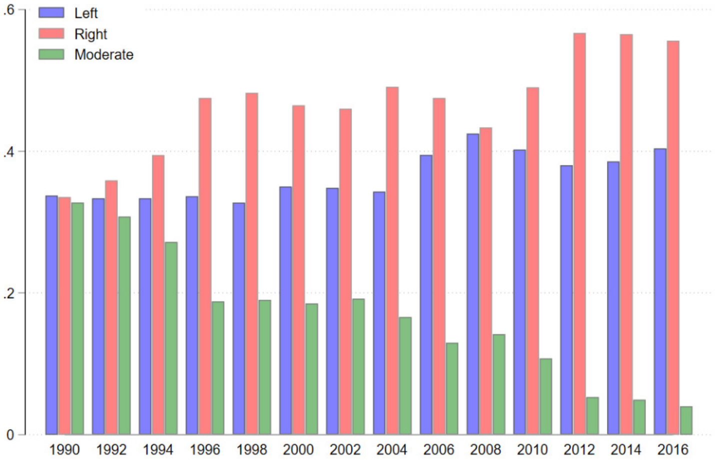
Descriptives

Party Ideology in the House of Representatives



Descriptives

Share of Contributions to the House of Representatives



Identification: Shift-Share IV

Second Stage:

$$Ideology_{it} = \alpha + \beta \frac{\hat{Immigrants_{it}}}{Pop_{it}} + \gamma X_{zt} + \mu_{it} + \phi_t + \epsilon$$

Instrument:

$$\sum_{n=1}^{N} Immigrants_{nt} * Immigrantshare_{ni,1980} / Pop_t * Popshare_{i,1980}$$

Identifying assumption: Ideology in counties with differing immigrant shares will not be affected differently by changes in the respective country-wide immigrant flows, other than via the impact of immigration in the respective counties.

Identification: Shift-Share IV

Second Stage:

$$Ideology_{it} = \alpha + \beta \frac{\hat{Immigrants_{it}}}{Pop_{it}} + \gamma X_{zt} + \mu_{it} + \phi_t + \epsilon$$

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$$\sum_{n=1}^{N} Immigrants_{nt} * Immigrantshare_{ni,1980} / Pop_t * Popshare_{i,1980}$$

μ_i = County FE, ϕ_t = Year FE

X_{zt} = share of voters income, afro-amerians, urban population, unemployed, males, married, trade, low-skilled natives, bartik voters, voters labor participation (all measured as change in the stock)

