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Essays in Decisions, Institutions, and the Environment

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by

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The Dissertation of Jacob R. Johnson is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

Chair

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DEDICATION

To my family, whose love and support made this possible.

EPIGRAPH

The conservation of natural resources is the fundamental problem. Unless we solve that problem it will avail us little to solve all others.

– Theodore Roosevelt

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ABSTRACT OF THE DISSERTATION

Essays in Decisions, Institutions, and the Environment

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Professor Joel Watson, Chair

The successful implementation of environmental policies is directly related to the functioning of government institutions. As such, the study of how these institutions – and the policymakers that serve them – make decisions is an important area of research. This dissertation makes two contributions in this area; the first and second chapters provide an empirical assessment of environmental voting in the U.S. Congress while the third chapter considers some theoretical aspects of international environmental agreements. In particular, chapter one explores how the environmental preferences legislators can be estimated from voting behavior and to what degree

these estimates can inform policy questions. Chapter two targets the question how does the accounting of carbon emissions influence individual voting behavior on climate change legislation. Chapter three applies a new equilibrium concept – one that includes a formal model of negotiation – to a standard pollution abatement game.

Chapter 1

From green hawks to brown doves: A model behind the monikers of U.S. environmental politics

1.1 Introduction

The environmental preferences of legislators – as revealed by their voting records – has been a subject of interest at least since the League of Conservation Voters (LCV) began tracking and publishing the environmental votes made by members of Congress in 1971. The ratings produced by the LCV – defined as the percentage of times a legislator voted for the pro-environment position – serve at least two useful purposes. First, they provide a meaningful way to describe and compare the environmental preferences of legislators. For example, an individual who is pro-environment may direct a political contribution toward a legislator who is rated highly by the LCV. Second, the ratings represent a quantifiable measure of environmental ideology which can then be used to explore alternative theories of legislative choice. For example, one could test whether legislators who receive higher levels of environment-related political contributions also have higher rates of pro-environment voting.

Consider this second purpose. Aside from environmentally-motivated political contributions, there are likely to be a variety of factors that contribute to a legislator voting for the pro-environment position. One of these is undoubtedly the legislator's own environmental preferences. However, if environmental preferences are typically described using LCV ratings – consistent with the first purpose described above– how can one control for these preferences when trying to explain why some legislators vote more pro-environment? After all, pro-environment votes determine LCV ratings. Researchers typically solve this problem by using an alternative measure of preference. Two common examples are Americans for Democratic Action (ADA) ratings or NOMINATE scores derived using the methods of Poole and Rosenthal (1997, 1991, 1985). These are thought to provide a useful proxy for preferences that fit within the familiar spectrum ranging from the liberal-left to the conservative-right. While it is certainly true that liberals are generally more pro-environment than conservatives the relationship is not perfect. One wonders what might be gained by finding a better proxy.

The key insight of this paper comes from the recognition that estimating legislator preferences toward the environment and also determining the correlates of environmental voting need not be done separately. In fact, I demonstrate how both tasks are readily accomplished by the direct inclusion of covariates into a roll call scaling method similar to that of NOMINATE. The analysis can be considered comprehensive in that it draws on twenty years of environmental voting in both the House and Senate which were linked to data on each of the individual legislators – such as party affiliation, age, gender, election results, and political contributions – as well as to data on their constituencies – such as demographic composition, income, unemployment, and energy production. The resulting panel is comprised of nearly 160,000 observations.

The analysis makes four contributions. First, it improves on LCV ratings by combining the spatial voting model with the environmental specificity associated with LCV votes. Ratings implicitly weight each roll call vote equally which likely diminishes the significance of certain votes. In fact, the LCV will occasionally count especially important roll calls as two votes in recognition of this fact. Scaling methods account for this by modeling each roll call uniquely. Snyder Jr (1992) and Poole and Rosenthal (1991) also show that interest group ratings typically make legislators appear more extreme than is actually the case and can obscure rankings due to the frequency of ties. Furthermore, Rivers et al. (2004) point out that an additional benefit of the spatial model is that the ideological estimates produced are also accompanied by estimates of their uncertainty. Improved estimates might better serve research such as Jenner et al. (2013), Langpap and Kerkvliet (2012), and Carley (2009) which rely on LCV ratings as a proxies.

Second, by eschewing the need for ideological proxies practical issues of collinearity and measurement error are avoided. Consider Jacobsen (2013) who looks at how unemployment influences LCV ratings using ADA ratings as a control. It is certainly possible that if pro-environment voting is significantly influenced by the unemployment rate then more liberal voting – as measured by the ADA ratings – is also significantly influenced by the unemployment rate. This exact issue is the main topic of discussion in Carson and Oppenheimer (1984).[1] Additionally, when used as dependent variables, ideological proxies introduce measurement error which may lead to inconsistent parameter estimates. Although not considering the estimation of legislator preferences, Herron and Shotts (2003) find noticeable bias when inferred voting rates based on precinct returns are used in place of actual voting rates based on ballots. This result motivated Lewis and Poole (2004) to assess the degree of measurement error associated with NOMINATE scores using the parametric bootstrap. Snyder and Groseclose (2000) – who actually find that measurement error leads to very small changes in their estimates of preferences – point out that the issue is frequently ignored.[2] Clinton and Meirowitz (2003) also point out that second-stage hypotheses may not be neutral with respect to the the models generating the ideological proxies. The approach taken here capitalizes on the wisdom in Herron and Shotts (2003) who argue that "the only guaranteed way to avoid second-stage inconsistency is to avoid second stage regressions altogether."

Third, previous research on environmental voting has focused on only one or two key variables. For instance, Herrnstadt and Muehlegger (2014) are interested in Google search intensity of climate change keywords as well as weather, Jacobsen (2013) considers the unemployment rate, Cragg et al. (2013) focus on carbon emissions, Kahn (2007a) examines Green Party membership, and Kahn (2007b) looks at shocks associated with the occurrence of environmental disasters. To be sure, these

[1] From Carson and Oppenheimer (1984): "... it is obvious that while the ADA rating is correlated with [ideology] (and hence a possible proxy for [ideology]), it is also correlated with everything else in the equation [of interest], giving rise to problems of extreme multicollinearity (and its associated problems: large standard errors in parameter estimates and unreliable tests of significance)."

[2] From Snyder and Groseclose (2000): "One way to deal with this problem is simply to ignore it and proceed with least-squares estimation as if the preferences were measured without error. In fact, this is the typical approach taken in previous studies – dozens of analyses have used roll call based scores from interest groups such as the ADA, or the parameter estimates from a scaling procedure such as NOMINATE, and treated these as errorless measures of preferences or ideology."

authors also include additional covariates as controls but nothing comparable to the data used here.

Finally, measures of ideology – like LCV ratings or NOMINATE scores – are derived from roll call data alone. This makes it difficult to discern to what extent these estimates reflect voting based on a legislator's own preferences or instead reflect the preferences of their constituents. This point is emphasized in Jackman (2009), Rivers et al. (2004), Carson and Oppenheimer (1984), and Kalt and Zapan (1984).[3] By incorporating additional data it becomes possible to disentangle the very plausible relationships between the voting behavior of legislators and the characteristics of their constituencies. From a consensus-building perspective, the distinction between legislators who vote pro-environment because of their district or in spite of their district is an important one since it may provide insights on who to whip or lobby.

The reminder of the paper is organized as follows. Section 2.2 discusses the data used in the analysis. Section 2.3 develops the spatial model of voting used with the data. Section 2.4 presents the main empirical results. Section 1.5 illustrates how the methods and results can be used to inform topics related to environmental policy in Congress. Section 3.4 concludes.

[3] From Jackman (2009): "A legislator's voting record reflects a number of different influences including personal ideology, the ideology of the legislator's constituency, lobbying by interest groups, and pressure from the party leaders. Without considerably more data... the effects of each these plausible sources of influence can not be ascertained. Accordingly, [the estimates from a spatial model] should not literally be treated as a measure of a [legislator's] personal ideology."

1.2 Data

The main outcome of interest is legislative voting on the set of roll call votes identified by the LCV for the 103rd to 112th Congress.[4] Basic descriptions of the votes considered are provided in Table 1.1. For both the House and Senate votes are categorized by the environmental issue they are most relevant to. The number of times the result of the vote was consistent with the LCV's position is also shown. Apparent from the table is the relatively hostile environmental record of Congress during this period; the House voted with the LCV 38% while the Senate voted with the LCV 45% of the time. The political party of the vote's sponsor is also shown in Table 1.1. Not surprisingly, the sponsorship data on its own illustrates a clear relationship between political party and sentiments towards the environment; since 1993, Democrats have sponsored 73 percent of the roll calls identified by the LCV by as pro-environment while Republicans have sponsored 83 percent of the roll calls deemed anti-environment.

Actual voting histories for the roll calls were taken from Poole and Rosenthal's website Voteview.com. Data specific to each legislator were collected from multiple sources. Party affiliation, first dimension DW-NOMINATE scores, age, and gender were compiled by linking datasets found at Voteview.com, GovTrack.us, and Project Vote Smart.[5,6] Election results were taken from Federal Election Commission records. Announced retirements were gathered from the "casualty lists" kept by CQ

[4] As the number of climate change votes is relatively small, I added fourteen additional climate change related votes (2 in the House and 10 in the Senate) to those considered by the LCV.

[5] Some of the data provided by Voteview.com are based on research by Martis (1989).

[6] As a simplification I reclassify Independents as either Democrats or Republicans. In the Senate, Dean Barkley, Jim Jeffords, and Bernie Sanders were reclassified as Democrats. In the House, Jim Jeffords and Bernie Sanders were reclassified as Democrats while Virgil Goode was reclassified as a Republican.

Table 1.1: League of Conservation Voters Scorecard votes for the 103rd to the 112th Congress

	LCV votes by chamber				Sponsorship by party			
	House		Senate		Anti LCV		Pro LCV	
	Votes	LCV ✓	Votes	LCV ✓	D	R	D	R
Air	16	4	8	6	3	17	3	1
Clean Energy	23	17	28	9	8	9	25	9
Climate Change	17	6	21	13	3	22	11	2
Dirty Energy	25	5	29	11	8	21	21	4
Drilling	28	14	21	10	4	23	19	3
Lands/Forests	85	36	39	15	6	48	46	24
Oceans	5	2	1	0	0	3	2	1
Other	58	14	41	22	7	49	25	13
Toxics/Public Right to Know	15	6	18	2	3	16	11	3
Transportation	3	2	1	1	1	1	1	1
Water	33	12	21	12	2	21	25	6
Wildlife	17	7	8	4	2	7	9	7
Total	325	125	236	105	47	237	198	74

Notes: The LCV ✓ column provides the number of votes whose result was consistent with the LCV's position. Sponsorship totals do not match totals by chamber due to the fact that roll calls on Presidential nominations are not included.

Roll Call. Political contributions were calculated using the Campaign Finance Data tables maintained by OpenSecrets.org; these include contributions from groups with an interest in environmental policy: agribusiness, environmental groups, energy, natural resources, and transportation. Contributions from political action committees associated with the two major parties and their leaders were also kept. In the Senate only, a dummy for an election cycle and whether a senator was appointed to a vacant seat is also used.[7] The former corresponds to the Congress in which, at its conclusion, the seat is up for reelection

Complementing this legislator-specific data are constituent-specific data. Unemployment statistics are from the Local Area Unemployment Statistics series maintained by the Bureau of Labor Statistics. Race, education, income, and workforce

[7] There are no counterparts to these in the House since all seats are up reelection at the end of each Congress and Representatives are not appointed to vacant seats.

Table 1.2: Table of means

	House		Senate	
	Mean	SD	Mean	SD
Republican	0.50	0.50	0.50	0.50
DW-NOMINATE score	0.11	0.49	0.03	0.41
Age	55.17	10.02	61.01	9.94
Election margin	0.69	0.15	0.23	0.20
Female	0.14	0.35	0.12	0.33
Retire	0.05	0.22	0.07	0.25
Democrat Leadership PACs	332327.78	1720519.51	567503.76	2533599.30
Republican Leadership PACs	801578.44	4131151.62	854088.50	3845520.91
Democrat committees	262366.52	1432206.49	233463.28	5460411.74
Republican committees	159174.70	953762.40	27740.07	224747.53
Agribuisness	711770.95	2860761.58	5508370.92	77695759.08
Energy / Natural resources	941531.85	3759942.50	11733393.76	180358011.36
Environment	58631.52	835172.95	2272262.03	62422988.94
Transportation	445392.79	1360162.80	4175307.07	58798034.06
Pct. 65 or older	12.62	3.07	12.70	1.89
Pct. black	12.44	15.49	9.93	9.39
Pct. Hispanic	12.70	16.50	8.06	9.13
Pct. college degree	31.18	10.09	31.06	6.12
Pct. employed in industry	44.07	13.30	44.67	12.36
Median income (household)	51088.73	15036.44	49206.98	10707.22
Avg. unemployment rate	6.00	2.01	5.58	1.94
Energy production (fossil fuels)	1435.67	2629.95	1044.49	2031.32
Energy production (renewables)	219.92	242.95	120.60	170.13

Notes: Data sources are discussed in the text. Employment in industry is the sum of employment in construction, manufacturing, and resource extraction. College degrees include associate, bachelor, and graduate.

composition statistics are from the U.S. Census. Energy production totals – in trillions of British Thermal Units – are from the State Energy Data System maintained by the Energy Information Administration; fossil fuel production includes coal, natural gas, and petroleum products while enewable production includes ethanol, geothermal, hydro, solar, wind, and wood waste. Note that only the U.S. Census data are available at the district level; in the other cases state values are used as a substitute. Further note, that the U.S. Census data is not annual but instead updated in 1993, 1999, 2005, and 2009. For those years without an update the most recent update in the past was used.

