A Polarized Environment: The Effect of Party, Ideology, and Constituent Interests on House Environmental Voting, 1989-2016

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Abstract

This project investigates the changing influence of constituent economic concerns, ideology, and partisanship on environmental voting behavior in the U.S. House of Representatives between 1989 and 2016. During these years, both public opinion and voting in Congress became increasingly polarized across a range of issues (Hare and Pool 2014), and the environment was no exception (Smith, Bognar, and Mayer 2024, Bergquist and Warshaw 2020). This project thus seeks to understand how the explanatory power of different factors has shifted in these polarizing conditions, lending insight into why representatives vote they way they do on a crucial issue. We use lawmaker scores from the League of Conservation Voters (LCV), an environmental advocacy group, to measure environmental voting behavior. To estimate LCV scores, we construct multiple regression models with the following predictive variables: (1) lawmaker ideology on two liberal to conservative axes, as measured by DW-NOMINATE, (2) lawmaker partisanship (an indicator variable), and (3) approximate number of fossil fuel extraction jobs in a lawmaker's district. Each model spans a different set of sessions of Congress within the period from 1989 to 2016. We find a significant effect of ideology, party, and fossil fuel jobs in all models, with the effect of party progressively increasing and the effect of jobs progressively decreasing over the time period. These findings are in line with an increased role of partisanship and decreased role of material constituent concerns in determining legislator environmental voting as polarization has grown.

I. Introduction

Environmental policy is an increasingly important issue worldwide. In particular, the most recent expert consensus holds that significant policy changes are necessary in the near future in order to avoid the most threatening possible effects of climate change (IPCC 2023). In the United States specifically, the environment is also an issue for which politics can be counterintuitive. Surveys show that a majority of American voters support a wide variety of pro-environmental policies, including increasing environmental regulations, limiting greenhouse gas emissions, and encouraging renewable energy generation (Gallup). However, most voters are unlikely to cast their vote based on the environment (Bergquist and Warshaw 2020). Moreover, certain communities, such as those with a large fossil fuel industry, can bear concentrated costs from pro-environment policy, leading to pockets of backlash and strong opposition (Stokes 2016). Thus, while pro-environmental actions are both broadly popular and necessary to address climate change, they are not a clear electoral winner.

Additionally, environmental policy preferences among both American voters and American lawmakers have become increasingly polarized along partisan lines over the last several decades. Since the early 1990s, Republican voters have become increasingly skeptical of climate change and opposed to environmental spending, while Democratic voters have moved in the opposite direction (Smith, Bognar, and Mayer 2024). In Congress, a similar trend holds: polarization on the environment has steadily increased since the 1970s, with voting patterns reflecting growing Democratic embrace and Republican rejection of pro-environmental measures. (Carlson Sirvent León 2024, 32). Lawmakers' voting on environmental issues has long been quite political, with Nelson (2002) identifying ideology as the most important predictor of environmental voting in the Senate as far back as 1988-1998. Since this period, though, the ideological and partisan gap on the environment has continued to widen in both houses (Carlson Sirvent León 2024). This divergence is in line with general trends in Congress. Across almost all issues, polarization has increased; moderates have dwindled in number, the voting behavior of Republicans has become more conservative, and that of Democrats has become more liberal (Hare and Poole 2014). Relatedly, Congress has become more "unidimensional" as legislator ideological preferences on all issues tend to align with a single liberal versus conservative axis (Hare and Poole 2014, Poole and Rosenthal 2007). The environment is no exception.

Even in this polarized era, the material concerns of constituents seem to impact how members of Congress vote on the environment. A foundational assumption in much of modern political science is that legislators, motivated by the goal of reelection, rationally attempt to align their actions with the preferences of the maximum share of their constituents (Downs 1957). Environmental issues appear to rarely determine the votes of constituents, except for concentrated minorities who face direct material consequences, such as people living nearby proposed clean energy developments or people employed in the fossil fuel industry (Bergquist and Warshaw 2020, Stokes 2016). Therefore, we would expect the presence of these direct material concerns in a lawmaker's district to have significant effect on their voting on environmental issues. Indeed, there is much evidence that this is this case. Cragg et al. (2012) find that members of Congress representing districts with greater per-capita carbon emissions and in particular a greater share of emissions from industrial activity are more likely to vote against legislation aimed at mitigating climate change. Elliot et al. (2023) find an effect of climate-related natural disasters on the environmental voting of Senators from impacted states. Kahane (2016) finds that representatives with higher oil-related employment in their districts were more likely to vote in favor of a 2011 House bill to lift Barack Obama's offshore drilling moratorium, while representatives from districts near the Gulf of Mexico, where the catastrophic Deepwater Horizon oil spill had recently occurred, were less likely to vote for the bill. These findings do not necessarily imply that constituent interests are the principal motivator of environmental voting, though: both Kahane and Cragg et al. note the strong effect of ideology, and Kahane also finds evidence for the impact of PAC donations from proponents and opponents of offshore drilling.

In recent years, some evidence has also supported the notion that environmental legislative behavior has decoupled from constituent material interests as environmental issues have increasingly become subsumed into unidimensional partisan politics. This dynamic is most evident in the case of the Inflation Reduction Act, passed in 2022 with unanimous Democratic support and unanimous Republican opposition, which includes by far the largest investment in renewable energy in American legislative history. Despite the Republican hostility towards it, the law spurred the largest investments in districts represented by Republicans, as of December 2023 (J. Smith 2023). This result is consistent with a fundamental contradiction in the politics of the American energy transition: many Republican-leaning parts of the Great Plains and Southwest have very consistent wind and sun, making them prime candidates to benefit from renewable energy investment. In 2023, the top four states in both wind power generation capacity and actual wind power generation were Texas, Iowa, Oklahoma, and Kansas (Climate Central 2024). However, given the partisan divide on climate and the fact that, until the passage of the Inflation Reduction Act, almost all climate policy took place at the state level, policy in these states has not necessarily encouraged clean energy development. As a result, Shrestha (2024) finds that the gap between "red" and "blue" states in per-capita carbon dioxide emissions widened from 1997 to 2021, with divides by party more pronounced than those by geographic location. The increasingly polarized and partisan nature of environmental attitudes would help explain this possible phenomenon of a mismatch between beneficiaries and supporters of climate policy. Theoretically, we might expect that the environmental policy preferences of both voters and elites have increasingly moved downstream of partisan identity, detaching from material interests. Overall, in the context of the energy transition and of increased environmental polarization, it is unclear to what extent the sometimes-competing priorities of party loyalty, general political ideology, and material constituent benefits influence legislation.

In this paper, we seek to examine how these factors have influenced environmental voting behavior in the House of Representatives in an increasingly polarized Congressional environment from 1989 – 2016. To measure alignment of a representative's votes with pro-environmental positions, we use scores published by environmental advocacy group the League of Conservation Voters (LCV). These scores, measured on a scale from 0-100, record the percentage of bills on which a legislator votes as the LCV advocates. Each year, the LCV publishes scores for all members of Congress for that year and for their entire careers. These scores are frequently used in the literature as a measure of lawmaker pro-environmental voting (Goldberg et al. 2020, Kahane 2016, Nelson 2002, Newman et al. 2015, Anderson 2011, Elliot et al. 2023). To measure lawmaker ideology, we use DW-NOMINATE scores, drawn from the Voteview dataset published by Keith Poole and Jeffery Lewis. DW-NOMINATE, developed by Poole and Howard Rosenthal, is a multidimensional scaling method widely used in political science to place members of congress along ideological axes. Finally, to represent the influence of material constituent interests, we construct data estimating the number of fossil fuel extraction jobs at the congressional district level throughout this time period. We draw this data from Census County Business Patterns surveys, which measure employment by industry at the county level, using GIS tools to approximate district-level data.

In section II, we discuss the methodology involved in creating this dataset and explore trends and relationships in the data. In section III, we discuss the multiple regression models that we applied to predict House member LCV scores from partisan identity, DW-NOMINATE scores, and district fossil fuel extraction employment. We also interpret the results of fitting these models to the data, finding an increase in the effect of partisanship and a decrease in the effect of district jobs over the time period. In section IV, we examine the implications of these results, including potential explanations for the trends observed and accompanying visualizations. In section V, we discuss conclusions and recommendations for further research.

II. Dataset Creation and Exploration

In our regression models, each observation represents one member of the House during one session of Congress. Therefore, we construct a dataset of lawmakers-by-session including partisanship, DW-NOMINATE scores, and LCV scores for the session as well as estimated district fossil fuel jobs based on County Business Patterns data from the first year of the session.

Our LCV score data comes from the LCV website. The LCV releases scores by year rather than Congress, so we create pooled LCV scores over both years of a Congress. Each annual LCV score is simply the percentage of roll-call votes deemed relevant to the environment on which the representative votes in line with the LCV's position. Thus, in order to create pooled score, we calculate the percentage of overall roll-call votes across the two-year period on which the representative votes in line with the LCV. We also need to account for the fact that LCV scores are rounded to the nearest integer. So we calculate pooled LCV score LCV_P as follows, given a representative's LCV scores (LCV_1, LCV_2) and the number of votes that the LCV deems relevant (v_1, v_2) for the first and second years of the Congress in question:

$$LCV_P = \left(\frac{\text{round}\left(\frac{LCV_1}{100} * v_1\right) + \text{round}\left(\frac{LCV_2}{100} * v_2\right)}{v_1 + v_2} \right) * 100$$

The equation above attempts to capture the sum of votes over the two-year period on which the member supported the LCV position divided by the total number of relevant votes and multiplied by 100. Therefore, the calculation is accurate if, for a given year with v votes and a lawmaker LCV score LCV, the number of votes s on which the candidate supported the LCV position is $\text{round}\left(\frac{LCV}{100} * v\right)$. We briefly prove that this is true for our data. Note that no year in the time period considered had more than 38 roll-call votes included in the annual LCV score calculation, so $v \leq 38$ for our data. Also note that LCV score is calculated $LCV = \text{round}\left(\frac{s}{v} * 100\right)$. So:

$$\begin{aligned}
\frac{100s}{v} - 1 <& LCV < \frac{100s}{v} + 1 \\
\implies \frac{s}{v} - 0.01 <& \frac{LCV}{100} < \frac{s}{v} + 0.01 \\
\implies s - 0.01v <& \frac{LCV}{100} * v < s + 0.01v \\
\implies s - 0.38 <& \frac{LCV}{100} * v < s + 0.38 \\
\implies \text{round}& \left(\frac{LCV}{100} * v\right) = s
\end{aligned}$$

So our calculation of pooled LCV scores is valid.

In order to measure ideology, we use DW-NOMINATE scores, widely accepted in political science as a quantitative measure of the theoretical ideal policy points of members of Congress. Howard Rosenthal and Keith Poole developed this metric using multidimensional scaling to map the positions of members of Congress relative to each other based on their roll-call votes (Poole and Rosenthal 1985). This theoretical policy space has two dimensions: the first dimension often captures general liberal versus conservative ideology, particularly on economic issues, whereas the second dimension often captures legislator preferences on different major issues of the day that are to some extent orthogonal to economic liberal-conservative alignment, such as civil rights in the mid twentieth century. Poole and Rosenthal write that, throughout the history of Congress, "the first dimension almost always divides the two major political parties while the second dimension picks up divisions within the parties" (Poole and Rosenthal 2007). In both dimensions, a positive score is associated with farther right policy preferences, and a negative score is associated with farther left policy preferences.