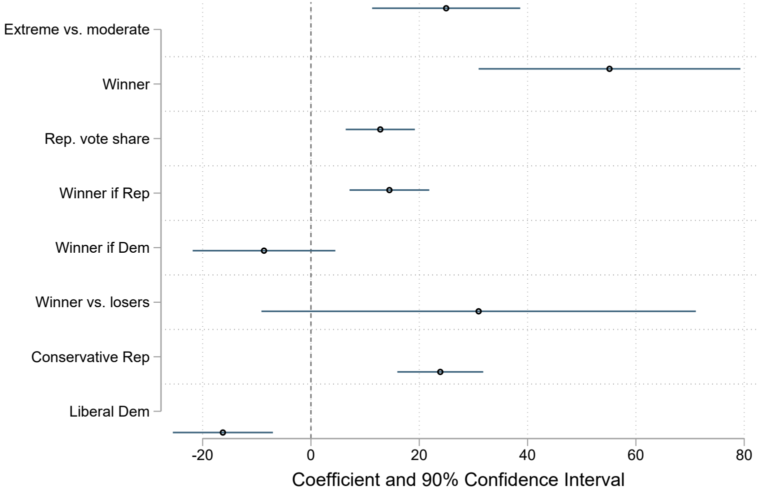
Results

Immigrants, Campaign Contributions and Local Ideologies

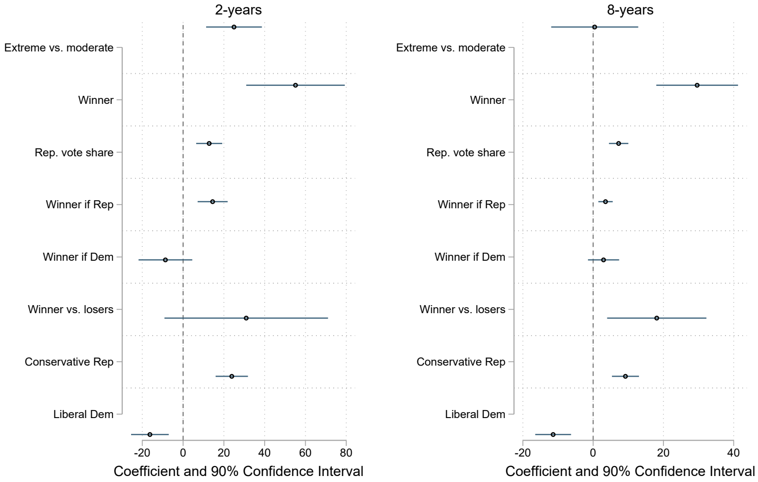
(1) Extreme Contributions	(2) Extreme Contributions	(3) Ideological Distance	(4) Ideological Distance
2-Years	8-Years	2-Years	8-Years
249.685***	4.430	30.963	18.103**
(81.515)	(73.814)	(23.902)	(8.416)
40,023	9,236	31,618	6,226
78.22	18.25	66.25	11.43

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Immigrants and Ideology - IV regressions



Immigrants and Ideology (short vs. medium run) - IV regressions



Results

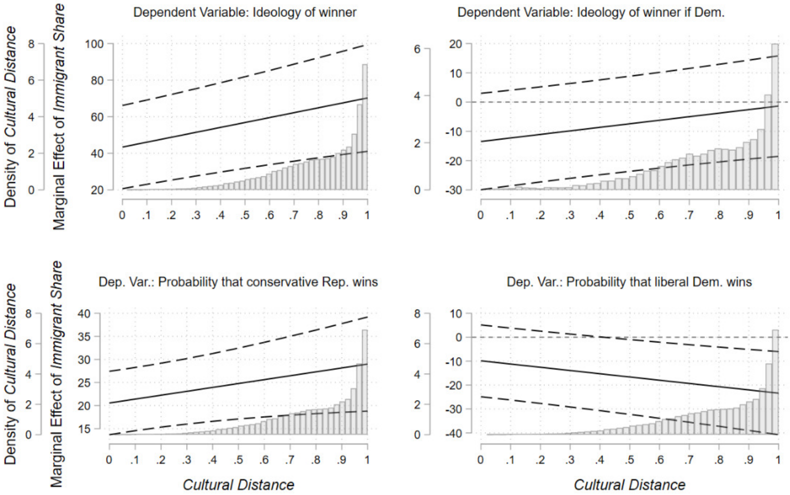
Educational Distance

- competition & labor market complementarities
- measure: difference in distribution
    - Highschool dropout, highschool graduate, some college, college, university

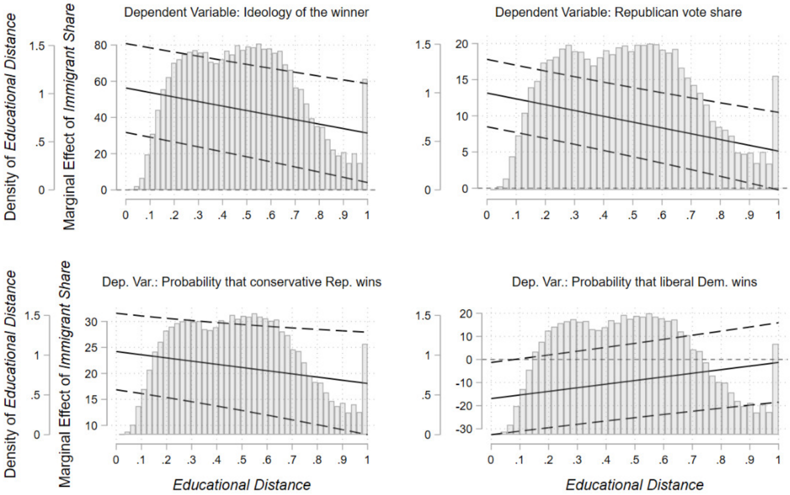
Cultural Distance

- competition of norms & values
- measure: difference in distribution
    - Western, Latino, Asian, African