Summary statistics for these data are provided in Table 2.1. Although I maintain the notation $\boldsymbol{x_{ij}}$ throughout this analysis, the data are in fact more accurately described as $\boldsymbol{x_{it}}$ since the indexing occurs by legislator and year. However, it is possible to refine this data even further which I demonstrate in Section 1.5.

1.3 Methods

Analysis of the data is based on the scaling methodology introduced by Poole and Rosenthal (1997, 1991, 1985). Their NOMINATE procedure – the core of which rests on the formalization of legislator choice using a spatial model of voting – has arguably become the predominant way in which ideology is measured in the social sciences. The model assumes each legislator's preferences can be represented as an an ideal point θ_i which occupies some position in an n dimensional space. The choices the legislators face – in the form of roll call votes – are also represented in this space with corresponding "yea" and "nay" positions. The theory predicts a legislator will vote for the outcome that is nearest their own position.

I make two assumptions concerning the spatial model. First, I assume that a single dimension – interpreted as a spectrum ranging from the pro-environment left to the anti-environment right – can accurately reflect environmental preferences. This assumption is very common in the literature and Poole and Rosenthal (1997, 1991) show that even when considering all the roll calls from a particular meeting of Congress, this unidimensional model fits the all data quite well. Second, I assume that the ideological positions of legislators are fixed. This assumption is relatively strong but is also consistent with the results found in Poole (2007).

Given a set of legislators $i \in \{1, ..., n\}$ and a set of roll call votes $j \in \{1, ..., m\}$ all that is required to operationalize the scaling procedure is an appropriate specification for each legislator's preferences. For example, I assume a legislator's preferences over roll call j are defined by the two utilities:

$$u_{ijy} = -||\theta_i - z_{jy}||^2 + \epsilon_{ijy} \tag{1.1}$$

$$u_{ijn} = -||\theta_i - z_{jn}||^2 + \epsilon_{ijn} \tag{1.2}$$

where z_{jy} and z_{jn} denote the "yea" and "nay" outcomes respectively and $||\cdot||$ denotes the operator for the Euclidean norm. The error terms ϵ_{ijy} and ϵ_{ijn} are assumed to be independent and identically distributed type I generalized extreme value random variables:

$$\epsilon_{ijy} \sim \text{GEV}(\mu, \sigma_j, 0) \tag{1.3}$$

$$\epsilon_{ijn} \sim \text{GEV}(\mu, \sigma_j, 0) \tag{1.4}$$

so that the probability of a legislator i voting "yea" on rollcall j is:

$$\text{P}(\text{"yea" on roll call } j) = \text{P}(u_{ijy} > u_{ijn}) = \text{logit}^{-1}(\beta_j \theta_i - \alpha_j) \tag{1.5}$$

where $\beta_j = \frac{2(z_{jy} - z_{jn})}{\sigma_j}$ and $\alpha_j = \frac{(z_{jy}^2 - z_{jn}^2)}{\sigma_j}$.[8]

A similar specification as (2.20) has also been used in Clinton and Jackman (2009), Bertelli and Grose (2009), Bafumi et al. (2005), Clinton et al. (2004), Bailey (2001), and Jackman (2001, 2000a,b). In each of these papers, estimation and

[8] This is a logit model with an unobserved regressor θ_i. It can also be interpreted as an item-response model with two-parameters.

inference are based on Bayesian or Markov Chain Monte Carlo (MCMC) simulation. Clinton and Jackman (2009) offer a variety of reasons why a researcher conducting roll call analysis might prefer the Bayesian approach over a maximum likelihood procedure like NOMINATE. For the purposes of this paper, foremost among them is that the procedure is well-suited to the analysis of smaller sets of roll calls and it is readily altered to use additional data.

Note that because the θ_i's are unobserved in (2.20) the model is unidentified. For example, the estimates $\hat{\theta}_i$ and $\tilde{\theta}_i$ are observationally equivalent when:

$$\tilde{\theta}_i = m\hat{\theta}_i + b \tag{1.6}$$

$$\tilde{\beta}_j = \hat{\beta}_j / m \tag{1.7}$$

$$\tilde{\alpha}_j = \hat{\alpha}_j - \tilde{\beta}_j b \tag{1.8}$$

The above equations characterize what are commonly referred to as scale and location problems.[9] One reason the Bayesian approach is useful is that both these problems can be solved by specifying appropriate priors for the θ_i's. For example, in this analysis I assume that Democrats have θ_i's that are distributed normally with mean negative one and variance one while Republicans have θ_i's are that distributed normally with mean one and variance one.

Additionally, I use a post-estimation transformation consistent with Bafumi

[9] Economists might better understand this by noting that the ideal points are similar in nature to a preference relation defined using ordinal utility theory. Thus, they are preserved under affine transformations.

et al. (2005) and Jackman (2000a,b) whereby the final estimates are normalized to:

$$\theta_i^F = (\theta_i - \bar{\theta})/s_\theta \tag{1.9}$$

$$\alpha_j^F = \alpha_j - \bar{\theta}\beta_j \tag{1.10}$$

$$\beta_j^F = s_\theta \beta_j \tag{1.11}$$

where $\bar{\theta}$ and s_θ are the mean and standard deviation of the raw θ_i's.

1.3.1 Basic model

The first specification I consider is the basic one given by:

$$\text{P}(\text{"yea" on roll call } j) = \text{logit}^{-1}(\beta_j \theta_i - \alpha_j) \tag{1.12}$$

$$\theta_i \sim \begin{cases} \mathcal{N}(\text{-}1, 1) & \text{if legislator } i \text{ is a Democrat} \\ \mathcal{N}(1, 1) & \text{if legislator } i \text{ is a Republican} \end{cases} \tag{1.13}$$

$$\alpha_j \sim \mathcal{N}(0, 25) \tag{1.14}$$

$$\beta_j \sim \mathcal{N}(0, 25) \tag{1.15}$$

This serves as a reduced form benchmark of the spatial model and is similar to the one implemented by default using the `ideal()` function built for `R` by Jackman (2015).

1.3.2 Hierarchical model

The next specification incorporates the data described in Table 2.1 is via a hierarchical model for the θ_i's. Such a specification is consistent with the notion of "constituent capture" discussed in Kalt and Zapan (1984) whereby a legislator's ideal point is presumed to be a function of the characteristics of their constituency. Formally:

$$\text{P(“yea” on roll call } j) = \text{logit}^{-1}(\beta_j \theta_i - \alpha_j) \tag{1.16}$$

$$\theta_i \sim \mathcal{N}(\mu_i, 1) \tag{1.17}$$

$$\mu_i = \gamma_0 + \gamma_1\, \mathcal{I}_i^R + \bar{\boldsymbol{x}}_{\boldsymbol{i}}'\boldsymbol{\delta} \tag{1.18}$$

$$\alpha_j \sim \mathcal{N}(0, 25) \tag{1.19}$$

$$\beta_j \sim \mathcal{N}(0, 25) \tag{1.20}$$

$$\gamma_0 \sim \mathcal{N}(\text{-}1, 1) \tag{1.21}$$

$$\gamma_1 \sim \mathcal{N}(2, 1) \tag{1.22}$$

$$\boldsymbol{\delta} \sim \mathcal{N}(0_k, 25 \times I_k) \tag{1.23}$$

where $\mathcal{I}_i^R$ is an indicator for being a Republican, k is the number of regressors included in $\bar{\boldsymbol{x}}_{\boldsymbol{i}}$, 0_k is an $k \times 1$ vector of zeros, and I_k represents the $k \times k$ identity matrix. The data included in $\bar{\boldsymbol{x}}_{\boldsymbol{i}}$ are modified from the data described in Table 2.1 by averaging $\boldsymbol{x_{ij}}$ over j.[10] The priors for γ_0 and γ_1 provide a similar effect as the priors used for the θ_i in the basic model.

1.3.3 Alternative model

As noted earlier, several papers emphasize that ideological estimates in the absence of additional data should not necessarily be interpreted as measures of per-

[10] In the economics literature, a similar version of this specification is often referred to as Chamberlain's random effects probit model. Although presented in the context of inference based on maximum likelihood, Chamberlain (1980) observes in the original paper “This approach introduces additional information and is most naturally formulated in Bayesian terms.”

sonal ideology. This provided part of the motivation for the analyses found in Carson and Oppenheimer (1984) and Kalt and Zapan (1984). In both cases, the authors were essentially interested in a model like:

$$v_{ij} = f(\theta_i + \boldsymbol{x}'_{ij}\boldsymbol{\delta}) \tag{1.24}$$

where vote v_{ij} is function of personal ideology and other relevant data. Recognizing that θ_i is unobserved both papers propose two-stage methods to estimate it. Carson and Oppenheimer (1984) propose a proxy for personal ideology based on the the correlated portion of the residuals from (1.24) using even and odd years separately. Kalt and Zapan (1984) propose first estimating:

$$\theta_i^{\text{LCV}} = \boldsymbol{x}'_i\boldsymbol{\zeta} + \nu_i \tag{1.25}$$

and then proxying for personal ideology in (1.24) using the residual from (1.25):

$$\hat{\theta}_i = \theta_i^{\text{LCV}} - \boldsymbol{x}'_i\hat{\boldsymbol{\zeta}} \tag{1.26}$$

This "splits" ideology into a constituent-specific component $\boldsymbol{x}'_i\hat{\boldsymbol{\delta}}$ and a legislator-specific component $\hat{\theta}_i$.[11]

Using the spatial model, a similar interpretation can be specified by altering

[11] From Kalt and Zapan (1984): "In the following analysis we assume that [measures of senatorial ideology... stand in for a detailed list of constituent characteristics]. We [split] measured ideology into that part that can be explained by constituent characteristics and the remaining senator-specific component. Our primary object is to examine whether the latter has any explanatory power."

the utilities to:

$$u_{ijp} = -||\theta_i - z_{jp}||^2 + \boldsymbol{x'_{ij}}\boldsymbol{\delta^p} + \epsilon_{ijp} \tag{1.27}$$

$$u_{ija} = -||\theta_i - z_{ja}||^2 + \boldsymbol{x'_{ij}}\boldsymbol{\delta^a} + \epsilon_{ija} \tag{1.28}$$

where z_{jp} and z_{ja} denote the "pro" and "anti" LCV outcomes respectively. A legislator's utility for a given outcome now depends on both the distance of that outcome from their ideal point and the data in $\boldsymbol{x_{ij}}$. The alternative model is then defined as:

$$\text{P(“pro” on roll call } j) = \text{logit}^{-1}(\beta_j\theta_i - \alpha_j + \boldsymbol{x'_{ij}}\boldsymbol{\delta}) \tag{1.29}$$

$$\theta_i \sim \begin{cases} \mathcal{N}(\text{-}1, 1) & \text{if legislator } i \text{ is a Democrat} \\ \mathcal{N}(1, 1) & \text{if legislator } i \text{ is a Republican} \end{cases} \tag{1.30}$$

$$\alpha_j \sim \mathcal{N}(0, 25) \tag{1.31}$$

$$\beta_j \sim \mathcal{N}(0, 25) \tag{1.32}$$

$$\boldsymbol{\delta} \sim \mathcal{N}(0_k, 25 \times I_k) \tag{1.33}$$

where k is the number of regressors included in $\boldsymbol{x_{ij}}$, 0_k is an $k \times 1$ vector of zeroes, and I_k represents the $k \times k$ identity matrix. Note that in (1.29):

$$\boldsymbol{\delta} = \boldsymbol{\delta^p} - \boldsymbol{\delta^a} \tag{1.34}$$

and thus represents the net incentives to vote "pro" corresponding to each of the regressors in $\boldsymbol{x_{ij}}$. This may lead to indeterminacy since $\delta_k = 0$ does not necessarily imply that $\delta_k^p = 0$ and $\delta_k^a = 0$. However, one might reasonably expect these effects to be mutually reinforcing. For example, if environment-related political contributions

Table 1.3: Summary of results

Model	House				Senate			
	$\bar{\theta}_{\text{Dem}}$	$\bar{\theta}_{\text{Rep}}$	Correct ✓	$\beta \neq 0$	$\bar{\theta}_{\text{Dem}}$	$\bar{\theta}_{\text{Rep}}$	Correct ✓	$\beta \neq 0$
Basic	-0.98	0.78	0.89	0.99	-0.87	0.86	0.89	0.97
Hierarchical	-0.99	0.79	0.89	0.98	-0.86	0.86	0.89	0.97
Alternative	-0.99	0.81	0.90	0.98	-0.88	0.86	0.90	0.95

Notes: The $\bar{\theta}_{\text{Dem}}$ and $\bar{\theta}_{\text{Rep}}$ columns report the average position of Democrats and Republicans. The 'Correct ✓' column reports the percentage or votes correctly predicted by the model. The '$\beta \neq 0$' columns reports the percentage of β_j's whose 95% HPD interval did not include zero.

increase u_{ijp} then presumably they decrease u_{ija}.

1.3.4 Implementation

MCMC simulation for each of the models above was implemented using `Stan` and its `R` interface `rstan` built by the Stan Development Team (2015a,b,c). For each chamber and specification, four separate MCMC chains were simulated starting from dispersed initial values. 1,000 samples from each of these chains were subsequently saved leading to a total of 4,000 samples to draw inferences from for each model. Further discussion regarding the details of the implementation can be found in Appendix 1.A.

1.4 Results

Table 1.3 presents a basic summary of the results from estimating ideology using the the three methods just described. Not surprisingly, the ideal points exhibit a bimodal distribution. In the House, the average Democrat is further left than the average Republican is right while in the Senate, the average ideal positions of each party are roughly symmetric about zero. Two assessments of model fit are shown.