Specifically, we use Nokken-Poole DW-NOMINATE scores, which differ from standard DW-NOMINATE scores in one key respect: instead of modeling lawmakers' ideal points as fixed, Nokken-Poole scores allow them to fluctuate from Congress to Congress (Nokken and Poole 2004). We use these scores rather than typical DW-NOMINATE scores because our analysis is at the Congressional session level. We are thus estimating how a lawmaker's ideological preferences within a given Congress (not over their entire career) affect their environmental voting within that Congress.

Estimated district-level fossil fuel employment data comes from the U.S. Census Bureau's County Business Patterns (CBP) data, which the Census Bureau has published annually at the county, state, and national level since 1986. At each geographical level, CBP records employment during the week of March 12 by industry. It also includes data on payroll and number of establishments, but we focus on the employment data. For our analysis, the job numbers associated with each Congress come from the CBP dataset for the first year of that Congress. Until 1997, CBP used the four-digit codes of the Standard Industrial Classification (SIC) system to classify industries. Since 1998, CBP has used the six-digit codes of the North American Industry Classification System (NAICS). For the years 1989-1997, we define fossil fuel extraction jobs as those classified under SIC codes 1200 ("coal mining") and 1300 ("oil and gas extraction"). For later years, we consider coal mining jobs to be those classified under NAICS codes 2121// and 213113 ("support activities for coal mining"), which jointly classify the same jobs classified under 1200 in SIC (Census Bureau). We consider oil and gas extraction jobs to be those classified under NAICS codes 211///, 213111 ("drilling oil and gas wells"), and 213112 ("oil & gas operations support activities"). All of the jobs in these categories are also categorized under SIC code 1300, but there are a few jobs classified under SIC code 1300 that are not classified under these NAICS codes: namely, about 30% of jobs under NAICS code 54136 ("geophysical surveying and mapping services") (Autor et al. 2020). However, it is not certain that a consistent portion of surveying and mapping jobs across different counties will be in oil and gas extraction. Also, the effect of excluding these jobs is likely negligible: there were only eleven counties in 2015 with more than 100 surveying and mapping jobs. Overall, the change from SIC to NAICS codes does not seem to greatly impact our data. There was no noticeable shift in distribution of fossil fuel jobs before and after 1998, as shown in figure 1 below (we use the log-transformed version of the jobs variable here, which will eventually also use in our regression models, because the raw variable is extremely right-skewed, making visualization of distribution difficult). If anything, estimated jobs seemed to increase slightly after the change in classification, so the missing surveying and mapping jobs do not appear to have much impact.

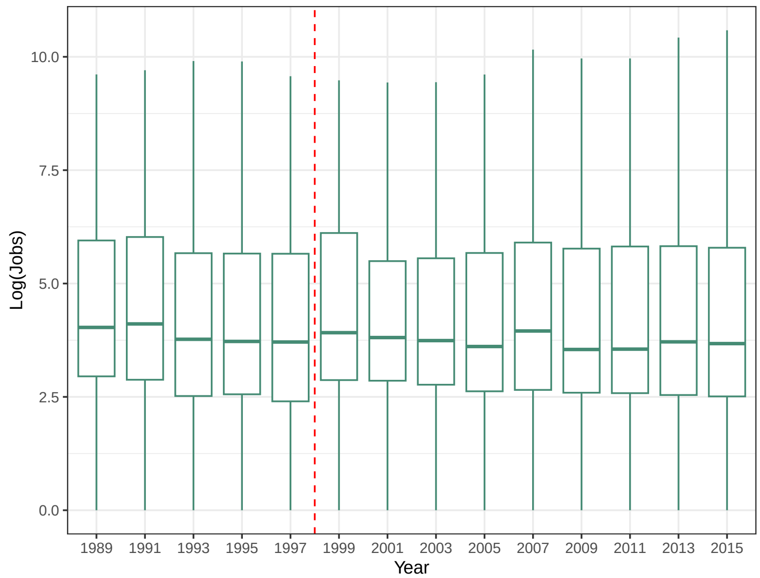

Figure 1: Boxplots showing distribution of logarithm of estimated fossil fuel jobs for each year that calculations were performed. Red line marks 1998, the year of a major change in industry classification system.

For privacy reasons, the Census also censors some employment values and instead gives an employment range for an industry in a county. In these cases, we used the midpoint of the given range as an estimate of jobs in that industry and county. Kahane (2016) uses the same method. Once we have an estimate of jobs in each industry, we calculate total fossil fuel jobs as the sum of estimated jobs across the industry categories discussed above.

In order to estimate fossil fuel extraction jobs at the congressional district level, we compare county borders with congressional district borders for each of the Congresses in the time period, calculating how much land area from each county falls within each district. For the 101st-112th Congresses (1989 - 2012) we computed these relationships using ArcGIS. For the 113th and 114th Congresses (2013-2016), we used datasets from the Census Bureau's Cartographic Boundary Files, which have included data summarizing counties within congressional districts since 2013. Jobs were assigned from counties to congressional districts in proportion to the percentage of the county's land area falling within the congressional district:

$$\text{District Jobs} = \sum_{\substack{\text{counties} \\ \text{overlapping district}}} \frac{\text{Land Area of County in District}}{\text{Total County Land Area}} * (\text{County Jobs})$$

So if a county is entirely within a district, all of its jobs are assigned to that district, and if a county is split between multiple districts, each district receives jobs from the county in proportion to the percentage of the county's area that it contains. This method assumes that jobs are evenly spatially distributed across counties, which is imperfect, but it gives an approximation of the importance of fossil fuel employment in a district. Due to GIS software difficulties, we were unable to perform the summary of counties within fossil fuel districts for the new districts in North Carolina, Virginia, New York, and New Jersey for the 106th Congress and in the aformentioned states plus Texas for the 107th Congress. Thus, we drop lawmakers representing those states in those Congresses from the data used to fit our models.

We combine all this data into a dataset providing lawmakers' pooled and lifetime LCV scores, Nokken-Poole and standard DW-NOMINATE scores, and estimated district fossil fuel employment for each Congress from the 101st (1989-1990) to the 114th (2015-2016). The resulting dataset, which we hope can be a useful tool for further examination of the relationships between these variables, is publicly available here. This analysis stopped at 2016 because after that year, the Census Bureau changed its CBP data publication practices in a way that dramatically altered the distribution of jobs across counties and congressional districts, so post-2016 data would not have been directly comparable.

Examining this data, we first observe the well-documented phenomenon of increased polarization in Congress throughout this period, both in general ideology and in climate voting. Figure 2 shows that the distributions of Nokken-Poole first-dimension scores and LCV scores become progressively more bimodal from the 101st to 114th Congresses.

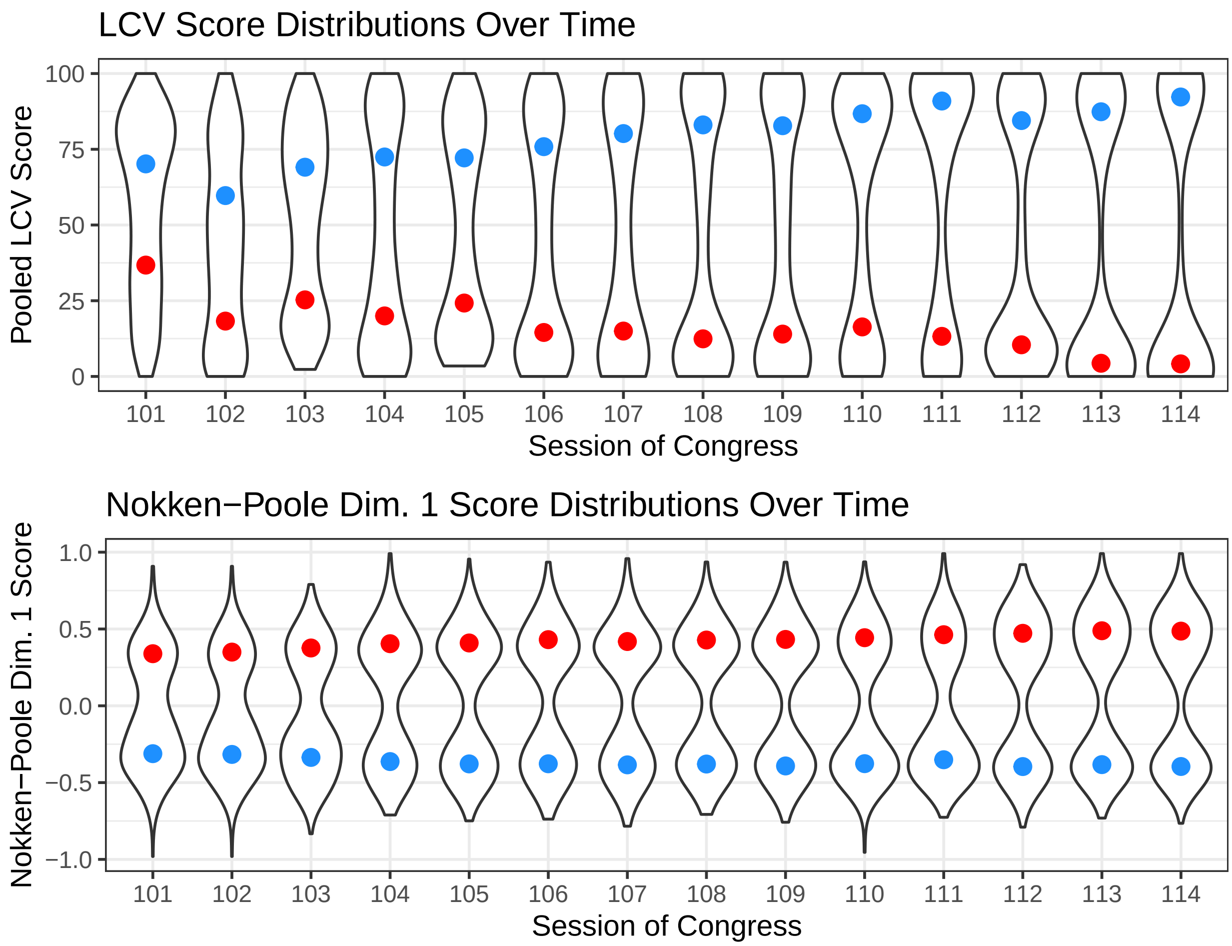

Figure 2: Violin plots illustrating the distribution of LCV scores and Nokken-Poole first-dimension scores in each session of Congress from the 101st (1989-1990) to the 114th (2015-2016). Blue points represent the mean Democratic score and red points represent the mean Republican score for each Congress

Clearly, our data reflects the trend observed in the literature of growing polarization throughout this time period. On both LCV and first-dimension Nokken-Poole scores, we see a decrease in distribution density in the middle and an increase at both extremes, as well as a widening gap between mean Democratic and Republican scores. This effect is particularly intense for LCV scores. Indeed, by the 114th Congress, the parties had little room for any more polarization in LCV scores, with the mean Democratic score at approximately 92 and the mean Republican score at approximately 4. The fact that LCV scores show greater polarization than DW-NOMINATE scores is in line with the documented tendency of interest group scores in general and LCV scores in particular to record exaggerated extremism compared to ideal-point-estimation measures (Snyder 1992, Jeong and Lowry 2021). Still, there seems to be a clear change from a more uniform LCV distribution in the first few Congresses studied to one highly clustered at the extremes in the last few. This pattern holds up when we look at histograms and summary statistics for each variable (excepting partisanship) over four subdivisions of the time period studied: 1989-1994, 1995-2000, 2001-2008, and 2009-2016. These are the year groupings over which we fit our different regression models, as discussed in Section III below.