Marginal Effect of Immigrant Share as Cultural Distance Changes



Marginal Effect of Immigrant Share as Educational Distance Changes



Extentions

Refugees

- Gross flows
- Short-run results similar in magnitude
- Only polarization of campaign contributions significant in medium run

Extentions

Exploit different identifying variation

- local allocation of refugees

Broaden polarization measures

- TV viewership, Pew surveys

Deepen ideological measures

- Donors: who reacts? (occupation, culture)

Robustness

- Rotemberg weights, Adao et al. Standard errors

Robustness

- Ideology score validation see (Bonica, 2014, 2016, 2019)
- Non-linear trends see (Christian & Barrett, 2017)
- Pre-trends see (Goldsmith-Pinkham et al. 2020; Mayda et al., 2020)
- Serial correlation in the shift-variable see (Jaeger et al., 2018)
- Randomization see (Christian & Barrett, 2017)

Conclusion

Question: Does immigration affect polarization and political ideologies?

Data: rich microdata on immigrants and refugees, ideology data for all candidates, 16 million contributions.

Results:

- Polarization of campaign contributions and candidates.
- Shift towards conservative Republicans.
- Cultural distance & educational similarity between new immigrants and residents increase the backlash.

Feedback Welcome!

Ideology Score: Validation

Predicitive Validity

- 88% of votes correctly classified Bonica, 2014
- High predictive power for 30 CCES policy items (24 above 0.8) Bonica, 2019

External Validity

- Correlation between DW-NOMINATE and CF-Scores: 0.92 Bonica, 2014
  - within party: 0.56 and 0.66.

Internal Valididty

- R2 of static and dynamic CFscores: 0.97 Bonica, 2014
- Ideal points of candidates are highly correlated with the ideal points calculated from these candidates contributors to others campaigns Bonica, 2016

Back to main robustness.

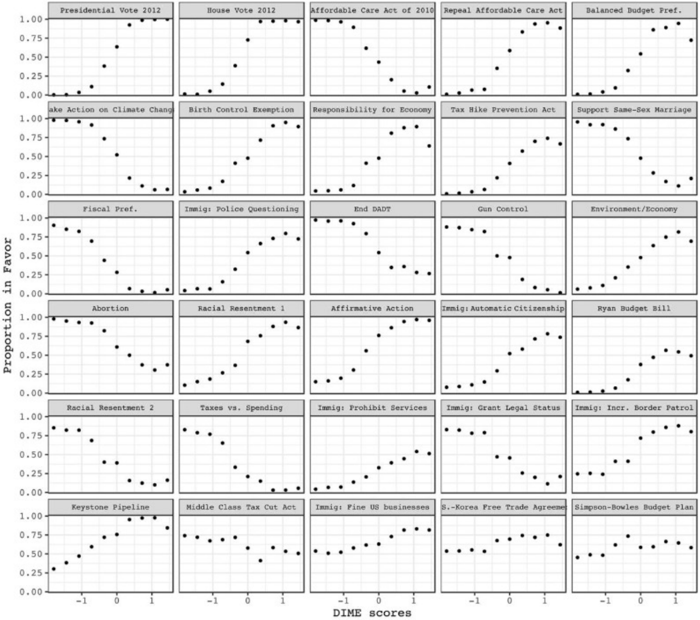


Figure 1. Binned scatter plots for CCES item responses against DIME scores. Ordinal items are dichotomized. Source: Hill and Huber (2017) merged CCES/ DIME data set.