The 'Correct ✓' columns provide classification statistics indicating the percentage of correct votes predicted by the models. The values are based on the standard definition where a predicted probability greater than or equal to one half is assumed to indicate a "yea" or "pro" vote. For both chambers, all the models have classification rates near 95% with the alternative specification performing slightly better than the basic and hierarchical. The '$\beta \neq 0$' column shows the percentage of the β_j's whose 90% percent highest posterior density (HPD) interval does not include zero. Jackman (2001) argues that β_j distinguishable from zero suggests that roll call j is supplying substantive content about the underlying policy dimension. In this case, the fact that so many of the β_j are distinguishable from zero lends support to using a unidimensional model.

Of course, an important point of comparison for the specifications is how they ultimately rank the legislators. Table 1.4 shows the Spearman rank-order correlations between the estimates using the three models and with the LCV ratings and DW-NOMINATE scores. Two things are apparent. First, the rankings using only LCV votes are all strongly correlated. This is an important result since it demonstrates that the ideological estimates with and without additional data are relatively stable. Second, there are clearly differences between the rankings using only LCV votes and DW-NOMINATE scores – which use all votes. This suggests that something may be lost when proxying for environmental preferences using such scores. I return to both of these points again in Section 1.5.

The precision of the estimates offers an additional point of comparison. Figure 1.1a shows how the standard deviations of the hierarchical and alternative specifications compare with the basic. In the House, the additional data leads to a modest

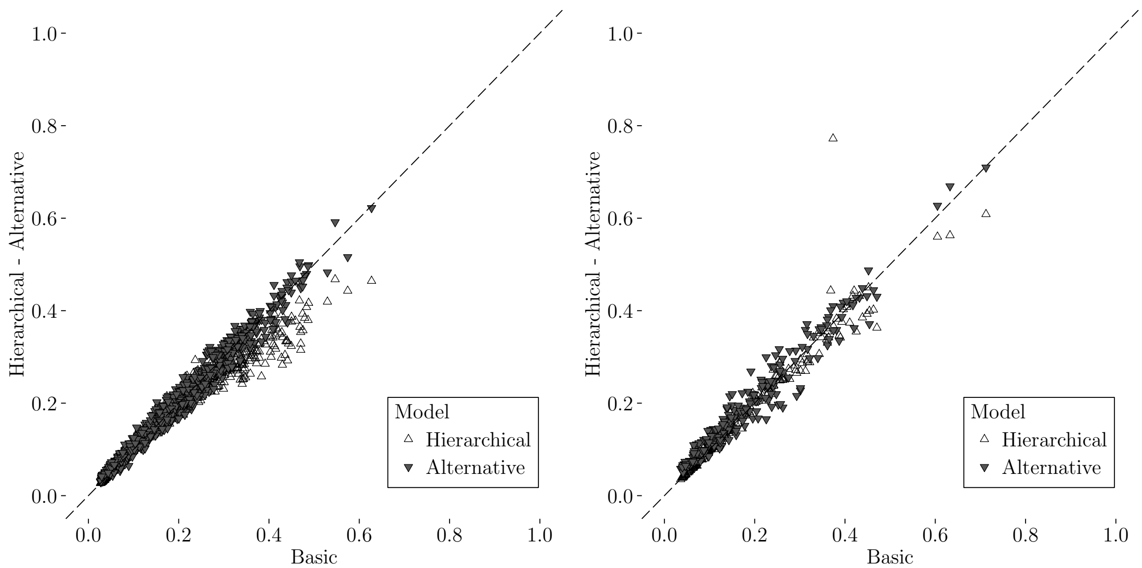
Table 1.4: Spearman rank-order correlation coefficients

Estimate	House					Senate				
	B	H	A	L	D	B	H	A	L	D
B: Basic	1.00	-	-	-	-	1.00	-	-	-	-
H: Hierarchical	1.00	1.00	-	-	-	1.00	1.00	-	-	-
A: Alternative	0.98	0.97	1.00	-	-	0.96	0.96	1.00	-	-
L: LCV Rating	0.96	0.96	0.92	1.00	-	0.97	0.96	0.92	1.00	-
D: DW-NOMINATE	0.87	0.87	0.89	0.82	1.00	0.92	0.92	0.92	0.90	1.00

Notes: A Spearman rank-order correlation coefficient of one occurs when each of the variables are a perfect monotone function of the other. To match the spatial orientation of the scaling estimates, the negative values of the LCV ratings were used.

increase in precision. As indicated by 1.1b, this result does not hold in the Senate where the precision of all three specifications are roughly the same. Both figures illustrate that the ideal points are estimated with a fair amount of uncertainty. In most cases, the higher standard deviations observed in Figure 1.1 are associated with having only a few votes to make inferences from. Regardless of magnitude, a major benefit of this approach is that this uncertainty is explicitly characterized. Consider the somewhat extreme example of representative Thomas Foley (D-WA). There is only one recorded vote made by Foley in the data set and he voted with the LCV's position in this case. Thus, his LCV rating is exactly 1. Consistent with this pro-environment vote, the posterior mean of Foley's estimated ideal point using the basic model is -0.83. However, the 95% HPD interval for his ideal point ranges from -2.01 to 0.31 indicating there is a high degree of uncertainty in his position. This of course would be expected given that only one choice has been observed but it highlights how LCV ratings can be potentially misleading.

Table 1.5 provides the posterior means, standard deviations, and 95% HPD intervals for γ_0, γ_1, and $\boldsymbol{\delta}$ in the hierarchical model. I follow the suggestion in Gelman (2008) by presenting the estimates after subtracting the mean and dividing by two



(a) House

(b) Senate

Figure 1.1: Comparison of standard deviations

times the standard deviation of each of the continuous input variables. Each coefficient can then be interpreted as the change in μ_i associated with moving from a low to high value of the observed input variable.[12] The distinguishable effects found in Table 1.5 illustrate how the ideal points of legislators are ultimately shaped by party affiliation, age, gender, political contributions, and constituent characteristics.

Immediately, one will notice that in each chamber the coefficients associated with party affiliation – the constant term and the indicator for Republican – are both distinguishable from zero. Recall that these coefficients provide the scale for the spatial model. Thus, it should come as no surprise that party affiliation has the largest single influence on the ideal points. The stronger influence of constituent characteristics in the House – as reflected by the number of parameters that are distinguishable from zero – suggests that a representative's ideology does seem to reflect the pref-

[12] For example, if this transformation were to be imposed on an indicator then the coefficient would correspond to a change from 0 to 1.

Table 1.5: Estimates of γ_0, γ_1, and $\boldsymbol{\delta}$ in the hierarchical model

	House			Senate		
	Mean	SD	95% HPD	Mean	SD	95% HPD
(Intercept)	-1.21***	0.08	(-1.37, -1.05)	-1.18***	0.17	(-1.53, -0.86)
Republican	1.51***	0.04	(1.43, 1.59)	1.46***	0.10	(1.26, 1.66)
Democrat x Age	-0.03	0.05	(-0.13, 0.06)	-0.05	0.14	(-0.31, 0.23)
Republican x Age	0.01	0.05	(-0.08, 0.10)	-0.07	0.12	(-0.32, 0.17)
Democrat x Female	-0.21***	0.06	(-0.34, -0.09)	0.15	0.19	(-0.22, 0.51)
Republican x Female	-0.11	0.08	(-0.26, 0.05)	-0.34	0.23	(-0.79, 0.10)
Democrat Leadership PACs	0.08	0.07	(-0.06, 0.23)	-0.03	0.11	(-0.25, 0.17)
Republican Leadership PACs	-0.02	0.06	(-0.13, 0.08)	0.06	0.11	(-0.15, 0.28)
Democrat committees	0.07	0.07	(-0.06, 0.20)	-0.01	0.08	(-0.18, 0.15)
Republican committees	0.01	0.05	(-0.09, 0.11)	0.01	0.11	(-0.20, 0.22)
Agribuisness	0.07**	0.04	(0.00, 0.15)	-0.17	0.99	(-2.07, 1.79)
Energy / Natural resources	-0.00	0.04	(-0.07, 0.08)	-0.15	0.82	(-1.82, 1.38)
Environment	-0.08**	0.04	(-0.15, -0.01)	-0.07	0.38	(-0.81, 0.68)
Transportation	0.01	0.04	(-0.07, 0.08)	0.25	0.56	(-0.85, 1.34)
Pct. 65 or older	-0.13***	0.04	(-0.21, -0.05)	-0.13	0.13	(-0.37, 0.12)
Pct. black	-0.20***	0.04	(-0.28, -0.11)	0.03	0.17	(-0.29, 0.35)
Pct. Hispanic	-0.31***	0.05	(-0.39, -0.21)	-0.14	0.12	(-0.37, 0.12)
Pct. college degree	-0.41***	0.07	(-0.54, -0.27)	-0.05	0.20	(-0.47, 0.33)
Pct. employed in industry	0.13***	0.04	(0.05, 0.21)	0.18	0.12	(-0.07, 0.41)
Log median income (household)	-0.00	0.07	(-0.14, 0.14)	-0.26	0.23	(-0.75, 0.18)
Avg. unemployment rate	0.18***	0.04	(0.10, 0.27)	-0.03	0.12	(-0.24, 0.22)
Energy production (fossil fuels)	0.24***	0.06	(0.14, 0.36)	0.26**	0.12	(0.03, 0.47)
Energy production (renewables)	0.12	0.07	(-0.03, 0.26)	-0.03	0.12	(-0.27, 0.22)

Notes: Dummies for U.S. Census division included but not shown. Continuous inputs are standardized by substracting their means and dividing by two times their standard deivations.
*$0 \notin$ 90% HPD; **$0 \notin$ 95% HPD; ***$0 \notin$ 99% HPD

erences of their district. By the same logic, it appears that a senator's ideology is perhaps more a reflection of their own personal preferences as opposed to those of their state. A partial explanation for this difference might be that Representatives face reelections after each meeting of Congress giving them a greater incentive to vote in manner consistent with their constituents.

Representatives who are more pro-environment receive more environment-related political contributions. They also tend to come from districts with higher percentages of people over the age of 65, higher percentages of minorities, and higher rates of educational attainment. These trends are consistent with explanations put forth in Kahn (2002) who posits that older people might support environmental preservation in order to leave a legacy, minorities might support environmental preservation because they are often disproportionately exposed to pollution, and educated people might support environmental preservation since they are more well-informed about the social costs associated with environmental degradation. Table 1.5 also shows that women tend to be more pro-environment than their male counterparts although the effect is only distinguishable for female Democrats.

Conversely, one can see in Table 1.5 that representatives who receive more political contributions from pollution-intensive sectors such as agribusiness tend to be more anti-environment. They also tend to come from districts with higher percentages of people employed in industry, higher unemployment rates, and higher levels of energy production. With the debates over many environmental policies often being framed as choices between environmental preservation or economic activity, these relationships would be expected.

Interpreting the empirical magnitudes of the coefficients in Table 1.5 is challenging given the nonlinearity of (1.16) and the fact that each roll call has its own set of estimated parameters. For example, *ceteris paribus* moving from a low to high level of the percentage of people with a college degree would change the probability of voting "yea" on roll call j by:

$$\Delta_{ij} = \text{logit}^{-1}(\beta_j(\theta_i - 0.41) + \alpha_j) - \text{logit}^{-1}(\beta_j\theta_i + \alpha_j) \tag{1.35}$$

Even if one were considering a political moderate with an ideal point of zero, (1.35) still depends on which roll call is being considered. Furthermore, one would need to know whether the LCV's position on roll call j was "yea" or "nay."

Framing the effects using the spatial dimension is more useful. For example, the same change in educational attainment would shift a Republican from the New England U.S. Census division toward the political center since:

$$\delta_{\text{(Intercept)}} + \delta_{\text{Republican}} + \delta_{\text{College}} = -1.21 + 1.51 - 0.41 = -0.11 \tag{1.36}$$

Alternatively, moving from low to high levels of the percentage of people employed in industry, average unemployment, and energy production from fossil fuels results in a similar shift for a Democrat from the New England U.S. Census division since:

$$\delta_{\text{(Intercept)}} + \delta_{\text{Industry}} + \delta_{\text{Unemployment}} + \delta_{\text{Fossil fuel}} = -1.21 + 0.13 + 0.18 + 0.24 = -0.66 \tag{1.37}$$

Both these effects are easy to interpret spatially and also seem plausible.

Table 1.6 provides the posterior means, standard deviations, and 95% HPD intervals for $\boldsymbol{\delta}$ in the alternative model. Once more the continuous inputs have been standardized by subtracting their means and dividing by two times their standard deviations. Unlike the hierarchical model, the distinguishable effects found in Table 1.6 illustrate how factors other than the ideal points of the legislators influence environmental voting. The question now is not how are these variables related to a legislator's preferences toward the environment but rather how are they related to environmental voting directly. In their analysis of a similar model, Clinton et al. (2004) refer to these effects as "inducements" since they are thought to induce legislators – regardless of their own ideological preferences – to vote one way or the other.