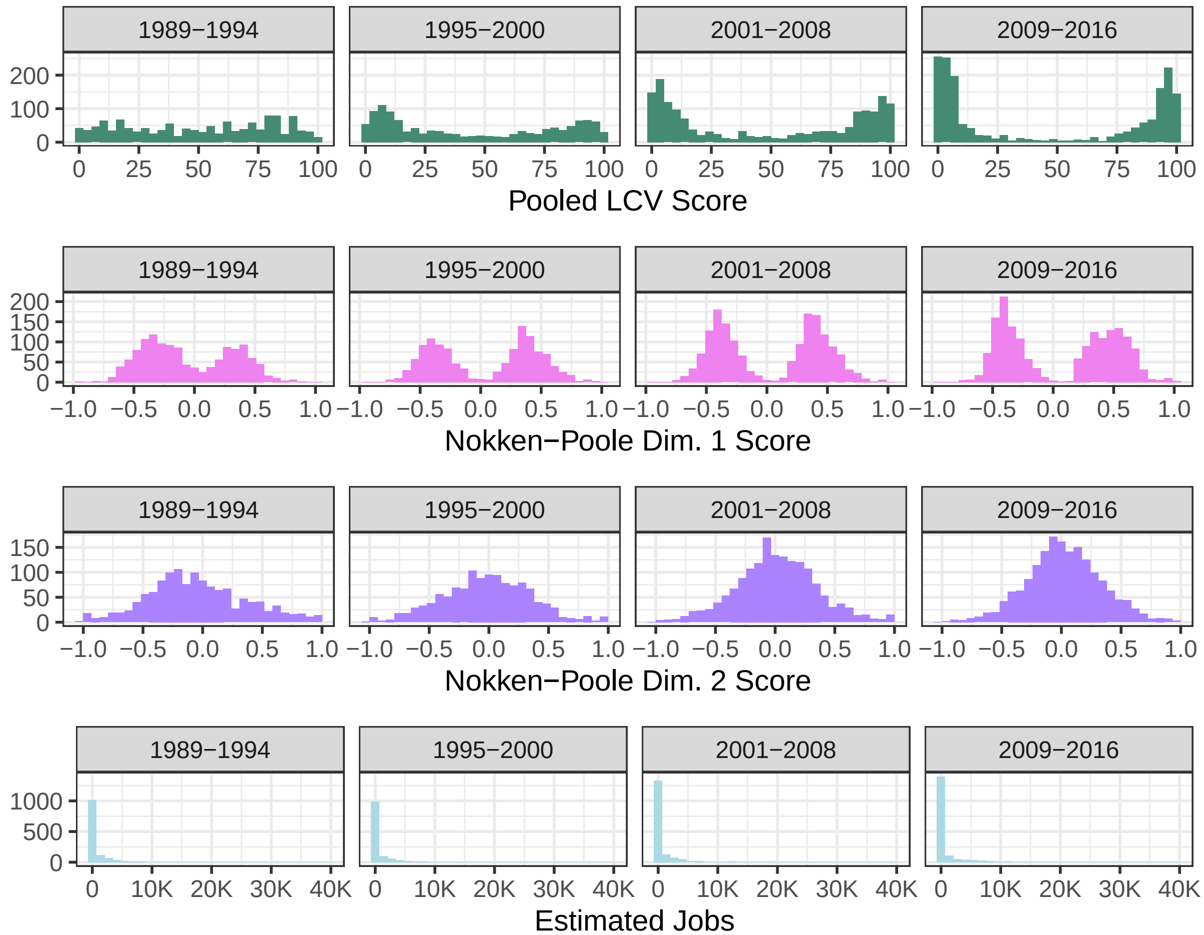

Figure 3: Histograms showing the distribution of each continuous variable in each of the time periods examined

Again, we observe that the distribution of LCV scores goes from being fairly uniform to being highly polarized towards the extremes, with a similar dynamic present to a less dramatic extent in the distribution of Nokken-Poole first dimension scores. Nokken-Poole second dimension scores appear to have a fairly normal distribution over the time period, and polarization appears to move in the opposite direction, with more scores near zero and narrower spread of scores after 2000. This trend would be consistent with a "unidimensional" Congress in which variation in lawmaker preferences is more and more constrained to the first dimension of DW-NOMINATE. Finally, estimated jobs are extremely right-skewed, to the extent that it is difficult to discern any trends in the data from these histograms, though there seem to be slightly more observations near zero in the last two time periods. This heavily right-skewed distribution is also evident from examining summary statistics of the data, which are given for the entire dataset and for each subdivision in the tables below:

Table 1: Summary Statistics Over Entire Dataset

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Nokken-Poole Dim. 1	-0.98	-0.38	-0.01	0.03	0.41	0.99
Nokken-Poole Dim. 2	-1.00	-0.24	-0.01	0.00	0.22	1.00
LCV Score	0.00	8.33	44.83	47.51	87.10	100.00
Estimated Jobs	0.00	13.17	42.20	865.71	333.86	39536.39

Table 2: Summary Statistics, 1989-1994

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Nokken-Poole Dim. 1	-0.98	-0.36	-0.14	-0.05	0.30	0.91
Nokken-Poole Dim. 2	-1.00	-0.32	-0.08	-0.05	0.20	1.00
LCV Score	0.00	22.22	52.63	50.37	77.78	100.00
Estimated Jobs	0.00	14.34	51.25	808.67	382.30	20066.34

Table 3: Summary Statistics, 1995-2000

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Nokken-Poole Dim. 1	-0.75	-0.37	0.18	0.04	0.40	0.99
Nokken-Poole Dim. 2	-1.00	-0.26	-0.01	-0.02	0.23	1.00
LCV Score	0.00	10.34	37.93	45.09	80.77	100.00
Estimated Jobs	0.00	12.68	42.03	774.55	322.40	19882.39

Table 4: Summary Statistics, 2001-2008

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Nokken-Poole Dim. 1	-0.95	-0.38	0.18	0.04	0.41	0.96
Nokken-Poole Dim. 2	-0.99	-0.20	0.00	0.01	0.23	1.00
LCV Score	0.00	6.45	45.45	47.98	90.32	100.00
Estimated Jobs	0.00	13.91	41.59	761.80	304.68	25797.18

Table 5: Summary Statistics, 2009-2016

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Nokken-Poole Dim. 1	-0.79	-0.39	0.22	0.07	0.49	0.99
Nokken-Poole Dim. 2	-0.97	-0.18	0.02	0.02	0.22	0.98
LCV Score	0.00	4.17	29.17	46.65	92.86	100.00
Estimated Jobs	0.00	12.10	35.62	1071.57	334.12	39536.39

Jobs data is extremely right skewed in all time periods, with the mean more than doubling the 75th percentile in each period. Moreover, the interquartile range (IQR) of LCV scores greatly expands during this period, while the IQR of first-dimension Nokken-Poole scores slightly expands and the IQR of second-dimension Nokken-Poole scores slightly shrinks, all of which aligns with the trends observed in the histograms. We note that the most recent time period has the highest mean jobs and the lowest median jobs, perhaps supporting the possible trend towards even greater right-skewness seen in the histograms. Overall, though, the quartiles of job data seem fairly consistent over time, aligning with the consistent distribution of log(Jobs) observed in figure one.

As for variable relationships, simple scatterplots offer evidence for strong relationships between ideology, party, and environmental voting. However, the shape of these relationships changes as voting becomes more polarized over this period.

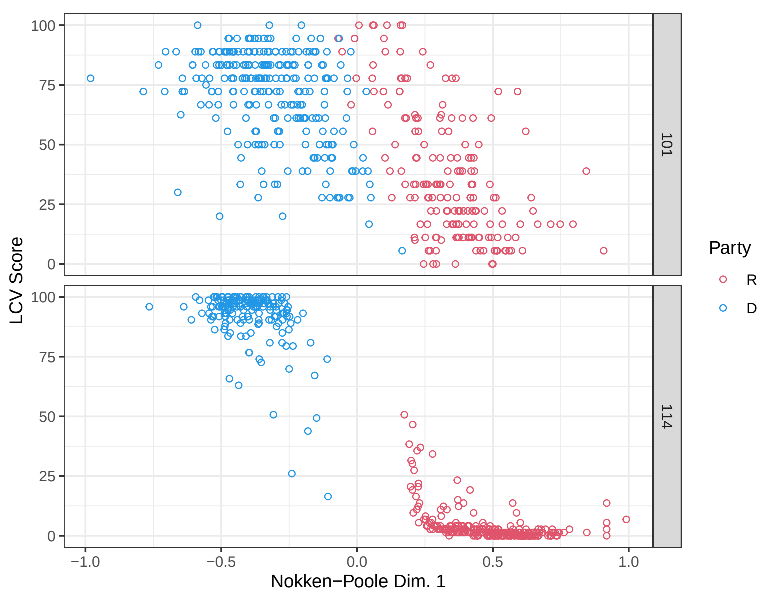

Figure 4: Scatterplots of legislator LCV vs. Nokken-Poole first dimension scores, colored by legislator party, for the earliest (101) and latest (114) Congresses in our data

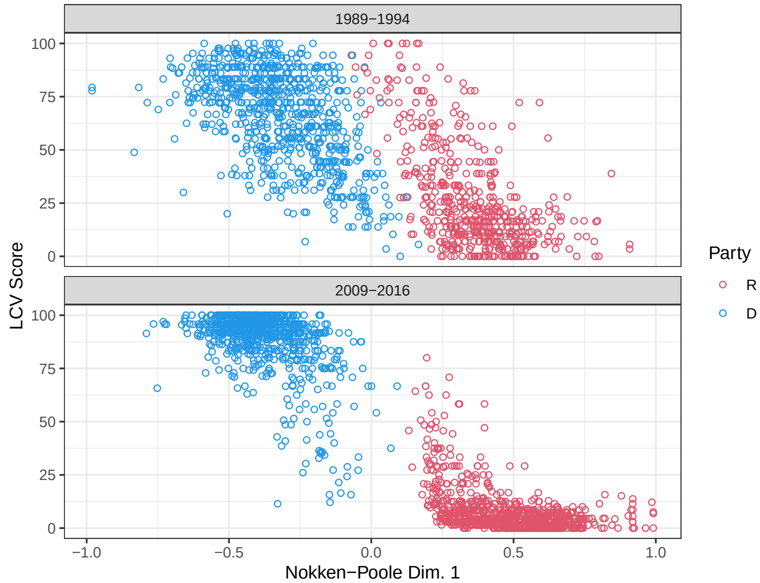

Figure 5: Scatterplots of legislator LCV vs. Nokken-Poole first dimension scores, colored by legislator party, for the earliest (1989-1994) and latest (2009-2016) time periods in our data

In the 101st Congress (and in general across the 1989-1994 time period) party and ideology appear to be predictive of LCV score, with Republicans and conservatives generally having lower LCV scores than Democrats and liberals. However, there is plenty of variation in LCV scores even after accounting for these factors. By the 2009-2016 period, particularly within the 114th Congress, there is much less variation within parties, with most Democrats clustered near 100 and most Republicans clustered near zero. While there appears to be a consistent linear relationship between Nokken-Poole scores and LCV scores in the earlier data, the clustering of LCV scores at the extremes - particularly that of Republicans near zero - in the later data appears to give a nonlinear shape to the relationship.