Ideology Score: Examples

Tea Party

- Michele Bachmann (1.36)
- Timothy Huelskamp (1.42)

Main Street Republicans

- Doug Ose (0.79)
- Amory Houghton (0.45)

Conservative donors

- Club for Growth
- American Future Fund

Democratic socialists

- Alexandria Ocasio-Cortez (-1.69)
- Rashida Tlaib (-1.17)

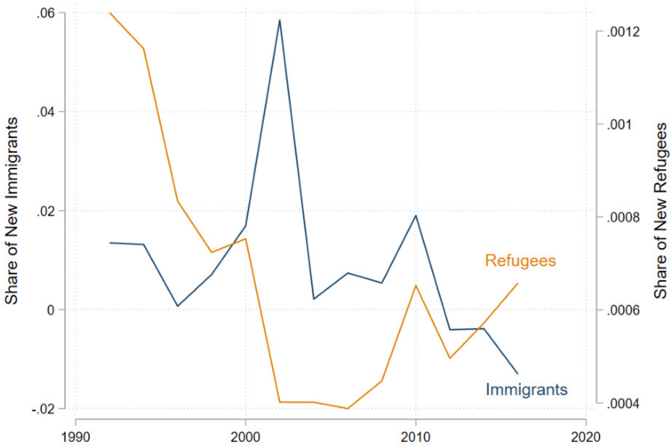
Blue dog democrats

- John Barrow (-0.16)
- Kurt Schrader (-0.54)

Liberal donors

- End Citizen United
- For our Future

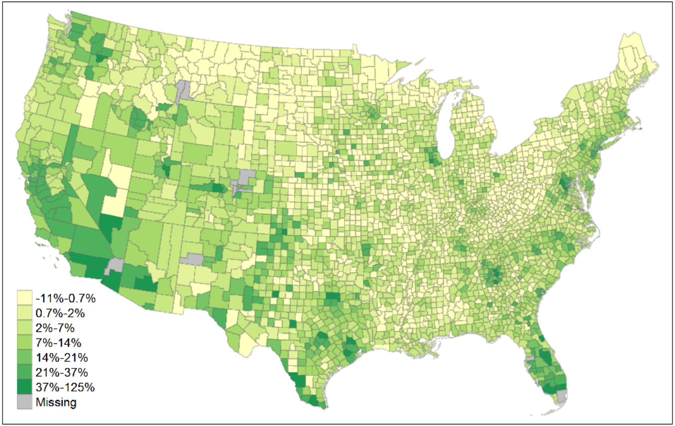
Immigrant and refugee flows, 1992-2016



Notes: The figure shows net (gross) inflows of immigrants (refugees) as a shareof the adult population.

Back to robustness.

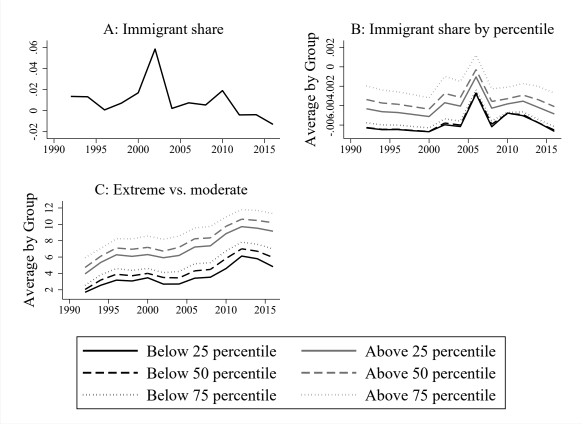
Immigrants by county, 1992-2016, net flows



*N*otes: The map shows the net flow of immigrants over the 1992-2016 period divided by the 1992 adult population.

Back to robustness.