Table 1.6: Estimates of $\boldsymbol{\delta}$ in the alternative model

	House			Senate		
	Mean	SD	95% HPD	Mean	SD	95% HPD
Democrat x Age	-0.41***	0.05	(-0.51, -0.31)	-0.16	0.13	(-0.41, 0.10)
Republican x Age	-0.32***	0.05	(-0.43, -0.22)	-0.48***	0.13	(-0.74, -0.23)
Democrat x Appointed	-	-	-	0.48	0.48	(-0.42, 1.45)
Republican x Appointed	-	-	-	0.08	0.46	(-0.82, 0.99)
Democrat x Election cycle	-	-	-	-0.05	0.09	(-0.23, 0.14)
Republican x Election cycle	-	-	-	0.34***	0.10	(0.12, 0.53)
Democrat x Election margin	0.13***	0.04	(0.05, 0.20)	0.04	0.11	(-0.18, 0.24)
Republican x Election margin	0.02	0.04	(-0.06, 0.10)	-0.01	0.09	(-0.19, 0.17)
Democrat x Female	0.33***	0.07	(0.20, 0.48)	-0.06	0.18	(-0.40, 0.32)
Republican x Female	0.01	0.09	(-0.16, 0.19)	0.32	0.22	(-0.11, 0.75)
Democrat x Retire	-0.15**	0.07	(-0.29, -0.01)	-0.25	0.17	(-0.58, 0.07)
Republican x Retire	-0.08	0.07	(-0.22, 0.06)	0.04	0.19	(-0.33, 0.40)
Democrat Leadership PACs	-0.10***	0.03	(-0.17, -0.04)	-0.14**	0.07	(-0.27, -0.01)
Republican Leadership PACs	0.03	0.03	(-0.04, 0.09)	0.07	0.07	(-0.07, 0.21)
Democrat committees	0.01	0.02	(-0.04, 0.06)	0.57*	0.40	(-0.04, 1.35)
Republican committees	0.03	0.03	(-0.02, 0.08)	-0.11**	0.05	(-0.22, -0.01)
Agribuisness	-0.10***	0.03	(-0.16, -0.04)	-0.09	0.29	(-0.64, 0.52)
Energy / Natural resources	-0.01	0.04	(-0.09, 0.06)	-0.44	0.33	(-1.07, 0.23)
Environment	0.16***	0.05	(0.06, 0.26)	0.55	0.37	(-0.13, 1.27)
Transportation	-0.02	0.03	(-0.08, 0.04)	-0.04	0.29	(-0.62, 0.54)
Pct. 65 or older	0.14***	0.04	(0.06, 0.22)	0.61***	0.14	(0.34, 0.88)
Pct. black	0.10**	0.05	(0.00, 0.20)	-0.56***	0.18	(-0.93, -0.24)
Pct. Hispanic	0.38***	0.05	(0.28, 0.48)	0.61***	0.12	(0.37, 0.84)
Pct. college degree	0.86***	0.07	(0.71, 1.00)	-0.33	0.21	(-0.75, 0.08)
Pct. employed in industry	0.22***	0.07	(0.07, 0.36)	0.28	0.27	(-0.27, 0.77)
Log median income (household)	0.47***	0.07	(0.33, 0.61)	1.35***	0.25	(0.89, 1.85)
Avg. unemployment rate	-0.16***	0.06	(-0.27, -0.03)	0.02	0.12	(-0.24, 0.24)
Energy production (fossil fuels)	-0.30***	0.06	(-0.43, -0.19)	-0.16	0.13	(-0.39, 0.10)
Energy production (renewables)	0.06	0.08	(-0.10, 0.20)	0.10	0.14	(-0.16, 0.37)

Notes: Dummies for U.S. Census division included but not shown. Continuous inputs are standardized by substracting their means and dividing by two times their standard deivations.
*$0 \notin$ 90% HPD; **$0 \notin$ 95% HPD; ***$0 \notin$ 99% HPD

In the House, covariates associated with an increased probability of voting pro-environment include: environment-related political contributions, the percentage of people over the age of 65, the percentage minorities, the percentage with a college degree, and the log of median household income. This latter relationship is consistent with the Environmental Kuznets Hypothesis. Curiously, the percentage of people employed in industry also correlates positively. Covariates associated with a decreased probability of voting pro-environment include: political contributions from agribusiness, the average unemployment rate, and energy production from fossil fuels.

In the Senate, covariates associated with an increased probability of voting pro-environment include: the percentage of people over the age of 65, the percentage of Hispanic people, and the log of median household income. One can see this latter effect is quite strong. Covariates associated with a decreased probability of voting pro-environment include only percentage of black people.

The variables that have been interacted with party merit a separate discussion. Perhaps the most natural way to interpret these coefficients is to assume that each variable has a heterogeneous effect on voting which depends on party. For example, Democrats in the House with stronger election performances tend to vote more pro-environment and Republican senators tend to vote more pro-environment during election years. An alternative explanation for these effects is that party influence depends on the characteristics of the legislators themselves. This interpretation is consistent with the analysis of Snyder and Groseclose (2000) and Clinton et al. (2004) and may be more suitable in some cases. For example, Table 1.6 shows that older legislators tend to vote more anti-environment. Rather than being interpreted as a decline in support for environmental policy as legislators age, this could instead indicate that older members receive more pressure from their party to vote anti-environment. If the LCV's positions are relatively extreme then this explanation would be consistent with the idea that older – and possibly more experienced – legislators tone down their environmentalism perhaps in an effort to build a consensus.

1.5 Applications

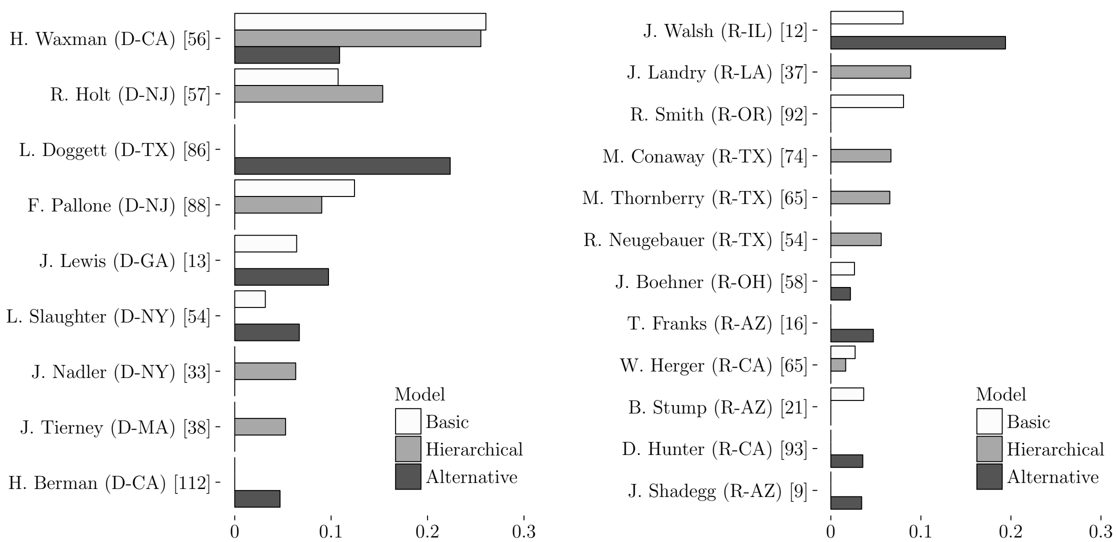
In this section, I illustrate how the estimated ideal points using the three models differ from DW-NOMINATE. In Sections 1.5.1 and 1.5.2, I draw on a nice feature of the MCMC approach which is the ability to derive posterior distributions for the rank of each legislator. These in turn can be used as a basis for identifying both extreme and moderate legislators. In Section 1.5.3, I use a parsimonious version of the alternative model to assess the role of political contributions on the passage of contentious environmental bills.

1.5.1 Extreme legislators

Rivers et al. (2004) use the basic model to assess the *National Journal's* claim that John Kerry was the most liberal Senator in 2003.[13] Here I provide similar inferences for who the most pro- and anti-environment legislators were during the 103rd to the 112th Congress. To do so, I calculated the proportion of times a given legislator occupied the most extreme positions using the 4,000 samples from each model.

Figure 1.2 and Figure 1.3 present the five legislators with the highest proportions of occupying these positions. For example, Figure 1.2a shows that Representative Henry Waxman occupies the most pro-environment position with the highest proportions – approximately 25% using the basic and hierarchical models while Lloyd Doggett does using the alternative model. In contrast, Figure 1.2b shows that the prediction for who occupies the most anti-environment position is even less sharp with

[13] Similar analyses of *National Journal* votes can be found in Clinton and Jackman (2009) and Jackman (2009).



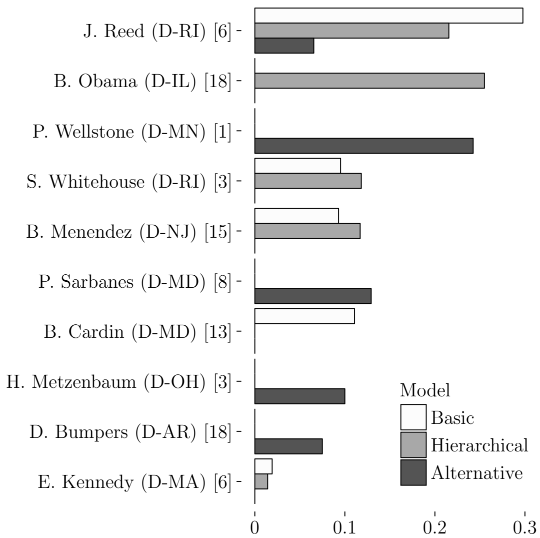
(a) Pro-environment (b) Anti-environment

Figure 1.2: The most pro- and anti-environment representatives during the 103rd to 112th Congress

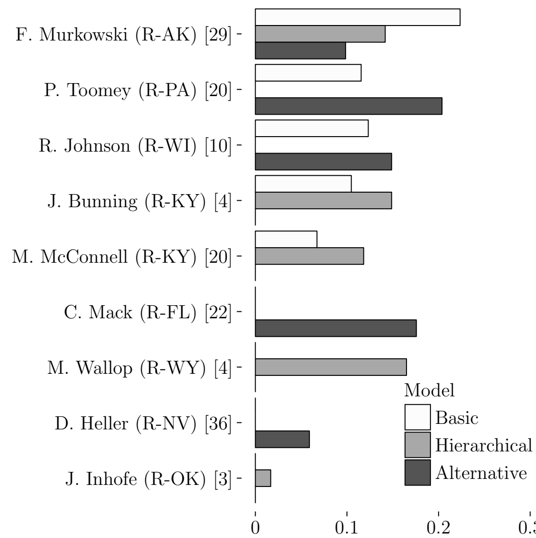
Notes: The x-axis shows the percentage of samples that the legislator listed on the y-axis occupied the most extreme position. Legislators sorted by total frequency across the three models. Average rank of the legislator's DW-NOMINATE score shown in $[\cdot]$.

each of the models favoring a different Representative. Figure 1.3a shows that in the Senate, Jack Reed occupies the most pro-environment position using the basic specification, Barack Obama does using the hierarchical specification, and Paul Wellstone does using the alternative specification. Similarly, in Figure 1.3b one can see that Frank Murkowski occupies the most anti-environment position using the basic model, Jim Bunning does using the hierarchical model, and Patrick Toomey does using the alternative model.

Importantly, both figures illustrate two things. First, that there is a fair degree of uncertainty inherent in the estimation of these ideal points. Second, the rankings based on only the LCV votes do differ substantively from alternative measures of ideology. This is apparent by noting that the differences between these extreme rank-



(a) Pro-environment



(b) Anti-environment

Figure 1.3: The most pro- and anti-environment senators during the 103rd to 112th Congress

Notes: The x-axis shows the percentage of samples that the legislator listed on the y-axis occupied the most extreme position. Legislators sorted by total frequency across the three models. Average rank of the legislator's DW-NOMINATE score shown in [$\cdot$].

ings with the average rank of each legislator's DW-NOMINATE score. For example, Waxman is on average the 56th most liberal representative. Equally interesting in this regard is that some of these average rankings are quite close or the same. For example, Waxman and Holt, Pallone and Doggett, Thornberry and Herger, Reed and Kennedy, Whitehouse and Metzenbaum, Toomey and McConnell, as well as Bunning and Wallop each have identical average rankings. This suggests these legislators are ideologically similar both with respect to the environment and more generally.

Analyzing these extreme positions also allows for a qualitative assessment of model fit. For example, it is worth noting that the two committees responsible for environmental quality in Congress – the House Committee on Energy and Commerce and the Senate Committee on Environment and Public Works – are both well-represented in Figure 1.2 and Figure 1.3. In the House, Waxman was formerly the ranking member and Pallone is now the current one. In the Senate, Cardin, Metzenbaum, Obama, Whitehouse, and McConnell were all members at one point.

Attitudes toward climate change – a common bellwether for environmental ideology – also adds plausibility to these names. In the House, Waxman sponsored numerous pieces of legislation aimed at addressing climate change including co-sponsoring the American Clean Energy and Security Act (commonly known as the Waxman-Markey bill). Rush Holt – a Ph.D. physicist – is now the chief executive officer of the American Association for the Advancement of Science (AAAS) which recently took the rare step of becoming a policy advocate in regards to climate change. In the Senate, Sheldon Whitehouse recently sponsored the American Opportunity Carbon Fee Act and has delivered weekly speeches on the Senate floor urging legislators to act on climate change.[14] Obama – although acting as President – is instituting strict standards on coal-fired electricity plants. Conversely, McConnell (2015) has advocated that states oppose such an initiative arguing that the administration lacks the appropriate legal authority.

1.5.2 As The World Burns

In *As The World Burns*, Lizza (2010) chronicles the efforts of the so-called Three Amigos – Senators John Kerry, Joseph Lieberman, and Lindsey Graham – to pass companion legislation to the American Clean Energy and Security Act during the 111th Congress. It describes in detail how the Senators attempted to build a coalition of support for their draft legislation – the American Power Act – only to

[14] The series is known as "Time to Wake Up."