As displayed in figure six, over the entire dataset, there is a strong negative correlation and apparent inverse linear relationship between first-dimension Nokken-Poole and LCV scores. We also see a weaker negative correlation between second-dimension Nokken-Poole and LCV scores. Finally, there is a weak positive correlation between the logarithm of fossil fuel jobs and both Nokken-Poole dimensions and a weak negative correlation between log(Jobs) and LCV scores. These observations suggest that conservative ideological leanings and presence of district fossil fuel jobs are associated with more anti-environmental lawmaker voting, while district fossil fuel jobs are also somewhat associated with generally more conservative representation. There is virtually no correlation between first and second dimension Nokken-Poole scores, which is expected, since DW-NOMINATE creates these scores to represent perpendicular axes of lawmaker ideology. In line with the summary statistics and histograms examined above, LCV and first-dimension Nokken-Poole scores have bimodal distributions, while second-dimension Nokken-Poole scores have an approximately normal distribution. The log-transformed jobs variable has a much more normal-appearing distribution than the raw jobs variable, though it is still somewhat right-skewed. There are also no clear nonlinear relationships between variables. The slight correlation between our predictor variables (Nokken-Poole scores and log(Jobs)) warns of possible issues with collinearity, which will be discussed further in section III.

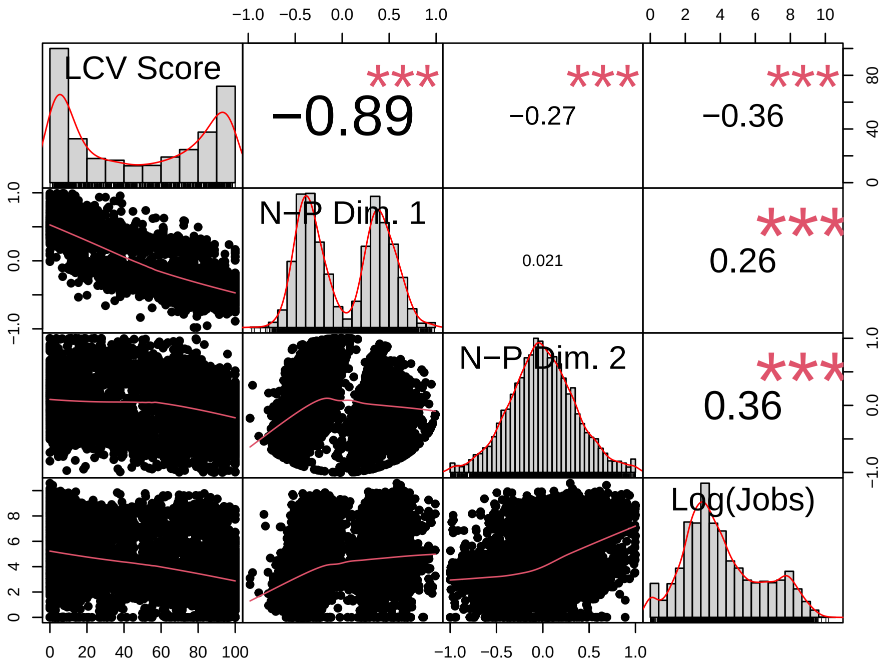

Figure 6: Correlation plot matrix of LCV scores, Nokken-Poole first and second dimension scores, and log(Jobs) from the entire dataset, including all sessions of Congress. The bottom-left half displays scatterplots of pairs of variables with lines of best fit, while the top-right half displays correlations. The diagonal shows histograms and lines of best fit for the distribution of each variable. Plots created using Peter Carlson's PerformanceAnalytics R package.

III. Modeling and Analysis

We fit four multiple regression models, one each for the time periods 1989-1994 (101st-103rd Congresses), 1995-2000 (104th-106th Congresses), 2001-2008 (107th-110th Congresses) and 2009-2016 (111th-114th Congresses). Our analysis starts on the eve of the 1990s, the decade in which environmental polarization began to take off among the general public (Smith, Bognar, and Mayer 2024). We end the first time period in 1994, the year that Republicans won control of the House for the first time in four decades. The midterm elections of 1994 are often viewed as a key turning point in the increasing polarization of Congress (Aldrich and Rohde 2000). Each of the other time periods ends with the election of a new presidential administration, which represents a significant change in federal politics. To enable comparison across time periods, each of these models is the same. In each, our response variable is the LCV score $LCV_{m,c}$ of House member m in congress c, which we model as follows:

$$
\begin{aligned}
LCV_{m,c} = \beta_0 + \beta_1 N^{(1)}_{m,c} + \beta_2 N^{(2)}_{m,c} + \beta_3 \log(J_{m,c}+1) + \beta_4 P_{m,c} + \beta_5 N^{(1)}_{m,c} P_{m,c} + \epsilon_{m,c} \quad \text{where:} \\
N^{(i)}_{m,c} = i^{th}\text{-dimension Nokken-Poole score of member } m \text{ in Congress } c \\
J_{m,c} = \text{Estimated fossil fuel extraction jobs in } m\text{'s district in the first year of } c \\
P_{m,c} = \mathbf{1}\{m \text{ is a Democrat in Congress } c\} \\
\epsilon_{m,c} isanerrorterm
\end{aligned}
$$

Note that, in order to make sure the $P_{m,c}$ variable is correctly classifying partisan differences, we remove the handful of independent elected officials from our dataset. Otherwise, independents like Bernie Sanders that tend to vote very similarly to many Democrats would be classified along with Republicans, possibly creating outliers with outsize effects on the model.

In defining this regression, we sought to find the best fit for the first model, which uses data from 1989-1994. Since we wanted to compare influence of different predictor variables over time, we then applied this same model to each time period. The regression diagnostic plots below show why log-transforming jobs and adding an interaction variable between party and ideology was necessary to find a good fit (in each set of plots, "d" represents the Democrat indicator variable and est_jobs represents estimated fossil fuel jobs). In a linear model using raw jobs data and no interaction term, the jobs residual plot shows very clear heteroskedacticity as well as nonlinearity of residual errors. Every single variable in this model fails a Tukey test for non-additivity, indicating nonlinear relationships with residuals. In particular, the first-dimension Nokken-Poole plot shows especially intense nonlinearity After log-transforming jobs, but before adding an interaction term, we see much more linear, homoskedactic residuals for log(Jobs), but first-dimension Nokken-Poole scores still have egregiously nonlinear residuals. Adding a party-ideology interaction term makes sense in the context of the slightly steeper-looking relationship between first-dimension Nokken-Poole and LCV scores for Republicans in the 1989-1994 time period (see figure 5). This addition also helps fix the issues with first-dimension Nokken-Poole score residuals.

After log-transforming the jobs variable and adding an interaction term, unlike in previous models, every single variable's relationship with residuals passes a Tukey test for non-additivity. However, there is still evidence of heteroskedacticity and nonlinearity in the overall fitted values versus residuals plot. Moreover, the relationship between fitted values and residuals still does not quite pass a Tukey test for non-additivity, though it is much closer to doing so than the models considered above were. This apparent slightly nonlinear relationship between fitted values and residuals is likely due to the fact that LCV score values are bounded by zero and 100 and tend to skew towards these extremes (Snyder 1992, Jeong and Lowry 2021). This unusual distribution of our response variable possibly results in the heteroskedacticity observed near the extremes in the fitted values vs. residuals plot below. A quantile-quantile plot of residuals shows that their distribution is approximately normal, though with some skew at the extremes. Overall, log-transforming jobs and adding an interaction term makes the fit much more appropriately suit the key multiple regression assumptions of homoskedacticy, linearity, and normality of residuals. However, the resulting model is still imperfect.

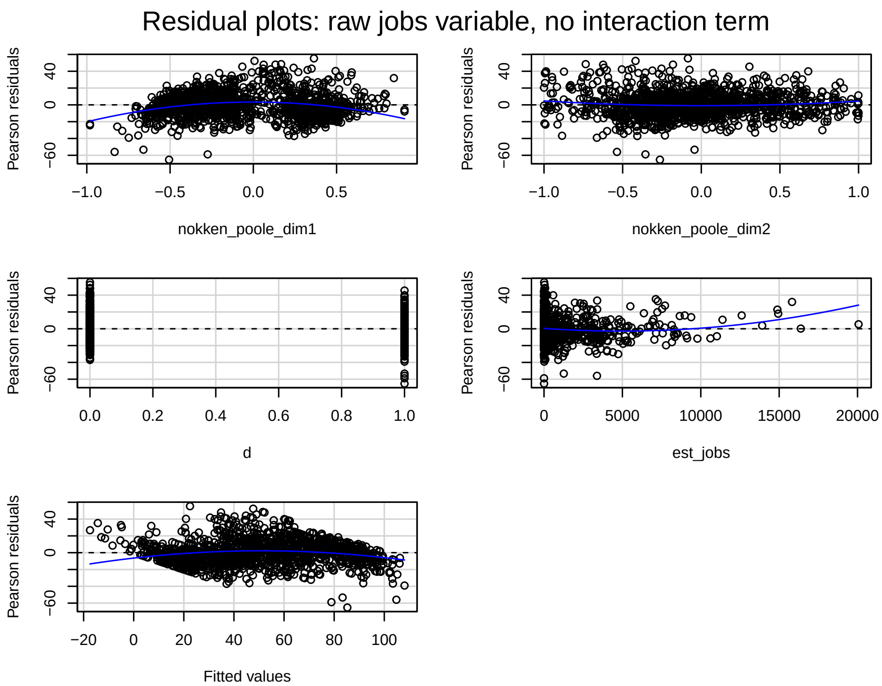

Table 6: Results of Tukey tests for non-additivity (raw jobs variable, no interaction term)

	Test stat	Pr(>|Test stat|)
N-P Dim. 1	-7.530	0.000
Democrat	2.982	0.003
N-P Dim. 2	-2.283	0.023
Jobs	3.520	0.000
Tukey test	-5.770	0.000

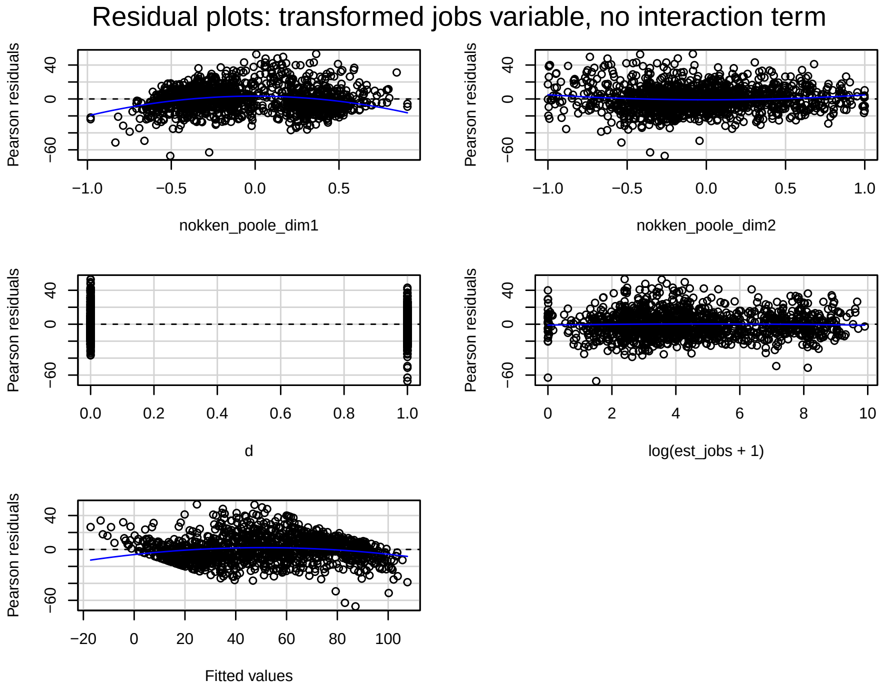

Table 7: Results of Tukey tests for non-additivity (transformed jobs variable, no interaction term)

