The Rise in Constituents' Political Polarization

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The rise of political polarization among Congress members is a salient feature of American politics in the last 45 years. While this polarization decreased between 1913 and 1957, it increased dramatically since the 1970s (McCarty et al., 2016). Although much attention has been paid to increasing polarization in institutional politics such as the Congress, there is less evidence on the evolution of polarization among constituents.[1] In this context, the aim of this project is to study how has constituents' political polarization evolved in the last couple of decades, what are the causes behind this evolution and what are its implications. Uncovering these patterns and studying its causes and consequences is of paramount importance to understand better how American politics works.

One of the main challenges of a project like this is measurement. In order to measure constituents' political polarization, we propose to use questions from surveys that directly ask respondents their preference towards different ideological dimensions.[2] By combining these dimensions with self-reported party slant, we evaluate how has the ideological stand of constituents in these ideological issues evolved with respect to their party affiliation, i.e., a proxy for political polarization. By combining these measures with data from the Michigan Survey, the US Census, elections outcomes and Congress roll call votes,[3] we document three main sets of novel facts. The first is that constituents' political polarization doubled after 2007.[4] This fact appears to be fractal in the sense that it occurs in a similar magnitude at the individual level, within counties, between counties and controlling for a rich set of demographics.[5] Furthermore, this polarization is purely along party lines. Besides demographics, other economic factors such as trade exposure to China imports, unemployment, immigration, declining manufacturing and automatization, are not independently important. Finally, this feature is driven by views on the government role in the economy, efficiency of the welfare state and immigration. The second fact is a sharp and historic increase in economic pessimism among whites after 2007.[6] This feature is not driven by observable economic factors and is robust to demographics and geography. Furthermore, we find that this economic pessimism among whites actually reflects economic pessimism among conservatives and that this pattern and the increase in polarization are correlated in time and space. Finally, presidential elections respond with a lag to rising constituent polarization: 2016 Trump election is the first to *capture* polarizing constituents. Furthermore, voting in the House of Representatives, responds to rising constituent polarization before Trump's presidential election.

To the best of our knowledge, we are the first to document these patterns of constituents' political polarization, and connect them with a wide range of features of both the US economy and political system. Nevertheless, there are two main caveats that this analysis has so far. The first is that it ignores the role that media plays. This is an important issue given that the literature hasn't arrived to a definitive answer on the role of media in rising polarization.[7] In particular, we are interested in testing whether media generates or not these polarization patterns. The fact that this hasn't been included so far in our analysis is due to the absence of a rich media dataset that can be merged with the

[1]There are some exceptions, such as Boxell et al. (2017) and Webster and Abramowitz (2017).

[2]These dimensions are related to government inefficiencies, government regulation, issues related to the welfare state, racial discrimination, immigration, the role of the military, the role of corporations, environmental change and homosexuality. These are the same dimensions that PEW surveys use to define the ideology of respondents.

[3]We combine these different datasets at the county level.

[4]We show that these measures of polarization behave very differently to self-reported ideology, which is usually used in the literature.

[5]These results are also robust to using the American National Election Studies (ANES). Evenmore, they are robust to using other ideological dimensions.

[6]Economic pessimism is measured from the Michigan survey as the difference between constituents' economic expectations of the economy and their economic current conditions.

[7]For example, take Martin and Yurukoglu (2014) and Boxell et al. (2017) for different results on the subject.

aforementioned datasets at a detailed geographic level. The second, and most important limitation so far, is that all the aforementioned results are correlations. We are interested in testing whether the increase in polarization is causing the increase in economic pessimism and some of the 2016 presidential election outcomes. For these 2 main purposes is that we are applying to the NBER-Nielsen Media Projects.

In order to address the first caveat, that is, whether media can cause some of the patterns of political polarization, we propose to analyze the following relationship:

$$p_{it} = \alpha_0 + \alpha_1^C m_{it}^C + \alpha_1^L m_{it}^L + \mathbf{X}_{it}\beta + \delta_t + \epsilon_{it} \tag{1}$$

where i and t are indices of counties and year, respectively, p_{it} is a measure of constituents' ideology, m_{it}^C is a measure of media consumption of a conservative provider, m_{it}^L the one of a liberal provider[8] and $\mathbf{X}_{it}$ is a set of controls. Given the potential endogeneity concern given by the simultaneity and reverse causality between ideology and media consumption, we plan to measure m_{it}^j as consumption of different cable channels and instrument for it, in the spirit of Martin and Yurukoglu (2014), with these channel's lineup. The idea is that the numerical ordering that a channel has in the TV program is unrelated to patterns of political behavior and preferences before those channels were available, but they are related to viewership of these channels, i.e., channels with a higher numerical order, have less viewership.[9] Therefore, this instrument is an exogenous shifter in the cross-section of consumption of different channels. The coefficient of interest are α_1^C and α_1^L. If these are statistically differently from zero after being instrumented, then one would conclude that media exposure causes political ideology. Furthermore, the signs of α_1^C and α_1^L would indicate whether media reinforces or dampens ideological divide.

In order to address the second caveat, that is, whether increasing political polarization causes some of the aforementioned patterns such as pessimism or presidential election outcomes, we propose the following research design:

$$y_{it} = \gamma_0 + \gamma_1 p_{it} + \mathbf{X}_{it}\beta + \delta_t + \epsilon_{it} \tag{2}$$

where i, t and p_{it} are the same as before, y_{it} is an outcome variable such as economic pessimism or Republican's vote share in presidential elections and $\mathbf{X}_{it}$ is a set of controls. As before, there is a potential endogeneity problem due to simultaneity and reverse causality between y_{it} and p_{it}. In order to address this concern, we plan to instrument p_{it} with the same instrument as in the previous strategy. The coefficient of interest would be γ_1. It will tell us how exogenous shifts to constituents' ideology impact the aforementioned outcomes.

Data Request

For both of the aforementioned goals, we require a rich dataset of media at a disaggregated geographic level (at least, DMA level, but ideally at the county or zip-code level). We request the following datasets to the NBER-Nielsen Media Projects initiative:

1. Nielsen's basic TV ratings data:
   (a) Ratings analysis. Both at national and local levels, and disaggregated in all the available categories.
   (b) Unification.
   (c) All demographic groups.
   (d) Local TV across 210 DMA regions.
   (e) All available years.
2. Nielsen's advanced TV ratings data.
   (a) Currency metrics.
   (b) Reach & frequency schedules and reports.
   (c) MarketBreaks.

[8] This stark characterization of media providers is for simplicity of exposition. Eventually, we can measure also the ideology of media as in Martin and Yurukoglu (2014).

[9] Martin and Yurukoglu (2014) perform other tests of the validity of an instrument like this. All those tests are passed.

(d) Viewing segmentation.

(e) Universe estimate.

(f) Length of tune.

(g) All available years.

3. Radio.

   (a) All metrics. Both at national and local level.

   (b) Across all demographic groups.

   (c) All available years.

4. Syndicated Surveys.

   (a) Scarborough.

   (b) Behavior track.

   (c) CINA.

As was previously mentioned, this data request will be merged with the aforementioned dataset that this study has already used. The merge of these different datasets will be done at either the zip-code level, the county level or the DMA level depending on the datasets.

Finally, we could be able to provide funds if needed from Princeton University and/or the University of Chicago to help facilitate the NBER-Nielsen Media Projects initiative meeting our data request.

References

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