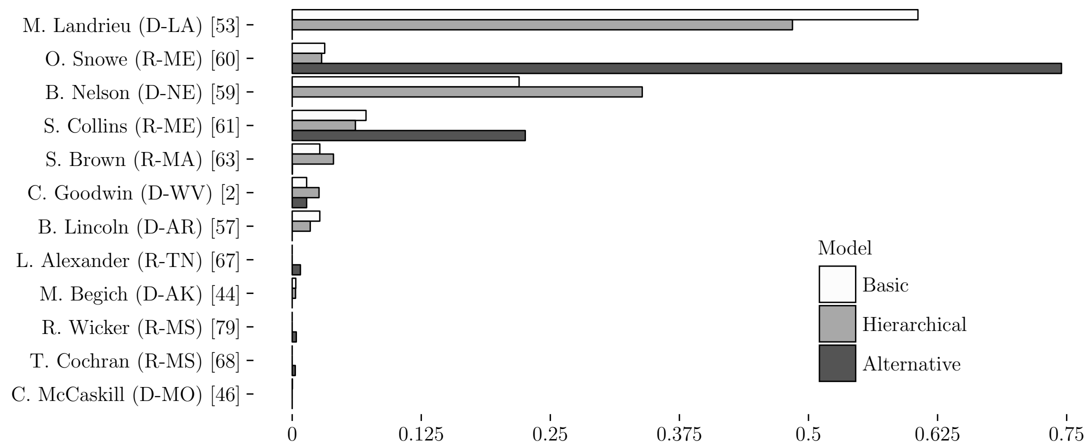


Figure 1.4: Identity of the filibuster pivot in the 111th Senate

Notes: The x-axis shows the percentage of samples that the legislator listed on the y-axis occupied the 60th most pro-environment position. Average rank of the legislator's DW-NOMINATE score shown in [·].

see it ultimately fail to even be referred to committee. Explanations for this outcome include a lack of support from a Presidential administration weakened by fighting for healthcare, pressure from the Tea Party on potential Republican supporters, and significant demand for concessions by other Senators and special interest groups.

The subtitle of the article suggests that the Senate missed its "best chance" to address climate change since the Three Amigos seemed – at least initially – capable of getting sixty senators to support their proposal.[15] In an op-ed for the *New York Times*, Kerry and Graham (2009) acknowledge the sixty vote threshold explicitly as a precondition for any bill's subsequent passage and emphasize the importance of bipartisanship in this regard. Aside from Graham, Lizza discusses how the Three Amigos actively sought – and anticipated – support from Republican moderates Scott Brown, Susan Collins, George LeMieux, and Olympia Snowe.

[15] The sixty vote threshold is significant since it is required to invoke cloture and thereby overcome a filibuster.

In the context of this analysis, Lizza's "best chance" conclusion generates two testable hypotheses. First, was the the 111th Senate more pro-environment than other recent sessions? Second, were the Republican moderates being sought for likely to be pivotal? Affirmative answers to both of these questions would certainly support the notion that an important opportunity was missed.

With respect to the first question, the answer seems to be yes. Regardless of specification, the 111th Senate ranks first in terms of most pro-environment mean, median, and 60th quantile. Of course, the 111th Senate was also comprised of 58 Democrats, one Independent, and 41 Republicans; only the 103rd Senate had a comparable Democratic majority.

With respect to the second question, the answer is less definitive. Figure 1.4 illustrates why this is the case by showing the proportion of times an individual senator occupied the 60th most pro-environment position. The alternative model - as well as the DW-NOMINATE scores – support the conclusion that Collins or Snowe were likely to occupy the filibuster pivot. However, the basic and hierarchical models point to Mary Landrieu or Ben Nelson. One explanation for this difference is that the alternative model is providing an estimate for personal ideology which fails to account for other factors that might further influence voting. For example, the alternative model ranks Landrieu 53rd but this is before accounting for the fact that she was one of the top recipients of energy-related political contributions which – as Table 1.6 – shows correlates negatively with pro-environment voting. Interestingly, she was one of only four Democrats who voted against invoking cloture on a filibuster of the Lieberman-Warner Climate Act in 2008. Also worth noting is that Ben Nelson was the pivotal vote needed to pass the Affordable Health Care Act. Roberts (2010)

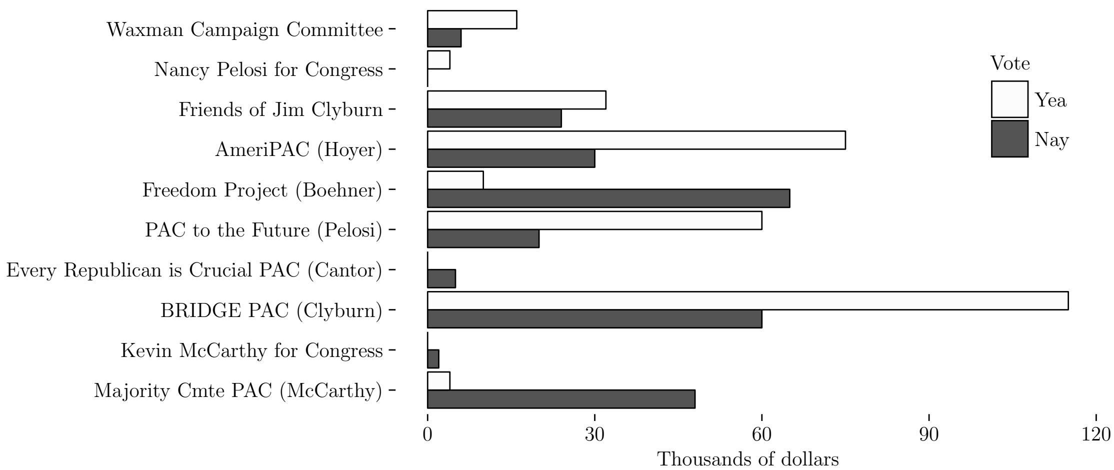


Figure 1.5: Leadership contributions during the ten days prior to the Waxman-Markey vote

Notes: Data from OpenSecrets.org

argues that "centrist Democrats" such as Landrieu and Nelson likely played a role in the legislation's failure. As opposed to Lizza, he concludes "there was probably no combination of policy and messaging that had a chance [of leading to a successful outcome]."

1.5.3 The role of political contributions

Lizza's story would be less interesting if the House had not actually passed the Waxman-Markey bill. The bill is well-known if for no other reason than it is the only piece of legislation aimed at regulating carbon dioxide to be passed in either chamber of Congress. As such, it is not surprising that the vote was controversial and passed by the narrow margin of seven votes which included three abstentions. Also not surprising is the fact that the vote was highly partisan although not perfectly so; 44 Democrats voted "nay" with one abstaining while eight Republicans voted "yea" with two abstaining.

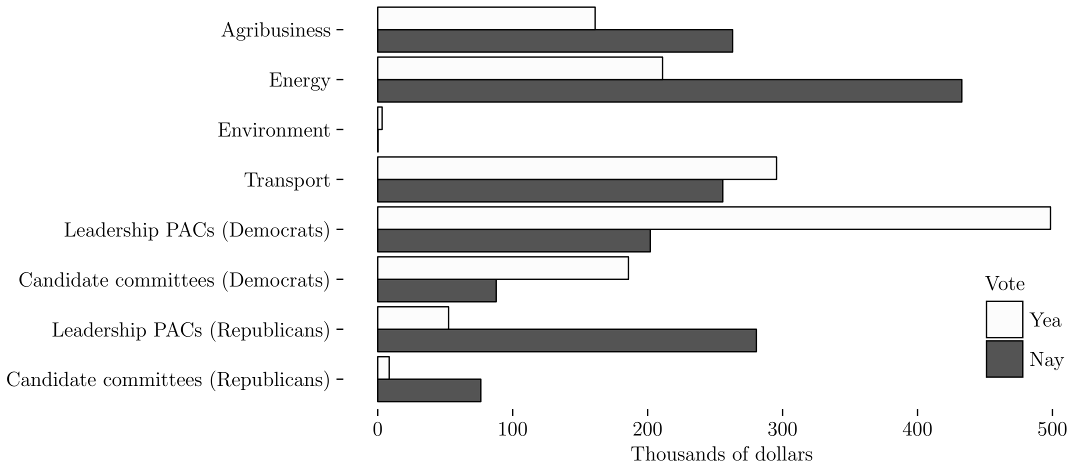


Figure 1.6: Political contributions during the ten days prior to the Waxman-Markey vote

Notes: Data from OpenSecrets.org

Thrush (2009) points out that Democratic leaders in the House made thousands of dollars in campaign donations in the days leading up to the vote. Although suggestive of "quid pro quo" behavior he notes that campaign dollars were also likely to be flowing since the the vote coincided with the end of a Federal Elections Commissions filing deadline.[16] Figure 1.5 illustrates this point. Contributions made by the bill's co-sponsor Henry Waxman, Speaker Nancy Pelosi, Majority Leader Steny Hoyer, and Majority Whip Jim Clyburn skewed towards legislators who voted for the bill's passage. Similarly, contributions made by Minority Leader John Boehner, Minority Whip Eric Cantor, and Chief Deputy Minority Whip Kevin McCarthy skewed towards those who voted against the bill. Figure 1.6 expands on this point showing that environmental contributions, although small, skewed towards supporters of the bill while contributions from agribusiness and energy skewed toward its opponents. Transportation-related contributions were distributed relatively evenly.

[16] Indeed, Thrush mentions that a spokesman for Waxman indicated that the contributions were part of normal of normal "end-of-quarter-activity."

To examine the relationship between contributions and voting more rigorously I applied a strategy similar to one used in Snyder and Groseclose (2000) and Clinton et al. (2004). First, I identified the 49 LCV votes in the House that concerned the passage of a bill which were also decided by a margin less than 60%. This captures instances where the political stakes were likely to be highest and therefore more likely to stimulate contribution activity. Next, I identified all legislators who received contributions associated with the categories listed in Figure 1.6 during the ten days prior to each of these vote.[17] These data were added to the alternative model to determine whether contributions are associated with changes in voting behavior. Formally:

$$\text{P(``pro'' on roll call } j) = \text{logit}^{-1}\left(\beta_j\theta_i - \alpha_j + \mathcal{I}^D_{ij}\boldsymbol{x'_{ij}}\boldsymbol{\delta^D_j} + \mathcal{I}^R_{ij}\boldsymbol{x'_{ij}}\boldsymbol{\delta^R_j}\right) \tag{1.38}$$

$$\theta_i \sim \begin{cases} \mathcal{N}(\text{-}1,1) & \text{if legislator } i \text{ is a Democrat} \\ \mathcal{N}(1,1) & \text{if legislator } i \text{ is a Republican} \end{cases} \tag{1.39}$$

$$\alpha_j \sim \mathcal{N}(0,25) \tag{1.40}$$

$$\beta_j \sim \mathcal{N}(0,25) \tag{1.41}$$

$$\boldsymbol{\delta^D_j} \sim \mathcal{N}(0_k, 25 \times I_k) \tag{1.42}$$

$$\boldsymbol{\delta^R_j} \sim \mathcal{N}(0_k, 25 \times I_k) \tag{1.43}$$

where $\boldsymbol{x_{ij}}$ now denotes political contribution data, $\mathcal{I}^D_{ij}$ ($\mathcal{I}^R_{ij}$) is an indicator that legislator i is a Democrat (Republican) that received a contribution prior to roll call j, k is the number of regressors included in $\boldsymbol{x_{ij}}$, 0_k is an $k \times 1$ vector of zeroes, and I_k represents the $k \times k$ identity matrix. Note that (1.38) is still identified since $\boldsymbol{\delta^D_j}$

[17] The two restrictions used to identify each vote resulted in no overlap of these ten-day periods.

Table 1.7: Party-specific political contributions and the Waxman-Markey bill

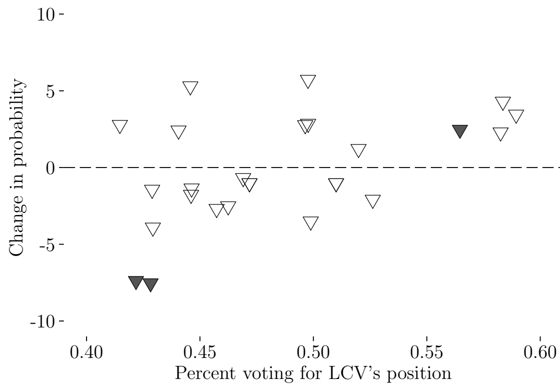
	Democrats			Republicans		
	Mean	SD	95% HPD	Mean	SD	95% HPD
α_j	1.29***	0.37	(0.61, 2.03)	1.29***	0.37	(0.61, 2.03)
β_j	-5.64***	0.78	(-7.14, -4.13)	-5.64***	0.78	(-7.14, -4.13)
Agribusiness	-0.04	0.32	(-0.67, 0.59)	-1.49	1.80	(-5.17, 1.23)
Energy / Natural Resources	0.12	0.22	(-0.30, 0.56)	-2.63	2.07	(-6.65, 0.93)
Environment	2.74*	1.62	(-0.14, 6.08)	3.74	3.10	(-2.05, 10.06)
Transportation	-0.01	0.33	(-0.64, 0.63)	-0.81	0.93	(-2.62, 0.93)
Candidate committees	-0.36	0.25	(-0.85, 0.12)	-0.77	0.94	(-2.81, 0.85)
Leadership PACs	0.14	0.17	(-0.18, 0.47)	0.72	0.53	(-0.33, 1.75)

Notes: Dummies for U.S. Census division included but not shown. Continuous inputs are standardized by substracting their means and dividing by two times their standard deivations.
*0 $\notin$ 90% HPD; **0 $\notin$ 95% HPD; ***0 $\notin$ 99% HPD

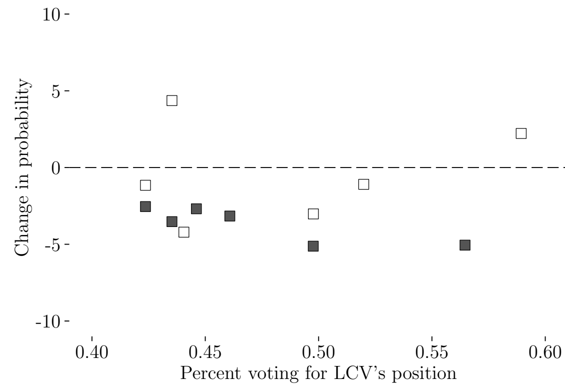
and $\boldsymbol{\delta_j^R}$ are only estimated if roll call j concerns the passage of a bill and also has a deciding margin of less than 60%. Additionally, the indicators are not exhaustive since some legislators did not receive any contributions prior these particular votes.