	Test stat	Pr(>|Test stat|)
N-P Dim. 1	-7.532	0.000
Democrat	3.141	0.002
N-P Dim. 2	-2.425	0.015
log(Jobs)	-0.791	0.429
Tukey test	-5.510	0.000

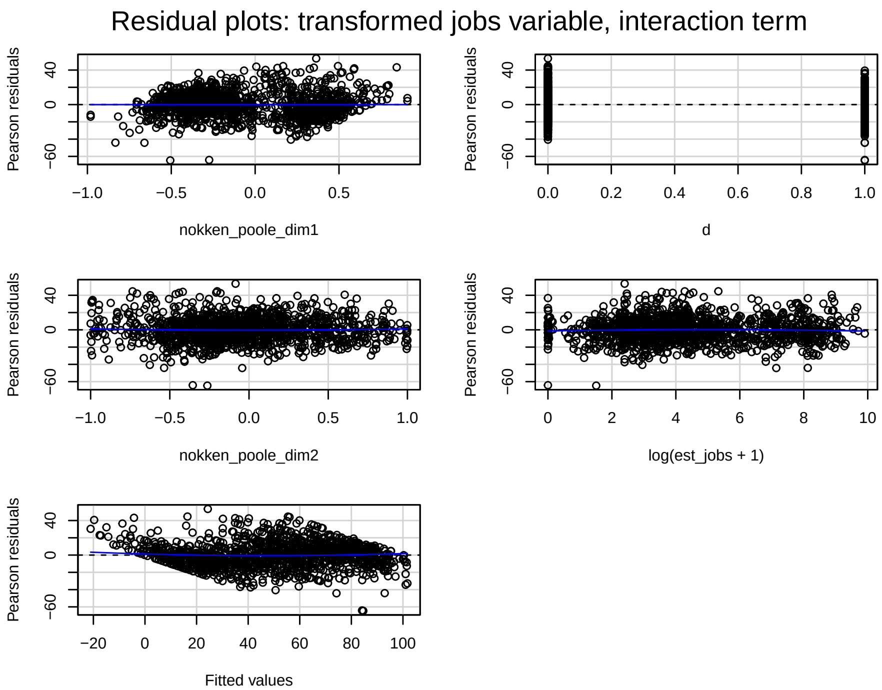

Table 8: Results of Tukey tests for non-additivity (transformed jobs variable, interaction term)

	Test stat	Pr(>|Test stat|)
N-P Dim. 1	-0.029	0.977
Democrat	-0.387	0.699
N-P Dim. 2	0.856	0.392
log(Jobs)	-1.002	0.317
Tukey test	2.044	0.041

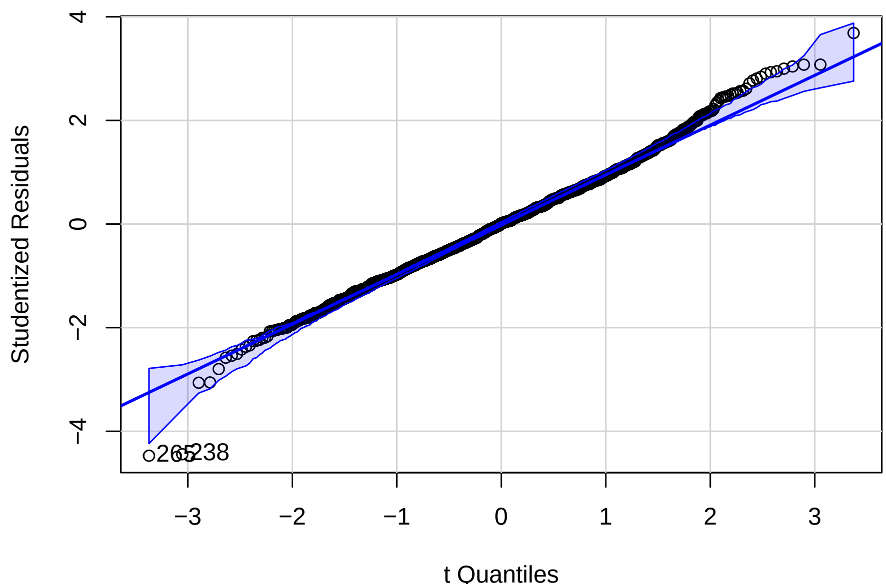

Figure 7: Quantile-quantile plot assessing normality of residuals for the 1989-1994 model fitted with a log-transformed jobs variable and an interaction term

The fit becomes increasingly flawed in later time periods, as the distribution of LCV scores becomes increasingly clustered towards zero and 100. By 2009-2016, we see troubling issues with heteroskedacticity, as well as clear evidence of non-normal residuals. Interestingly, the overall fit here does pass a Tukey test for nonadditivity. However, observation of the relationship between fitted values and residuals shows a much clearer version of the "cutoff" effect at the extremes that was already visible in the 1989-1994 time period. In addition, a quantile-quantile plot of residuals shows a very non-normal distribution, which makes interpretation of coefficients and their confidence intervals flawed. The fact that these issues increase from the first to the last time period is a reflection of the much greater environmental polarization in more recent data: as seen in figure 5 above, when LCV scores are grouped near zero and 100, it is difficult to fit a linear relationship. To maintain consistency, we use the same model for all time periods, but we keep this issue in mind. In our interpretation below, we will show that applying two modified models aiming to address the extreme clustering of LCV scores does not majorly alter our results.

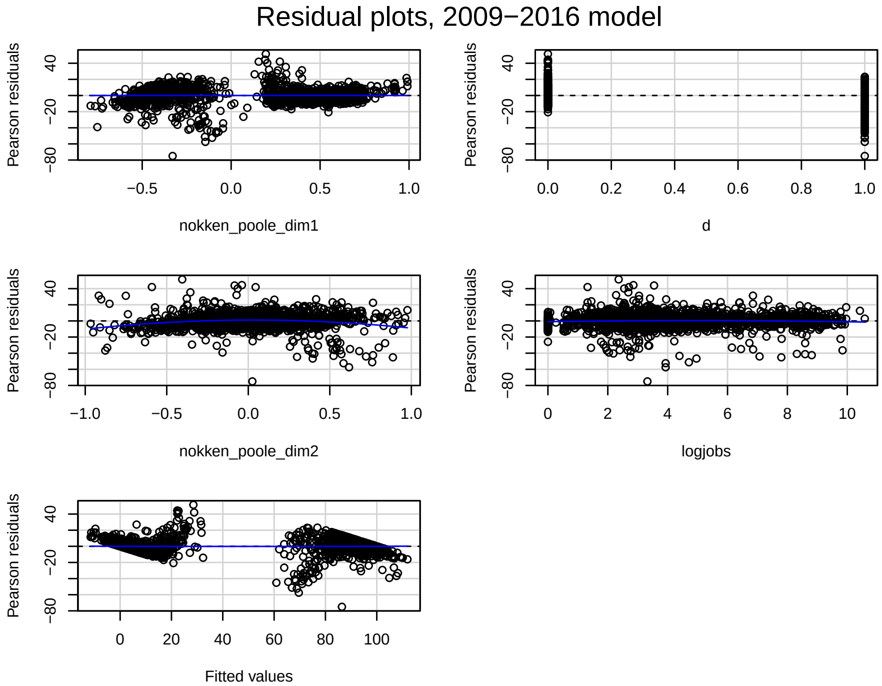

Table 9: Results of Tukey tests for non-additivity, 2009-2016 model

	Test stat	Pr(>|Test stat|)
N-P Dim. 1	0.090	0.928
Democrat	-0.949	0.343
N-P Dim. 2	-6.724	0.000
log(Jobs)	-1.511	0.131
Tukey test	0.290	0.772

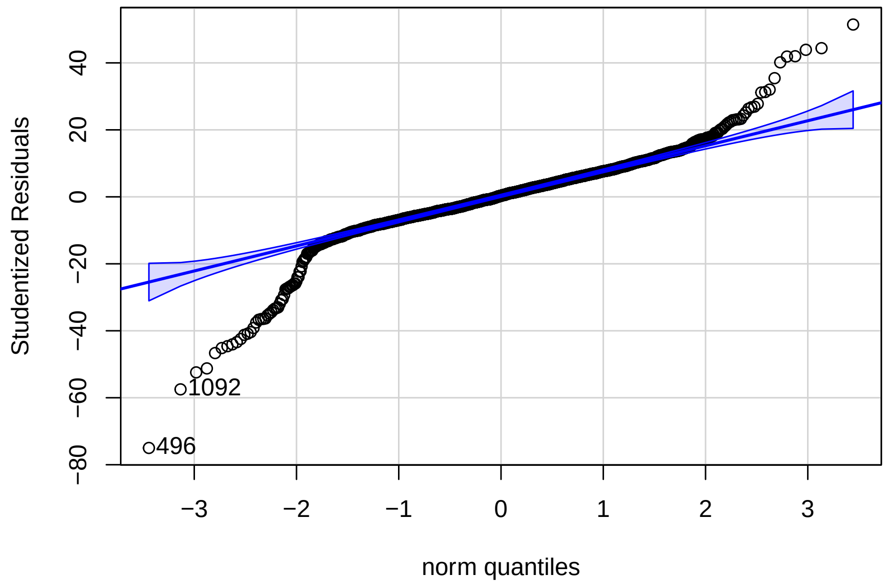

Figure 8: Quantile-quantile plot assessing normality of residuals for the 2009-2016 model

We also see some potential issues with multicollinearity of predictors, as discussed in section II above. In particular, the variance inflation factors (VIFs) of the first-dimension Nokken-Poole, party indicator, and interaction terms are rather high for the 1989-1994 model, as shown in table 10 below. However, the fact that party and liberal-conservative ideology are highly correlated is no surprise; indeed, by including the party and interaction terms, we seek to determine whether there is an effect of ideology after accounting for the closely-related variable of party. By examining VIFs for models that include only one of the first-dimension Nokken-Poole score and party indicator variables, we see that collinearity between other variables does not seem to be an issue (table 11). Thus, we are content with accepting the relationship between the predictor variables of first-dimension ideology and party.

Table 10: VIFs of predictors, 1989-1994 data

Variable	VIF
N-P Dim. 1	13.95
Democrat	7.03
N-P Dim. 2	1.61
log(Jobs)	1.24
N-P Dim 1 * Dem.	6.51

Keeping these assumptions in mind, we fit our multiple regression model to data from each time period.

Table 11: VIFs excluding either party (left) or N-P dim. 1 (right) variables, 1989-1994 data

Variable	VIF	Variable	VIF
N-P Dim. 1	1.10	Democrat	1.21
N-P Dim. 2	1.21	N-P Dim. 2	1.39
log(Jobs)	1.24	log(Jobs)	1.21

We fit one version with unscaled predictors and another in which all predictors are scaled to have standard deviation equal to one, which does not affect the significance of any results but does enable better comparison of the effects of predictors that have different spread. Examining the results, we find that district fossil fuel jobs, representative ideology, and representative partisan affiliation are all significant predictors of a representative's LCV score in every time period examined. However, the effect of fossil fuel extraction jobs significantly declined from the first time period to the last time period, while effect of the representative's party affiliation climbed dramatically. Regression results for both scaled and unscaled predictor variables across all four time periods are summarized in the tables below.

