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

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Motivation

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

Source: Voteview

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


First to consider the political impact of US refugees


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)

⇒ 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

[Graph showing the ideology of parties from 1990 to 2020, with lines representing different periods and parties.]
Share of Contributions to the House of Representatives
Identification: Shift-Share IV

Second Stage:

\[ \text{Ideology}_{it} = \alpha + \beta \frac{\hat{\text{Immigrants}}_{it}}{\text{Pop}_{it}} + \gamma X_{zt} + \mu_{it} + \phi_{t} + \epsilon \]

Instrument:

\[ \sum_{n=1}^{N} \text{Immigrants}_{nt} \ast \text{Immigrantshare}_{ni,1980} / \text{Pop}_{t} \ast \text{Popshare}_{i,1980} \]

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.
Second Stage:

\[ \text{Ideology}_{it} = \alpha + \beta \frac{\hat{\text{Immigrants}}_{it}}{\text{Pop}_{it}} + \gamma X_{zt} + \mu_{it} + \phi_{t} + \epsilon \]

Instrument:

\[
\sum_{n=1}^{N} \text{Immigrants}_{nt} \times \text{Immigrantshare}_{ni,1980} / \text{Pop}_{t} \times \text{Popshare}_{i,1980}
\]

\[\mu_{i} = \text{County FE}, \phi_{t} = \text{Year FE}\]

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

**Immigrants, Campaign Contributions and Local Ideologies**

<table>
<thead>
<tr>
<th></th>
<th>(1) Extreme Contributions</th>
<th>(2) Extreme Contributions</th>
<th>(3) Ideological Distance</th>
<th>(4) Ideological Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-Years</td>
<td>249.685***</td>
<td>4.430</td>
<td>30.963</td>
<td>18.103**</td>
</tr>
<tr>
<td></td>
<td>(81.515)</td>
<td>(73.814)</td>
<td>(23.902)</td>
<td>(8.416)</td>
</tr>
<tr>
<td>8-Years</td>
<td>40,023</td>
<td>9,236</td>
<td>31,618</td>
<td>6,226</td>
</tr>
<tr>
<td></td>
<td>78.22</td>
<td>18.25</td>
<td>66.25</td>
<td>11.43</td>
</tr>
</tbody>
</table>

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Immigrants and Ideology - IV regressions

Coefficient and 90% Confidence Interval

Extreme vs. moderate

Winner

Rep. vote share

Winner if Rep

Winner if Dem

Winner vs. losers

Conservative Rep

Liberal Dem

-20 0 20 40 60 80
Immigrants and Ideology (short vs. medium run) - IV regressions

Extreme vs. moderate
Winner
Rep. vote share
Winner if Rep
Winner if Dem
Winner vs. losers
Conservative Rep
Liberal Dem

Coefficient and 90% Confidence Interval

2-years

8-years

Coefficient and 90% Confidence Interval

-20 0 20 40 60 80

-20 0 20 40
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

Dependent Variable: Ideology of the winner

Dependent Variable: Republican vote share

Dep. Var.: Probability that conservative Rep. wins

Dep. Var.: Probability that liberal Dem. wins
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  
  (Bonica, 2014, 2016, 2019)
- Non-linear trends  
  (Christian & Barrett, 2017)
- Pre-trends  
  (Goldsmith-Pinkham et al. 2020; Mayda et al., 2020)
- Serial correlation in the shift-variable  
  (Jaeger et al., 2018)
- Randomization  
  (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

Predictive 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 Validity

- 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
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
Notes: The figure shows net (gross) inflows of immigrants (refugees) as a share of the adult population.
Immigrants by county, 1992-2016, net flows

Notes: 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

Notes: 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.
Randomized immigrants, extreme vs. moderate contributions

Notes: 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.
Correlation between extreme vs. moderate contributions and changes in immigration

Notes: 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

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

Notes: 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.