Table 1.7 shows the estimated party-specific relationships between receiving a low or high amount of political contributions and the probability of voting in favor of the Waxman-Markey bill. There is a positive association between environment-related contributions and voting pro for Democrates but there is no statistical evidence that supports the notion that Democrat-related contributions were associated with an increased likelihood of voting for the bill. In fact, the results are mixed. Contributions from Democratic candidate committees are associated with a decreased probability of voting "pro." while contributions from Republican leadership PACs are associated with an increased probability of voting "pro." However, neither of these relationships are distinguishable from zero.

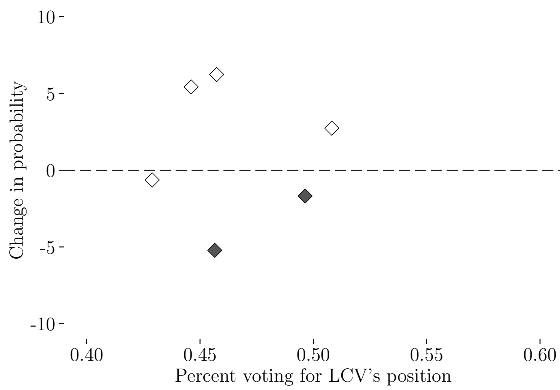
Going beyond just the Waxman-Markey vote, Figure 1.7 illustrates all the distinguishable party-specific coefficients by percentage of legislators who voted for



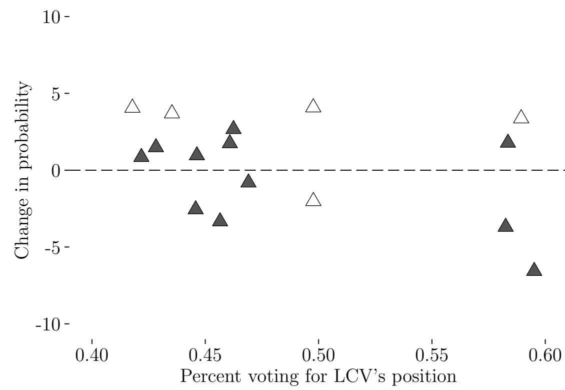
(a) Agribusiness



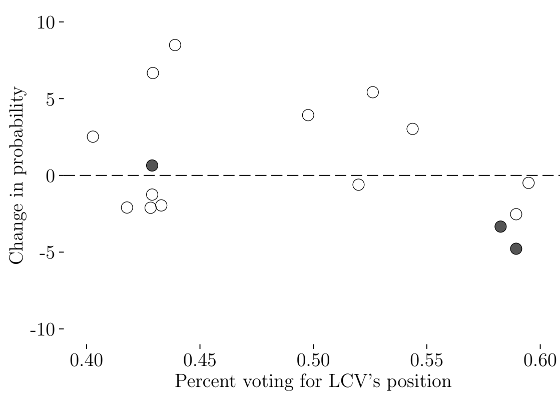
(b) Energy / Natural Resources



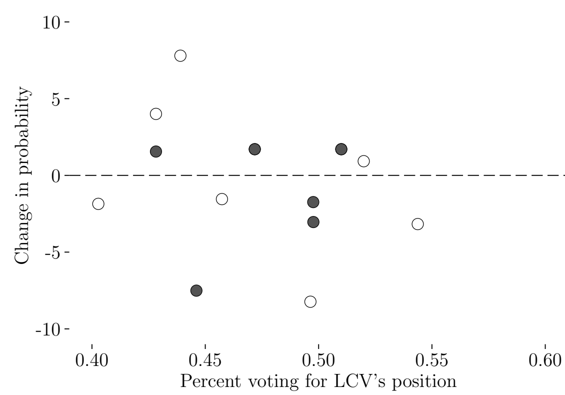
(c) Environment



(d) Transportation



(e) Candidate committees



(f) Leadership PACs

Figure 1.7: Party-specific political contributions by LCV margin and category

Notes: Solid points correspond to Republican-specific contributions. The y-axis denotes the change in the logit of the probability of voting for the LCV's position.

the LCV's position and by category. The relationships are shown as the change on the logit scale of comparing a candidate who received a low contribution to one who received a high one. Once again there is no statistical evidence that candidate committee and leadership PAC contributions are associated with Demorats and Republican voting for or against the LCV's position. Moreover, most of the other expected relationships between contributions and voting with the LCV are not prominent. For example, only energy-related contributions has the expected negative relationship with voting for the LCV and even in this case the relationship does not always hold with Democrats. Similarly, there are no roll calls where environment-related contributions to Republicans were associated with a noticeable increase in pro-environment voting. In fact, Figure 1.7 shows that there were two roll calls where environment-related contributions to Republicans were associated with decreases in the probability of voting with the LCV. Contributions from agribusiness and transportation have similarly mixed effects.

Of course, it's important to point that the relationships shown above are not causal and should not be regarded as evidence of "quid pro quo" behavior between contributors and legislators. However, the analysis does illustrate how the spatial voting model can be used to better inform conclusions that might otherwise be suggested by a graphic like Figure 1.5. In this case it would appear that although leadership contributions from each party certainly skewed toward either supporters or opponents of the Waxman-Markey bill there is little evidence to suggest that these additional dollars actually caused legislators to vote differently than would already be expected given their ideal point.

1.6 Conclusion

That the LCV has for nearly 50 years continuously produced an annual ranking of legislators based on their environmental voting record is perhaps evidence enough that people – voters, lobbyists, politicians, and researchers – are interested in environmental ideology. This in turn makes the determinants of such ideology interesting. This paper provides a concise methodology to explore these topics by harmonizing the spatial model of voting with additional variables of interest. This provides an arguably clearer description of environmental preferences and their correlates. The reasoning for this is simple: previous models of environmental voting rely on ideological proxies which are themselves derived from other models of voting. The analysis above illustrates how such redundancy is unnecessary.

1.A MCMC convergence

MCMC simulation done using `Stan` – an increasingly popular programming language which implements Bayesian inference using the No-U-Turn Sampler introduced by Hoffman and Gelman (2014). Each chain of the four MCMC chains were run for a total of 2,000 iterations with the first 1,000 iterations being used to tune the sampler. The chains were initialized by taking the random draws:

$$\theta_i^0 \sim \begin{cases} \mathcal{N}(\text{-}1,1) & \text{if legislator } i \text{ is a Democrat} \\ \mathcal{N}(1,1) & \text{if legislator } i \text{ is a Republican} \end{cases} \tag{1.44}$$

$$\alpha_j^0 \sim \mathcal{N}(0,25) \tag{1.45}$$

$$\beta_j^0 \sim \mathcal{N}(0,25) \tag{1.46}$$

In the hierarchical model, initial values for γ_0^0, γ_1^0, and $\boldsymbol{\delta^0}$ were obtained by regressing:

$$\theta_i^0 = \gamma_0^0 + \gamma_1^0\, \mathcal{I}_i^R + \boldsymbol{\bar{x}_i'\delta^0}$$

In the alternative model, initial values for $\boldsymbol{\delta^0}$ were taken from the random draws:

$$\delta_k^0 \sim \mathcal{N}(0,25) \tag{1.47}$$

where k is the number of regressors in $\boldsymbol{x_{ij}}$.

Gelman and Shirley (2011) note that two of the main difficulties with using MCMC methods – regardless of sampler – are ensuring that the chains run long enough to converge and that the samples accurately reflect the target distribution. `Stan` conveniently outputs two statistics which can help diagnosis whether these dif-

Table 1.8: MCMC convergence diagnostics

Model	Parameter	House			Senate		
		$\hat{R}$		n_{eff}	$\hat{R}$		n_{eff}
		Mean	SD	Mean	Mean	SD	Mean
Basic	α_j	1.00	0.00	1517.64	1.00	0.00	3897.39
	β_j	1.02	0.01	239.62	1.00	0.00	1422.75
	θ_i	1.03	0.04	1325.59	1.00	0.01	1813.07
Hierarchical	α_j	1.01	0.01	3008.65	1.00	0.00	3731.27
	β_j	1.00	0.00	3893.56	1.00	0.00	3967.30
	$\boldsymbol{\gamma}$, $\boldsymbol{\delta}$	1.00	0.01	3849.12	1.00	0.00	3368.97
	θ_i	1.08	0.04	209.86	1.00	0.00	2102.83
Alternative	α_j	1.02	0.01	933.06	1.01	0.00	500.74
	β_j	1.00	0.00	3599.62	1.00	0.00	2093.46
	$\boldsymbol{\delta}$	1.01	0.02	1864.34	1.00	0.00	1316.76
	θ_i	1.00	0.00	3791.24	1.01	0.01	1252.40

ficulties have been overcome.

The first statistic is the "potential scale reduction factor" originally proposed by Gelman and Rubin (1992). Generally denoted $\hat{R}$, this value measures the ratio of the average variance of the samples within each MCMC chain to the variance of the pooled samples between all the MCMC chains. If the chains were sampling from the same distribution – suggesting convergence – then this value would equal one. Gelman and Rubin (1992) recommend that each of the chains be initialized with diffuse starting values – like those above – and to continue sampling until $\hat{R}$ is less than 1.1 for all of the model parameters.

The second statistic is the effective sample size n_{eff} which estimates the number of independent samples within each chain after correcting for autocorrelation. `Stan` uses a variogram-based approach – see Stan Development Team (2015c) for a more detailed discussion – to provide these estimates.

Table 2.12 provides a summary of the two statistics. The average $\hat{R}$'s across all parameters are close to one suggesting the chains converged. Furthermore, the table shows that the 4,000 actual samples stored from the simulations generally provide several thousand effective samples for each of the parameters. It is impossible to formally demonstrate convergence but the combination of results shown above does provide some confidence that the two difficulties highlighted by Gelman and Shirley (2011) at the beginning of this section have been overcome.

Chapter 2

Consumption-based accounting of carbon emissions and its relationship to congressional climate change policy

2.1 Introduction

Most of the recent congressional bills aimed at addressing climate change have two aspects in common: they regulate carbon emissions from the electric power sector and they almost never pass. In fact, very few even result in an actual votes related to their passage.[1] For example, a search of GovTrack.us returns a total of 569 proposed bills – out of over 100,000[2] – between 1996 and 2015 which contain the subjects

[1] They may still result in other types of votes such as those concerning amendments, motions to table, and cloture motions.

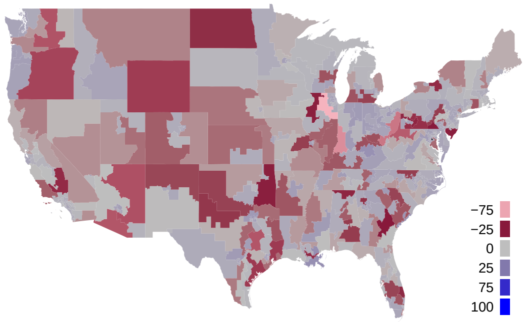
[2] Some bills are proposed multiple times or are almost identical. For example, the Lieberman-Warner Climate Security Act of 2008 appears as S. 2196 and S. 3036. The former resulted in no

"climate change and greenhouse gases" and "environmental protection." Of the 569, 114 include the word "energy" or "power" in its title. Of the 114, 17 resulted in a vote relating to their passage. Of the 17, only one included a mandatory cap on carbon emissions: the American Clean Energy and Security Act of 2009 or Waxman-Markey bill.

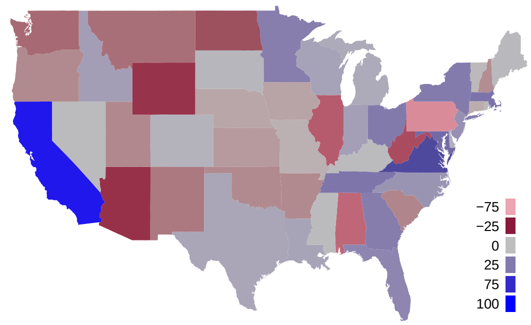
Neither of these trends are particularly surprising. Since 1980, the electric power sector has – on average – accounted for 37% of all the carbon emitted by the U.S. and it is the largest stationary source of such emissions. A lack of congressional action is also not surprising. One would expect this in general and especially on an issue as divisive as climate change. Indeed, with legislation lacking, President Obama (2013) acted by directing the Environmental Protection Agency (EPA) to begin regulating carbon emissions from power plants. At the end of last year, the EPA (2015b; 2015a) released the final rules of its Clean Power Plan which aims to do just that. Within months, the House and Senate both responded by passing symbolic votes of disapproval of two of these new rules. The plan is currently on hold while being challenged in court.