	1989-1994	1995-2000	2001-2008	2009-2016
Intercept	47.22 ***	33.30 ***	37.09 ***	30.71 ***
	(1.85)	(1.60)	(1.50)	(1.14)
Nokken-Poole Dim. 1	-62.46 ***	-32.14 ***	-46.60 ***	-41.61 ***
	(4.05)	(3.13)	(2.83)	(2.07)
Democrat	19.22 ***	28.31 ***	42.60 ***	45.95 ***
	(2.19)	(2.20)	(1.99)	(1.46)
Nokken-Poole Dim. 2	-32.34 ***	-39.29 ***	-32.01 ***	-17.05 ***
	(1.26)	(1.19)	(1.08)	(0.85)
Log(Est. Jobs)	-1.20 ***	-0.72 ***	-0.67 ***	-0.40 ***
	(0.20)	(0.17)	(0.15)	(0.11)
N-P Dim 1 * Dem.	39.76 ***	-12.03 *	26.24 ***	6.56
	(4.96)	(4.70)	(4.41)	(3.60)
N	1299	1239	1647	1740
R2	0.76	0.87	0.90	0.95

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 12: Regression results, unscaled predictors

	1989-1994	1995-2000	2001-2008	2009-2016
Intercept	47.22 ***	33.30 ***	37.09 ***	30.71 ***
	(1.85)	(1.60)	(1.50)	(1.14)
Nokken-Poole Dim. 1	-23.51 ***	-13.65 ***	-20.19 ***	-19.05 ***
	(1.52)	(1.33)	(1.22)	(0.95)
Democrat	14.84 ***	19.44 ***	29.72 ***	31.84 ***
	(1.69)	(1.51)	(1.39)	(1.01)
Nokken-Poole Dim. 2	-13.32 ***	-14.47 ***	-10.85 ***	-5.37 ***
	(0.52)	(0.44)	(0.37)	(0.27)
Log(Est. Jobs)	-5.94 ***	-3.46 ***	-3.20 ***	-1.96 ***
	(0.99)	(0.84)	(0.74)	(0.53)
N-P Dim 1 * Dem.	11.56 ***	-3.51 *	7.93 ***	2.08
	(1.44)	(1.37)	(1.33)	(1.14)
N	1299	1239	1647	1740
R2	0.76	0.87	0.90	0.95

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 13: Regression results, scaled predictors

As mentioned, all predictor variables are significant in each model, except for the interaction term in the fourth model. In each model, there is a positive relationship between the Democrat indicator and LCV score and a negative relationship between all other predictors (again, excepting the interaction term in the first and third models) and LCV score. This suggests that, across 1989-2016, status as a Democrat is associated with more pro-environmental voting, while more conservative general ideology and increased level of district fossil fuel employment is associated with less pro-environmental voting. All of these results are in line with expectations. The estimated coefficient of the interaction term describes a less clear effect: it is significantly positive in the first and third models, suggesting that the negative effect of first-dimension ideology is not as strong for Democrats as for Republicans, but significantly negative in the second model, and not statistically significant in the fourth model. Regardless of the effect of the interaction term, though, it is clear that there is a strong inverse relationship between more conservative ideology and more pro-environmental voting for both Democrats and Republicans, even after adjusting for party.

We also observe several notable trends between the time periods. First, R^2 climbs in each model, indicating that the models progressively explain more of the variance in LCV scores. This is likely due to the strengthening relationships of party and ideology with environmental voting in an increasingly polarized and unidimensional Congress: in the 1989-1994 time period, correlation between LCV score and party was 0.65, while correlation between LCV score and first-dimension Nokken-Poole score was -0.77. By 2009-2016, LCV and party correlation was 0.96, while LCV and first-dimension Nokken-Poole correlation was -0.95. In line with that trend, the estimated coefficient of the party indicator variable consistently climbed with each successive model. The coefficient of log(Jobs), meanwhile, generally decreased in magnitude, with its 2009-2016 estimate being less than one third the magnitude of its 1989-1994 estimate. Plots of our estimates and confidence intervals for the coefficients over the different time periods help elucidate these trends.

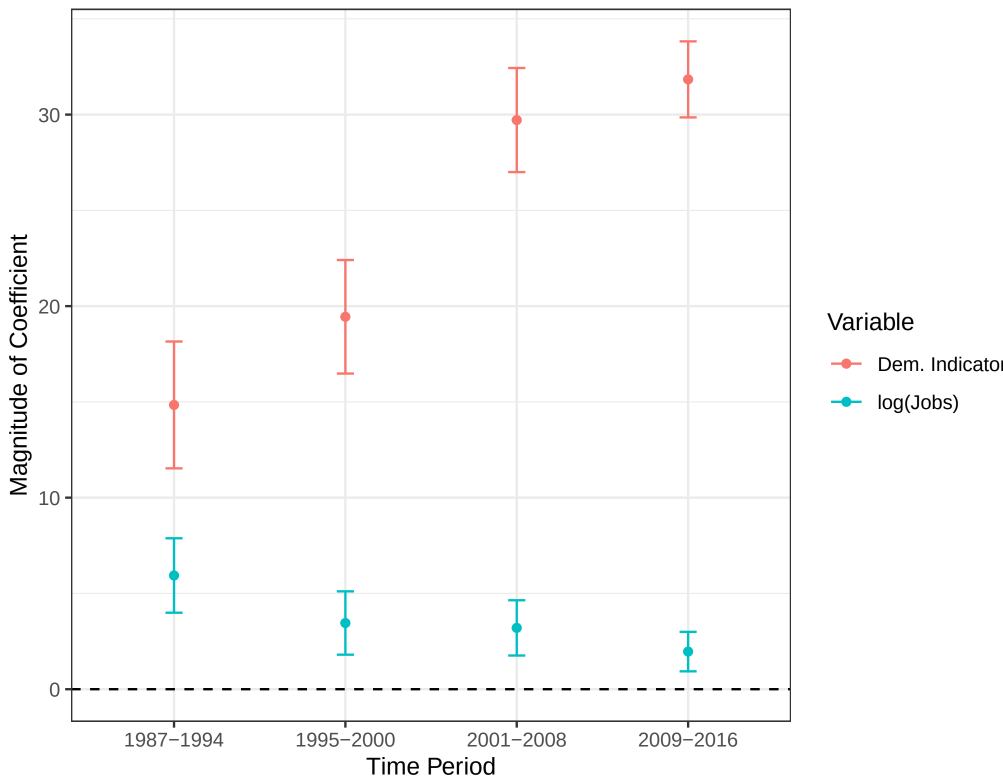

Figure 9: Magnitude of estimates and confidence intervals of party and log(Jobs) coefficients using scaled predictor variables

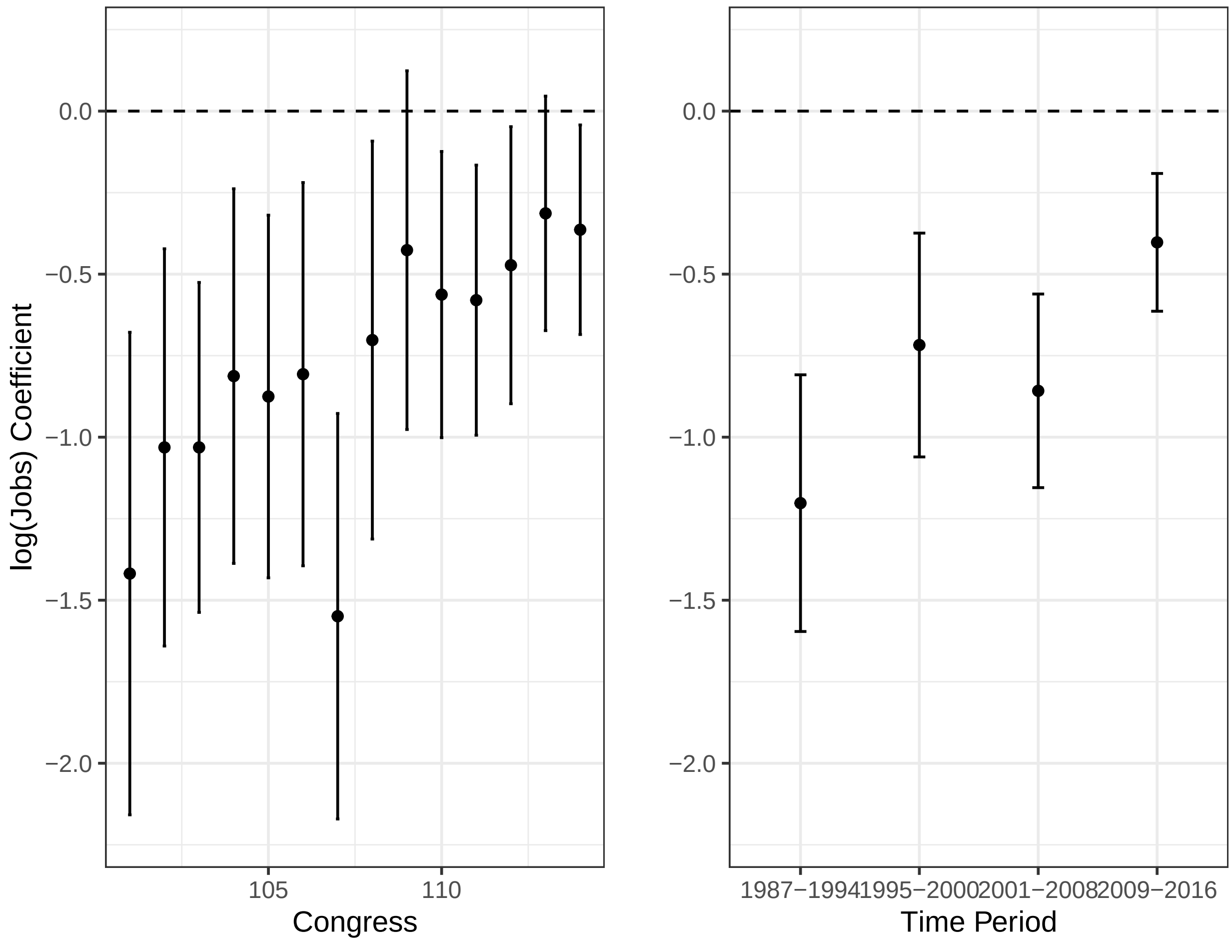

Figure 10: Estimates and confidence intervals for log(Jobs) coefficient in Congress-level (left) and time period regression models, unscaled predictor variables

Figure 9 illustrates the general decline in jobs effect and increase in party effect in models over time. Notably, we see that the the confidence intervals for the log(Jobs) coefficient in the 1989-1994 and 2009-2016 models do not overlap, so the effect of log(Jobs) was significantly lower in the final model than in the initial one. In figure 10, we show the estimates of log(Jobs) coefficient that result from fitting our model to lawmakers in each individual Congress. The trend in these models affirms the trend in the time-period-level models, with coefficient estimates successively getting closer to zero. The only major exception to this trend is in the model for the 107th Congress, which is perhaps influenced by the missing data discussed in section II. This is the only Congress for which we do not have data from Texas, a state with many high fossil-fuel-employment districts. Whatever the reason for this one seemingly anomalous Congress, the general trend of the log(Jobs) coefficient towards zero is clear. On the other hand, the effect of party climbs consistently, significantly, and dramatically across time periods, with the estimated coefficient in the 2009-2016 model more than double that in the 1989-1994 model. In particular, the effect of party is much more pronounced in the second two models, post-2000. Figure 9 shows that the confidence intervals for the two post-millenium models do not overlap with those of the two pre-millenium models.