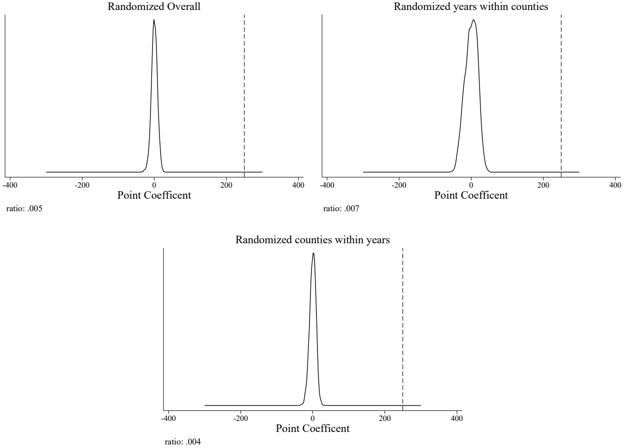
Nonlinear trends - Immigrant shares by percentile



*N*otes: Panel A shows net inflows of immigrants as a share of the adult population. Panel B shows the same variable at the county-level, according to percentiles of the initial share of immigrants in the year 1980 (and netting out the effect of the control variables we include in all regressions). Panel C shows extreme versus moderate campaign contributions for the same percentiles.

Back to robustness.

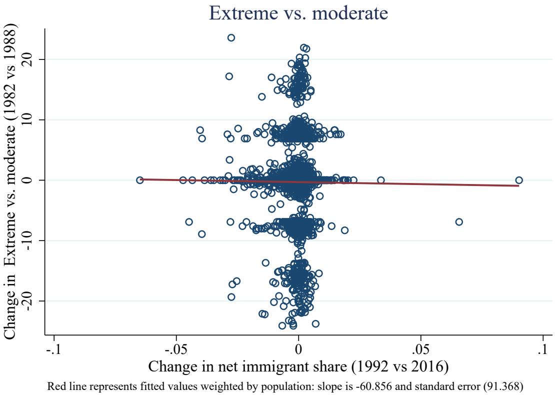
Randomized immigrants, extreme vs. moderate contributions



*N*otes: The figures show results from regressions based on column 1 in our main specification. Each figure graphically represents the coefficients of 5,000 regressions, where we have randomized immigration shares (i) across space and time, (ii) across counties within the same year, and (iii) across years within the same county. The dashed vertical line shows the coefficient for net immigration from our main specification.

Back to robustness.

Correlation between extreme vs. moderate contributions and changes in immigration



*N*otes: Shows the conditional correlation between the change in net immigration (1992-2016) and extreme vs. moderate campaign contributions (1982-1988), controlled for the other variables in our main specification.

Back to robustness .

Test for pre-trends

	(1)	obs.		(2)	obs.
Extreme vs. moderate	4.86e-06	36,916	Income	0.000857	36,940
	(1.56e-05)			(0.000548)	
Winner	-0.000172	32,680	Afr.-American	0.00779	36,940
	(0.000169)			(0.0237)	
Rep. vote share	0.000605	36,916	Share urban	0.000265	36,940
	(0.000708)			(0.000832)	
Winner if Rep.	0.00131*	13,772	Unemployment	-0.0259	36,940
	(0.000663)			(0.0216)	
Winner if Dem.	-0.00154	18,908	Share male	-0.0948	36,940
	(0.00110)			(0.0801)	
Winner vs. loser	0.000731	25,950	Share married	0.0139	36,940
	(0.000453)			(0.0197)	
Conservative Rep.	-0.000220	34,840	Import competition	0.00303	36,940
	(0.000301)			(0.00548)	
Mod. Rep.	2.54e-06	34,972	Labor participation	0.0156	36,940
	(0.000245)			(0.00939)	
Mod. Dem.	0.000414	34,840	Share low skilled	-0.000339	36,940
	(0.000268)			(0.00337)	
Liberal Dem.	0.000135	34,972	Share white low skilled	0.00511	36,940
	(0.000158)			(0.00413)	
			Share of white male lowskilled	0.0340	36,940
				(0.0216)	

*N*otes: The pre-trend variables are defined as the difference between 1982 and 1988 for column 1 and changes between 1980 and 1990 for column 2, while the dependent variables is defined as the two-year differences between 1992 and 2016. All specifications include the same controls variables as our main specification and year-fixed effects (we omit county-fixed effects). Each line represents a separate regression with the variables listed as the explanatory variables of interest.Each regression is weighted by the change in the citizen population of the county. Standard errors are clustered at the state-level in parentheses.

Back to robustness.