That regulating the electric power sector is significant for addressing climate change is obvious. Less obvious is whether the decisions on how this sector is regulated will significantly influence congressional support. In particular, because a substantial amount of electricity is traded across political boundaries, whether emissions inventories are based on where electricity is produced or where it is consumed is likely to be important. Figure 1 illustrates why. Figures 2.1a and 2.1b show the difference between electricity consumed and electricity produced in 2013. For example, one can

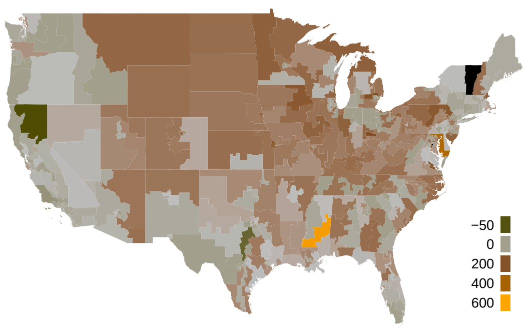
votes while the latter passed one cloture vote. It was then referred to committee and ultimately died after one of its amendments – S.A. 4825 – failed a cloture vote.



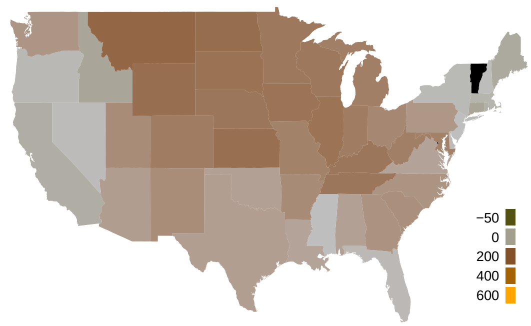
(a) Traded electricity (million GWh)



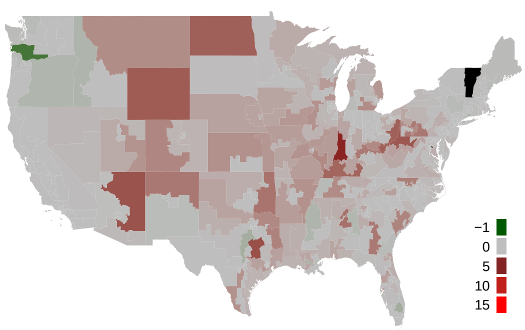
(b) Traded electricity (million GWh)



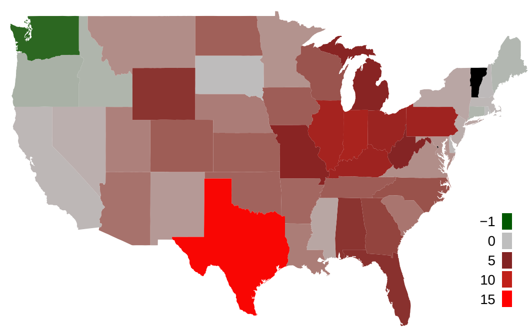
(c) Intensity reduction (MtC/GWh)



(d) Intensity reduction (MtC/GWh)



(e) Emissions reduction (million MtC)



(f) Emissions reduction (million MtC)

Figure 2.1: Traded electricity and the Clean Power Program

Notes: GWh stands for gigawatt hour. MtC stands for metric ton of carbon. Alaska and Hawaii are excluded from the CPP and Vermont has no affected power plants. Data from the EIA and the EPA. See Section 2.3 and Appendix 2.A for details.

see that California was a large importer of electricity while Pennsylvania was a large exporter. Figures 2.1c, 2.1d, 2.1e, and 2.1f show the production-based goals outlined in the Clean Power Plan; these are defined both in terms carbon intensity reductions and in emissions reductions.[3]

What the figures make clear is that the regulatory burdens falling on congressional districts and states are heterogeneous and the choice of inventory may potentially alter these burdens. This motivates an important question: would an approach aimed at regulating emissions where they are consumed result in different legislative voting than one that uses the traditional approach of regulating them where they are produced? This paper addresses this question.

I follow previous work by constructing production- and consumption-based emissions inventories at the district and state level after accounting for interstate trade of electricity. I then show how production-based inventories of carbon emissions correlate with roll call voting on climate change via each legislator's idealogical position. The consumption-based inventories are then substituted into the model to estimate counterfactual ideal points and the voting outcomes these imply. I find that the consumption-based measure leads to increased polarization in the House and a general reshuffling of ideology in the Senate. These patterns alter the probabilities of pro-climate outcomes occurring. For example, I find that the probability of major climate bills passing increases in the House but decreases in the Senate. More recent votes on the Keystone XL pipeline and the Clean Power Plan also become less likely to pass.

The discussion and quantification of emissions embodied in trade has tradition-

[3] To be clear, the Clean Power Plan is a state-based program. However, it is straightforward to extend its goal calculations to the district level. I discuss this in Appendix 2.A.

ally been at the international level and was in large part a response to the ratification of the Kyoto Protocol. A significant cause for concern was that carbon-intensive production might move to – or already be located in – unregulated nations and that this production would then flow back to regulated nations through international trade. Since emissions inventories are typically based on production this results in "carbon leakage" whereby emissions are simply shifted geographically rather than abated. Davis and Caldeira (2010), Peters and Hertwich (2008), and Matthews and Weber (2007) all find that these flows are significant – and in some cases quite large – with developed countries typically being large importers of emissions. Whether and how this issue might be addressed – including a discussion of the technical and political challenges likely to be encountered – is provided by Peters (2008).

At the national level, Aldy (2006, 2005) constructs production- and consumption-based emissions for each state in the U.S. after accounting for the interstate trade of electricity and tests the validity of the Environmental Kuznets Curve hypothesis using each inventory. He confirms the hypothesis using the production-based measure finding that carbon emissions peak and decline with income. With the consumption-based measure, however, he finds that emissions peak and then plateau. Another national-level study can be found in Springmann et al. (2014). They look at the impacts of production-based versus consumption-based policies in regulating emissions at the province-level in China finding that a balanced measure reduces overall losses in welfare by more equitably distributing mitigation.

Evidence that production-based emissions correlate with environmental voting is provided by Cragg et al. (2013). They find a statistically significant negative relationship between emissions and the probability of a legislator voting in favor of carbon mitigation policies. The votes analyzed include the two most recent bills aimed at direct regulation: the American Clean Energy and Security Act of 2009 in the House and the U.S. Climate Security Act of 2008 in the Senate.

Other studies of environmental voting and its correlates include Holland et al. (2014), Herrnstadt and Muehlegger (2014), Jacobsen (2013) and Kahn (2007a,b, 2002). Particularly relevant here are Holland et al. (2014) and Jacobsen (2013) since both represent attempts at making counterfactual inferences of legislative voting. The former estimate how the impacts from the American Clean Energy and Security Act correlated with voting in the House and then use these estimates to infer how they might have impacted voting in the Senate. The latter considers the impact of unemployment on pro-environment voting and then estimates the counterfactual voting that might have occurred if unemployment rates were always at their minimums.

The reminder of the paper is organized as follows. Section 2.2 discusses the data used in the analysis. Section 2.3 discusses how consumption-based emissions are derived and develops the spatial model of voting used with the data. Section 2.4 presents the main empirical results using the production-based measure. Section 2.5 illustrates how the results change when using the consumption-based alternative. Section 2.6 extends the spatial model in order to predict how representatives might have voted on important Senate roll calls and vice versa. Section 3.4 concludes.

2.2 Data

The outcome of interest is legislator voting on roll calls related to climate change. To identify such roll calls I rely on the League of Conservation Voters (LCV)

Table 2.1: Table of means

	District		State	
	Mean	SD	Mean	SD
Republican	0.50	0.50	0.50	0.50
DW-NOMINATE score	0.12	0.50	0.03	0.42
Median income (household)	51450.94	14979.91	49374.72	10447.60
Pct. employed in industry	44.63	12.82	45.28	11.82
Pct. employed in trade	33.05	8.47	32.21	7.00
Pct. 65 or older	12.68	3.07	12.78	1.87
Pct. black	12.44	15.34	9.98	9.39
Pct. Hispanic	13.19	16.72	8.39	9.27
Pct. college degree	31.85	10.22	31.75	6.27
Pct. homes w/ electric heat	30.95	22.87	28.36	18.49
Avg. unemployment rate	6.03	1.93	5.61	1.88
Cooling degree days	92.66	133.90	1100.82	777.44
Heating degree days	1450.23	766.32	5161.50	2024.63
Coal price	0.99	0.27	0.91	0.29
Electricity price	13.48	3.65	12.35	4.10
Natural gas price	4.06	1.25	4.07	1.49
Oil price	7.59	3.02	7.69	3.10

Notes: Employment in trade is the sum of employment in retail and wholesale trade. Employment in industry is the sum of employment in construction, manufacturing, and resource extraction. College degrees include associate, bachelor, and graduate. Energy prices are adjusted for inflation and are in dollars per million British thermal units (BTU).

national scorecards for the 104th to 113th Congress.[4] As the number of climate change votes identified by the LCV is relatively small, I added twelve additional votes – 2 in the House and 10 in the Senate – relating to this issue. These were identified using the THOMAS database maintained by the Library of Congress. The LCV also tracks more recent votes – in this case for 2015 – which may eventually be on the next scorecard. These roll calls provide another 19 climate change votes. Appendix 2.B provides additional information on each of these votes. Legislator voting records for these roll calls come from Voteview.com with additional information regarding each individual roll call coming from GovTrack.us.

[4] This range decreases to the 108th to the 113th Congress when considering the Senate only since the LCV did not categorize any votes as relevant for climate change.

The analysis also relies on additional data for the models of legislative voting and of electricity use. Party affiliation and DW-NOMINATE scores – discussed subsequently – for each legislator come from Voteview.com.[5,6] Income, workforce composition, race, education, and housing statistics are from the U.S. Census and the American Community Survey. Unemployment data are from the Local Area Unemployment Statistics series maintained by the Bureau of Labor Statistics (BLS). Cooling and heating degree day data at the district level were constructed by linking monthly climate data from the PRISM Climate Group with congressional district boundaries taken from Lewis et al. (2013). Corresponding degree day data at the state level are from the National Oceanic and Atmospheric Administration (NOAA). Energy prices by source – which include coal, electricity, natural gas, and petroleum products – are from the State Energy Data System maintained by the Energy Information Administration (EIA).

Its important to note that the data above are not perfect in scope. For example, the BLS and EIA data are only available at the state level and so these values were used as proxies at the the district level. The U.S. Census data is available for 1993, 1999, 2003, 2009, and 2013. Additionally, EIA data are only available through 2013. For those years without updates the most recent update in the past was used.

[5] Some of the data provided by Voteview.com is based on research by Martis (1989).

[6] As a simplification I reclassify Independents as either Democrats or Republicans. In the Senate, Dean Barkley, Jim Jeffords, Angus King, and Bernie Sanders were reclassified as Democrats. In the House, Jim Jeffords and Bernie Sanders were reclassified as Democrats while Virgil Goode was reclassified as a Republican.

2.3 Methods

2.3.1 Electricity generation and emissions embodied in trade

Let e^p_{st} denote state s's annual production-based carbon emissions from the electric power sector and let g_{st} denote state s's total generation of electricity in year t. Additionally, let X_t denote the set of states that exported electricity in a year t with x_{st} denoting state s's exports and let M_t denote the set of states that imported electricity in year t with m_{st} denoting state s's imports. Consumption-based estimates for an exporting state are defined as:

$$e^c_{st} = e^p_{st} - \left[\frac{e^p_{st}}{g_{st}}\right] x_{st} \tag{2.1}$$

where the bracketed term in (2.1) represents the average carbon-intensity of the state's electricity sector. Total emissions embodied in the trade of electricity in year t is defined as:

$$E_t = \sum_{s \in X_t} \left[\frac{e^p_{st}}{g_{st}}\right] x_{st} \tag{2.2}$$

with consumption-based estimates for importing states then defined as:

$$e^c_{st} = e^p_{st} + \left[\frac{m_{st}}{\sum_{\sigma \in M_t} m_{\sigma t}}\right] E_t \quad \text{for} \quad s \in M_t \tag{2.3}$$

where the bracketed term in (2.3) represents the share of total imports going to state s in year t.[7]

---

[7] Aldy (2005, 2006) uses the equation:

$$e^c_{st} = e^p_{st} + \left[\frac{\sum_{\sigma \in X_t} e^p_{\sigma t}}{\sum_{\sigma \in X_t} g_{\sigma t}}\right] m_{st} \quad \text{for} \quad s \in M_t$$

The values of e^p_{st}, g_{st}, x_{st}, and m_{st} can be found in Tables 7 and 10 of the EIA's State Electricity Profiles. The above procedure is made slightly more complicated by first partitioning X and M into subsets based on which interconnection they mostly belong to: the Eastern or the Western.[8] This accounts for the fact that electricity is traded regionally and that the electricity sectors of each region have different emissions profiles.[9]

At the district level, I first calculated plant-level electricity generation g_{pt} and emissions e^g_{pt} using fuel combustion data taken from EIA forms 795, 906, 920, and 923. The geographic locations of these plants –found in EIA form 860 – were combined with congressional district boundaries – taken from Lewis et al. (2013) – to obtain corresponding district-level generation g_{dt} and emissions e^g_{dt} from the electric power sector. Emissions from the residential, commercial, transportation, and industrial sectors were calculated as:

$$e^{\rho}_{dt} = \lambda^{pop}_{d}\, e^{\rho}_{st} \tag{2.4}$$

$$e^{\chi}_{dt} = \lambda^{den}_{d}\, e^{\chi}_{st} \tag{2.5}$$

$$e^{\tau}_{dt} = \lambda^{den}_{d}\, e^{\tau}_{st} \tag{2.6}$$

$$e^{\iota}_{dt} = \lambda^{ind}_{d}\, e^{\iota}_{st} \tag{2.7}$$

where λ^{pop}_{d}, λ^{den}_{d}, and λ^{ind}_{d} correspond to district d's population share, population density share, and industrial employment share in its corresponding state s. Estimates

to estimate consumption-based emissions.