As shown in figure 11, the trends in ideology coefficients are less clearly defined. Second dimension had a stronger effect in the 1995-2000 model, but its magnitude steadily declined in the next two models. Overall, it is much less influential in the final model, perhaps reflecting a unidimensional Congress in which first-dimension ideology generally encompasses more of every issue than second-dimension ideology does. First dimension was by far the most strongly negative in the first model, hovering around the same value in the next three. However, the interaction term was also much higher in the opposite direction in 1989-1994, so the apparent higher effect of first-dimension ideology in the first model is only actually present for Republican representatives. In general, the first dimension and interaction coefficients appear to move in opposite directions. The green dots in figure 11 represent the estimated effect of ideology for Democratic representatives, i.e. the sum of estimated first dimension coefficient and estimated interaction term coefficient. Thus, to consider the overall effect of first-dimension ideology, we should look at both the orange dots, representing effect for Republicans, and the green dots, representing effect for Democrats. With this in mind, figure 11 shows fairly level overall first-dimension effects across models. We seem to observe a declining influence of second-dimension ideology and a consistent influence of first-dimension ideology, which is consistent with expectations based on the increased unidimensional nature of Congressional voting over this period.

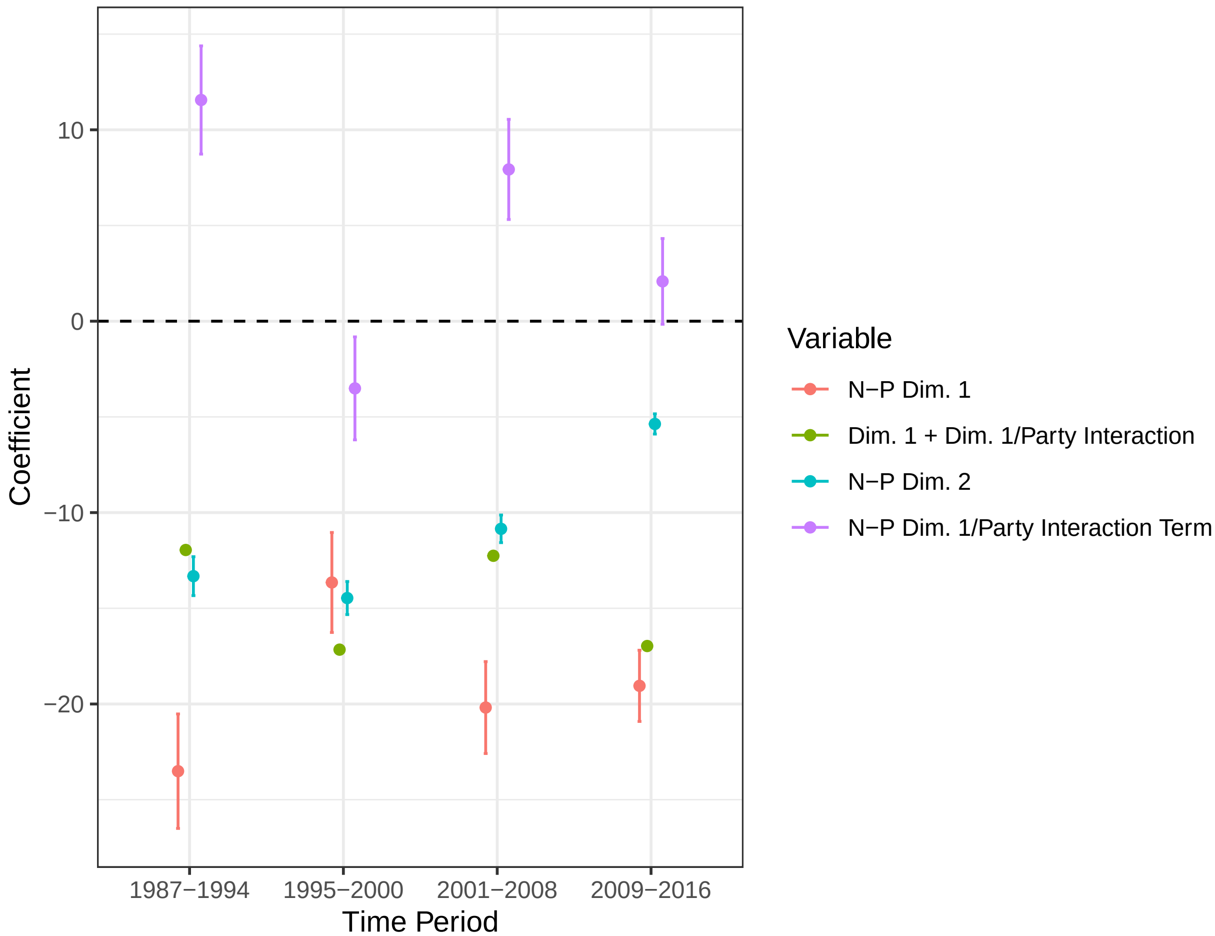

Figure 11: Estimates and confidence intervals of Nokken-Poole/interaction-term coefficients over time, scaled predictor variables. Only estimate (no confidence interval) shown for sum of first-dimension score and indicator coefficients.

These findings were robust to two other methods that attempt to account for the imperfections of our model's fit. First, following Anderson (2011), we fit a symmetric censored least squares (SCLS) regression model to the data from each time period in order to address the extreme clustering of LCV scores. This method attempts to fix issues with models whose response variables are "censored" by cutoffs above and below (here, zero and 100) by censoring the fitted response values that exceed the cutoffs (Powell 1986). However, as shown in table 14, the estimates of party and log(Jobs) coefficients given by SCLS models are similar to those given by OLS models in table 13, and they show an even greater decrease in the magnitude of the log(Jobs) coefficient.

Time Period	Dem. Coefficient	log(Jobs) Coefficient
1989-1994	14.81	-6.19

Time Period	Dem. Coefficient	log(Jobs) Coefficient
1995-2000	20.41	-3.55
2001-2008	30.55	-3.81
2009-2016	30.32	-1.80

Table 14: Coefficient estimates for the Democratic indicator variable and the log(Jobs) variable resulting from using SCLS regression (with scaled predictor variables). Note the similarity to the estimates from OLS in table 13.

To further test our results, we also use Carlson Sirvent León's metric of lawmaker environmental ideology, which aims to ameliorate some of the extreme, polarized nature of LCV scores (Carlson Sirvent León 2024). Carlson Sirvent León creates these scores by applying W-NOMINATE, a procedure similar to DW-NOMINATE, only to roll-call votes relevant to the environment. The scores measure lifetime environmental voting of members of Congress. As a result, we use standard, lifetime DW-NOMINATE scores instead of Nokken-Poole scores as predictors. All other predictors are unchanged. Figure 12 shows that, compared to LCV scores, these scores have a much less extreme-clustered distribution, and that their relationship with DW-NOMINATE scores appears much more clearly linear, especially in 2009-2016. When using these scores as the response variable, our model assigns a relatively higher weight to DW-NOMINATE scores, which makes sense given that they are created using a related procedure. Here, after accounting for ideology, party is not even a significant predictor in the first time period, and its coefficient multiplies by ten between the first and last time periods. Meanwhile, there is also a modest decline in the estimated coefficient of log(Jobs) between the two periods. So overall, the models using this response variable do not challenge the findings of our original models.

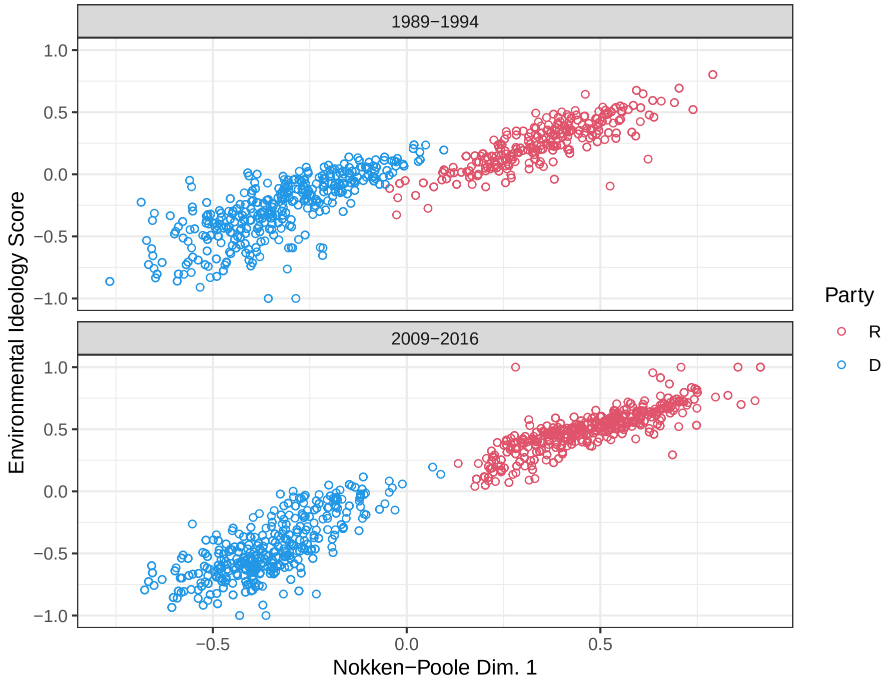

Figure 12: Scatterplots showing the relationship between DW-NOMINATE first dimension and Carlson Sirvent León's environmental ideology scores in the first and last time periods examined

	1989-1994	2009-2016
Intercept	-0.00584	-0.04590 ***
	(0.01461)	(0.01191)
NOMINATE Dim. 1	0.30450 ***	0.49010 ***
	(0.01204)	(0.01009)
Democrat	-0.00740	-0.07587 ***
	(0.01380)	(0.01045)
NOMINATE Dim. 2	0.09315 ***	0.08213 ***
	(0.00405)	(0.00271)
log(Jobs)	0.02098 **	0.01562 **
	(0.00750)	(0.00521)
Interaction	0.01415	-0.05190 ***
	(0.01135)	(0.01179)
N	1293	1738
R2	0.89528	0.96767

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 15: Regression results from using Carlson Sirvent León's measure of lawmaker environmental ideology as the response variable, 1989-1994 and 2009-2016 time periods.

IV. Interpretations and Explanations of Results

Our dataset contains evidence for at least two major trends that could help explain the apparent decrease in the importance of district fossil fuel jobs and increase in the importance of party in predicting environmental voting behavior between 1989 and 2016. One explanation for these trends is that the representation of fossil-fuel-heavy districts has become increasingly sorted to match party environmental platforms. Districts with over 1,000 fossil fuel jobs make up the top end of the jobs distribution, corresponding to the top 17% of districts in estimated jobs across the entire dataset. Democrats representing these districts were once commmon, as shown in figure 13. Given the correlation between high fossil fuel jobs and lower LCV scores, we expect these representatives to be more conservative on the environment than other Democrats. Now, almost 90% of these districts are represented by Republicans, so any pro-fossil-fuel stances that their representatives may take likely differ little from what our model would predict based on party affiliation and ideology alone.

This effect is especially notable in the South, which is home to many fossil fuel jobs and which used to elect many “blue dog” conservative Democrats, but now elects Republicans in large majorities. Jeong and Lowry (2021) show that Southern Democrats have had a moderating effect on energy policy polarization in Congress because they are more conservative on energy than the Democratic coalition as a whole. Jeong and Lowry’s analysis suggests that party realignment from Democrats to Republicans in the South has thus contributed to energy polarization. Moreover, as shown in figure 14, throughout this period, districts represented by Southern Democrats consistently had much higher average log(Jobs) numbers than districts represented by Democrats across all regions (note that, once again, the 107th Congress is an anomaly, likely because of the absence of data from Texas). Therefore, the disappearance of Southern Democrats with more conservative energy views, which overlap to a large degree with environmental views, also meant a disappearance of Democrats representing fossil-fuel-heavy districts with more conservative energy views. Figure 14 shows that, as party realignment took place in the South, the average log(Jobs) in Republican districts climbed, while that of Democratic districts dropped, and the remaining Southern Democrats also tended to represent less fossil-fuel-heavy districts. Regional party realignment also meant a realignment of parties relative to districts with major fossil fuel employment. In more recent sessions of Congress, since a large majority of the most fossil-fuel-dependent districts already have Republican representation, there is little need for district fossil fuel employment to help explain conservative environmental voting.

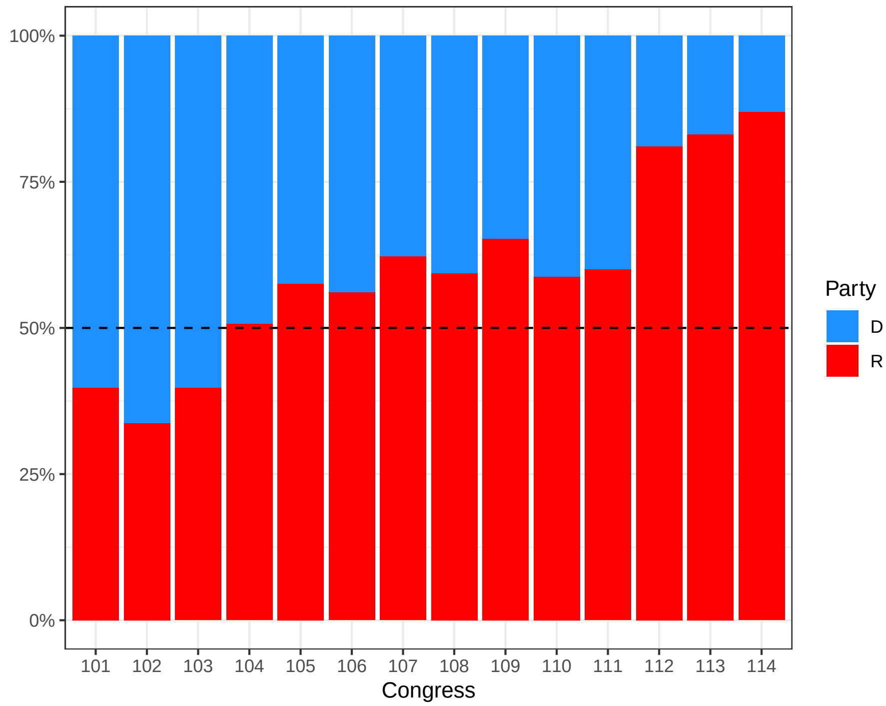

Figure 13: Changing partisan representation of districts with over 1000 fossil fuel jobs, 101st to 1114th congresses

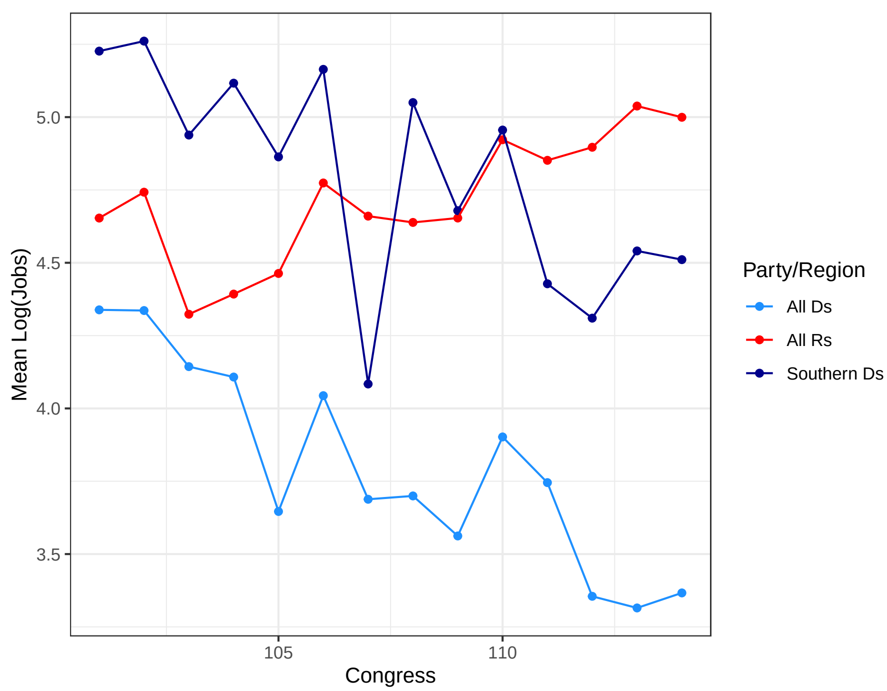

Figure 14: Mean log(Jobs) in all Democrat-represented districts, all Republican-represented districts, and Democrat-represented districts in the South, 101st to 114th Congresses. Following Jeong and Lowry (2021), the South is categorized as Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virigina

This interpretation suggests that the decrease in magnitude of our log(Jobs) coefficient is at least partly explicable by general shifts and sorting of the Republican and Democratic coalitions, meaning it does not necessarily represent a decline in the effect of constituent interests on lawmaker environmental stances. In addition to any sorting effect, though, it is clear that members of Congress have increasingly conformed to the party line on the environment, regardless of the importance of fossil fuels in their districts. Figure 15 shows how, across all possible combinations, the mean LCV scores of Democrats and Republicans with especially high or low numbers of district fossil fuel jobs uniformly trended towards party alignment. In particular, Republicans with few fossil fuel jobs and Democrats with many fossil fuel jobs have both moved away from the center and towards the rest of their parties on environmental issues. There are many possible explanations for this seeming decoupling of constituent material interests and legislator environmental voting. These include the increased polarization of ideologically-driven primary voters, interests groups, and activists aligned with both parties, all of whom may push legislators to take more extreme positions regardless of material concerns (Berguist and Warshaw 2020, Smith, Bognar, and Mayer 2024). Another potential factor is the influence of donations and lobbying, particularly from the fossil fuel industry (Smith, Bognar, and Mayer 2024, Farrell 2015).

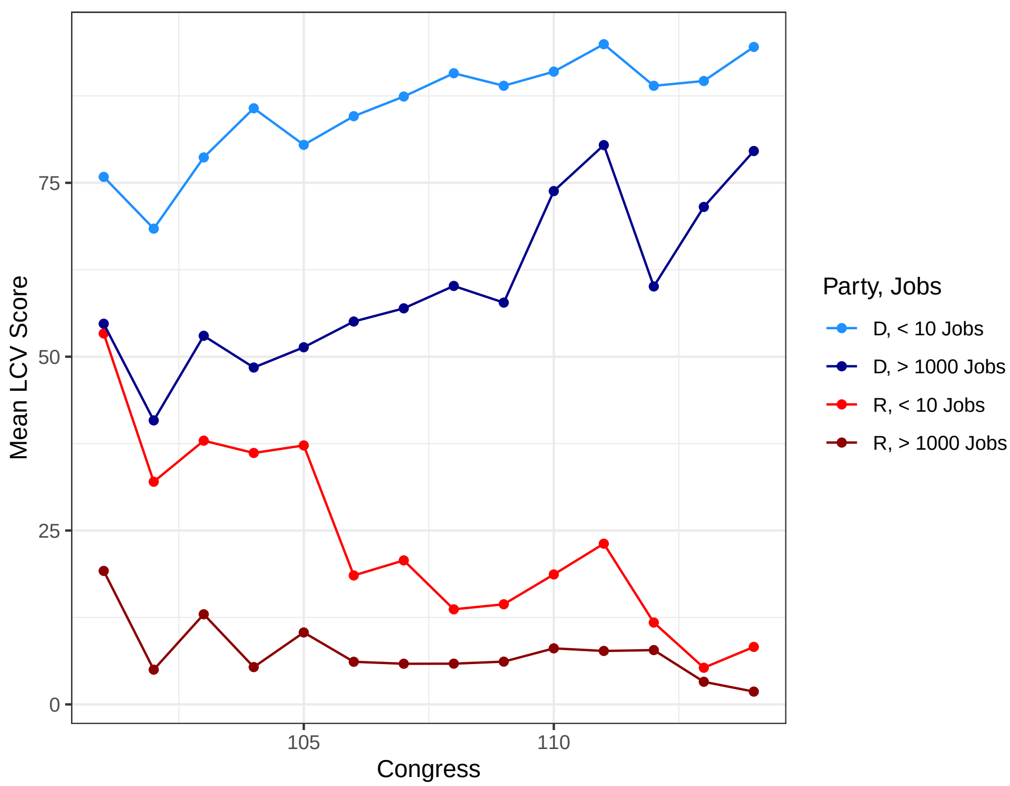

Figure 15: Mean LCV Scores of Democrats and Republicans with many (over 1,000) or few (less than 10) district fossil fuel jobs, 101st to 114th Congresses.

V. Conclusions and Recommendations

These findings give evidence for some decoupling of constituent economic interests from representative environmental voting as environmental issues became increasingly polarized between the 1980s and 2010s. However, since the end of our period of study in 2016, the landscape of environmental and energy issues in the U.S. has shifted significantly due to the increased viability of renewable energy: solar power generation in 2023 was more than eight times that in 2014, while wind power generation more than doubled over the same time period, during which the cost of renewable energy quickly declined (Climate Central 2024). As the renewable energy industry has expanded, it has employed increasing numbers of Americans, with the rate of job growth in renewable energy more than doubling that of the broader energy industry and of the economy as a whole in 2023 (U.S. Department of Energy 2024). More research will be necessary to see whether previous trends continue in this altered landscape. The rapid expansion of renewable energy in "red" states like Texas, Oklahoma, Kansas, and Iowa (Climate Central 2024) provides hope that political polarization does not preclude progress in the energy transition. The fate of the Inflation Reduction Act (IRA) under the incoming Trump administration may act as a natural case study on the how members of Congress respond to competing effects of district economic interests and party loyalty in context of renewable energy expansion. During his campaign, Donald Trump pledged to roll back the renewable energy investments of the IRA. However, even though the IRA initially passed with unanimous Republican opposition, Republican members of Congress have reportedly expressed hesitance to consider its repeal, partly due to its massive investment in their districts (Patterson 2024). If this issue comes to a vote, Republican lawmakers may be forced to decide between allegiance to Trump and prioritization of district investment. Given the unprecedented scale of the IRA's investments, even a small effect of constituent renewable energy jobs may influence legislator behavior. Either way, given the importance and increasing reality of decarbonization, the coming years are sure to bring political conflicts over environmental issues. Investigating how the influences of partisanship, ideology, and constituent benefits on legislators continue to evolve will be crucial to understanding the factors underlying these conflicts.

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