[8] Texas – which technically constitutes its own interconnection – is assumed to lie in the Eastern connection. Alaska and Hawaii represent their own interconnection and therefore satisfy $e^c_t = e^p_t$ for all t. Imports and exports out of the country are not considered.

[9] The EPA also makes this distinction in the Clean Power Program while Aldy (2005, 2006) does not.

of the state totals e^{ρ}_{st}, e^{χ}_{st}, e^{τ}_{st}, and e^{ι}_{st} are from the EIA's State CO_2 Profiles. District d's annual production-based carbon emissions is given by:

$$e^{p}_{dt} = e^{g}_{dt} + e^{\rho}_{dt} + e^{\chi}_{dt} + e^{\tau}_{dt} + e^{\iota}_{dt} \tag{2.8}$$

Obtaining consumption-based estimates is more complicated since district-level trade in electricity – x_{dt} and m_{dt} – are not observed. Using state-level data, I estimated the following model for determining per capita electricity use:

$$q_{st} = \alpha_s + \gamma_t + \boldsymbol{c'_{st}}\boldsymbol{\beta} + +\boldsymbol{w'_{st}}\boldsymbol{\delta} + \boldsymbol{p'_{st}}\boldsymbol{\eta} + \epsilon_{st} \tag{2.9}$$

where α_s is a state fixed effect, γ_t is a year fixed effect, $\boldsymbol{c'_{st}}$ contains demographic data, $\boldsymbol{w'_{st}}$ contains degree days data, and $\boldsymbol{p'_{st}}$ contains energy price data. Per capita electricity use at the district level is then estimated by the predicted values:

$$\hat{q}_{dt} = \hat{\alpha}_s + \hat{\gamma}_t + \boldsymbol{c'_{dt}}\hat{\boldsymbol{\beta}} + +\boldsymbol{w'_{dt}}\hat{\boldsymbol{\delta}} + \boldsymbol{p'_{st}}\hat{\boldsymbol{\eta}} \tag{2.10}$$

The sets of exporting and importing districts in year t are defined as:

$$\hat{X}_t = \{d : \hat{q}_{dt} < g_{dt}\} \tag{2.11}$$

$$\hat{M}_t = \{d : \hat{q}_{dt} > g_{dt}\} \tag{2.12}$$

with total traded electricity in year t estimated as the average:

$$\hat{G}_t = \frac{1}{2}\sum_{d \in \hat{X}_t}(g_{dt} - \hat{q}_{dt}) + \frac{1}{2}\sum_{d \in \hat{M}_t}(\hat{q}_{dt} - g_{dt}) \tag{2.13}$$

Corresponding estimates for district-level trade of electricity are then defined as:

$$\hat{x}_{dt} = \left[\frac{g_{dt} - \hat{q}_{dt}}{\sum_{\delta \in X_t}(g_{\delta t} - \hat{q}_{\delta t})}\right]\hat{G}_t \tag{2.14}$$

$$\hat{m}_{dt} = \left[\frac{\hat{q}_{dt} - g_{dt}}{\sum_{\delta \in M_t}(\hat{q}_{\delta t} - g_{\delta t})}\right]\hat{G}_t \tag{2.15}$$

where the bracketed terms represent district d's export or import share respectively. District-level consumption-based estimates e^c_{dt} are then calculated using equations analogous to (2.1), (2.2), and (2.3). Appendix 2.C provides a more detailed discussion of this district-level procedure including the estimated results of (2.9).

2.3.2 A spatial model of climate change voting

Roll call voting on climate change is assumed to follow a spatial model of the sort pioneered by Poole and Rosenthal (1985, 1991, 1997). I use their DW-NOMINATE scores as a benchmark for comparison in the next section. In its simplest form, the model assumes that legislators and roll call can be represented using a single spatial dimension. Each legislator i is defined by an ideal point θ_i and each roll call j is defined by "yea" and "nay" points z_{jy} and z_{jn}. Legislator i's preferences over roll call j are defined by the two utilities:

$$u_{ijy} = -||\theta_i - z_{jy}||^2 + \epsilon_{ijy} \tag{2.16}$$

$$u_{ijn} = -||\theta_i - z_{jn}||^2 + \epsilon_{ijn} \tag{2.17}$$

In this paper I asuume the error terms ϵ_{ijy} and ϵ_{ijn} are independent and identically distributed type I generalized extreme value random variables:[10]

$$\epsilon_{ijy} \sim \text{GEV}(\mu, \sigma_j, 0) \tag{2.18}$$

$$\epsilon_{ijn} \sim \text{GEV}(\mu, \sigma_j, 0) \tag{2.19}$$

so that the probability of a legislator i voting "yea" on rollcall j is:

$$\text{P(“yea” on roll call } j) = \text{P}(u_{ijy} > u_{ijn}) = \text{logit}^{-1}(\beta_j \theta_i - \alpha_j) \tag{2.20}$$

where $\beta_j = \frac{2(z_{jy} - z_{jn})}{\sigma_j}$ and $\alpha_j = \frac{(z_{jy}^2 - z_{jn}^2)}{\sigma_j}$.[11]

Estimation of the model above is based on a Bayesian approach identical to the one used in Johnson (2015) and similar to the one used in Bailey (2001). The primary difference between this empirical strategy and that of previous work is the fact that the θ_i's are estimated directly. As Bailey describes: "The key to the approach is that it models ideal points as stochastic functions of district and personal characteristics." Including this additional data in the model helps in measuring the θ_i's more precisely without having to use more votes. Jackman (2009) demonstrates this with an example using *National Key* votes. Furthermore, the relationship between these characteristics and the θ_i's are of direct interest.

[10] In Appendix 2.E, I make a less restrictive assumption concerning the error terms by allowing for their variance to depend on legislator i. As shown in that section the results are comparable to those shown below.

[11] A similar specification is used frequently in the political science literature. Examples include: Bertelli and Grose (2009), Bafumi et al. (2005), Clinton et al. (2004), Bailey (2001), and Jackman (2001, 2000a,b), with differences between these papers largely depending on the assumed distriubtion of the error terms.

Formally, voting on climate change is represented by the following model:

$$\text{P(“yea” on roll call } j) = \text{logit}^{-1}(\beta_j\theta_i - \alpha_j) \tag{2.21}$$

$$\theta_i \sim \mathcal{N}(\mu_i, 1) \tag{2.22}$$

$$\mu_i = \gamma_0 + \gamma_1\, \mathcal{I}_i^R + \bar{\boldsymbol{x}}_{\boldsymbol{i}}'\boldsymbol{\delta} \tag{2.23}$$

$$\alpha_j \sim \mathcal{N}(0, 25) \tag{2.24}$$

$$\beta_j \sim \mathcal{N}(0, 25) \tag{2.25}$$

$$\gamma_0 \sim \mathcal{N}(\text{-}1, 1) \tag{2.26}$$

$$\gamma_1 \sim \mathcal{N}(2, 1) \tag{2.27}$$

$$\boldsymbol{\delta} \sim \mathcal{N}(0_k, 25 \times I_k) \tag{2.28}$$

where equations (2.23) and (2.22) characterize a hierarchical model for the θ_i's. There are k regressors included in $\bar{\boldsymbol{x}}_{\boldsymbol{i}}$ thus 0_k is an $k \times 1$ vector of zeros and I_k represents the $k \times k$ identity matrix. The $\mathcal{I}_i^R$ term is an indicator that legislator i is a Republican and $\bar{\boldsymbol{x}}_{\boldsymbol{i}}$ includes averaged data relevant to legislator i and their constituency: log per capita production-based carbon emissions, log median income, the average unemployment rate, percentage of the population 65 or older, percentage of the population that is black, percentage of the population that is Hispanic, percentage of the population that has a college degree, and percentage of the population employed in industry. These covariates also used by Cragg et al. (2013), Jacobsen (2013), and Kahn (2002).

The priors for α_j, β_j, and $\boldsymbol{\delta}$ are intentionally vague so that their role is minimal in the posterior distributions. The priors for θ_i, γ_0, and γ_1 are less vague to help identify the model. The former solves the scale invariance problem arising from the fact that any estimated $\hat{\theta}_i$ and $\hat{\beta}_j$ are observationally equivalent to $\tilde{\theta}_i = a\hat{\theta}_i$ and

$\tilde{\beta}_j = \hat{\beta}_j/a$ for $a > 1$. The latter two solve the rotational invariance problem arising from the fact that any estimated $\hat{\theta}_i$ and $\hat{\beta}_j$ are also observationally equivalent to $\tilde{\theta}_i = -\hat{\theta}_i$ and $\tilde{\beta}_j = -\hat{\beta}_j$. An intuitive way to understand the latter priors is that they are akin to implementing a non-hierarchical model where the priors for the ideal points are:

$$\theta_i \sim \begin{cases} \mathcal{N}(\text{-}1,1) & \text{if legislator } i \text{ is a Democrat} \\ \mathcal{N}(1,1) & \text{if legislator } i \text{ is a Republican} \end{cases} \tag{2.29}$$

Note that this also generates a positive association between the values of θ_i and being a Republican which imposes the conventional assumption that conservatives occupy the right portion of the policy dimension.

Additionally, I use a post-estimation transformation consistent with Bafumi et al. (2005) and Jackman (2000a,b) whereby the final estimates are normalized to:

$$\theta_i^F = (\theta_i - \bar{\theta})/s_\theta \tag{2.30}$$

$$\alpha_j^F = \alpha_j - \bar{\theta}\beta_j \tag{2.31}$$

$$\beta_j^F = s_\theta \beta_j \tag{2.32}$$

$$\gamma_0^F = (\gamma_0 - \bar{\theta})/s_\theta \tag{2.33}$$

$$\gamma_1^F = \gamma_1/s_\theta \tag{2.34}$$

$$\boldsymbol{\delta}^{\boldsymbol{F}} = \boldsymbol{\delta}/s_\theta \tag{2.35}$$

where $\bar{\theta}$ and s_θ are the mean and standard deviation of the raw θ_i's.

With the policy dimensions oriented via the priors, it becomes easier to understand the role the model's covariates are likely to play. Naturally, one would expect that log per capita production-based carbon emissions would correlate positively with the θ_i's since higher emissions translate to increased regulatory burden. Percentage of the population employed in industry and the average unemployment rate would also be expected to correlate positively since regulation is perceived to be bad for jobs generally and bad for industrial jobs especially. Conversely, one would expect that log median income and percentage of the population with a college degree correlate negatively with the θ_i. This would be consistent with the widely held notions that richer and more educated people support environmental regulation. The role of age and race are arguably less clear although Kahn (2002) provides arguments for why they might also correlate negatively. In the case of the former, he argues older generations may prefer carbon regulation since it preserves the environment for posterity. In the case of the latter, he argues that because environmental degredation disproportionately affects minorities they are more likely to support legislation.

Markov Chain Monte Carlo (MCMC) simulation of the model was done separately for the House and Senate using `Stan` and its `R` interface `rstan` written by the Stan Development Team (2015a,b,c). In each case, four MCMC chains were simulated for 1,000 iterations after an initial 500 iterations were used as "warm-up" to tune the sampler. Each chain was initialized with the random draws:

$$\theta_i^0 \sim \begin{cases} \mathcal{N}(\text{-}1, 1) & \text{if legislator } i \text{ is a Democrat} \\ \mathcal{N}(1, 1) & \text{if legislator } i \text{ is a Republican} \end{cases} \tag{2.36}$$

$$\alpha_j^0 \sim \mathcal{N}(0, 25) \tag{2.37}$$

$$\beta_j^0 \sim \mathcal{N}(0, 25) \tag{2.38}$$

Table 2.2: Per-capita carbon emissions (metric tons) 1996 to 2015

	District				State			
	Min	Max	Mean	SD	Min	Max	Mean	SD
Production-based	0.40	37.09	5.33	4.46	2.23	38.36	6.83	5.49
Consumption-based	0.38	36.35	5.32	3.41	2.31	21.58	6.24	3.43

with values for γ_0^0, γ_1^0, and $\boldsymbol{\delta^0}$ resulting from ordinary least squares estimatation of:

$$\theta_i^0 = \gamma_0 + \gamma_1\, \mathcal{I}_i^R + \boldsymbol{x_i'\delta} \tag{2.39}$$

Appendix 2.D provides further discussion on the implementation.

2.4 Results

Table 2.2 provides summary statistics for the estimated per capita production-based and consumption-based inventories of carbon emissions. The reasonableness of the estimates is confirmed after comparing them with previous research. At the district level, Cragg et al. (2013) estimate a per capita production-based mean of 5.47 using Project Vulcan data. I estimate this value to be 5.33. To my knowledge, there is no comparable estimate of consumption-based emissions at the district-level. At the state level, Aldy (2005) estimates a production-based mean and standard deviation of 5.74 and 3.81 and a consumption-based mean and standard deviation of 5.34 and 2.34. I estimate a production-based mean and standard deviation of 6.83 and 5.49 and a consumption-based mean and standard deviation of 6.24 and 3.41. The differences are most likely due to the fact that Aldy (2005) considers the period 1960 to 1999 while I consider the period 1996 to 2015.

Tables 2.3 and 2.4 show the posterior means and standard deviations of the parameters in (2.23). Note that the μ_i's – as well as the θ_i's – lack substantive numerical meaning. While convention typically dictates a lower and upper bound for the θ_i's in the range of -1 to 1 there is no empirical justification for this. The real content comes from both the relative size and sign of the estimates as well as whether they can be statistically distinguished from zero. I follow the suggestion in Gelman (2008) by presenting the estimates after subtracting the mean and dividing by two times the standard deviation of each of the continuous input variables. Each coefficient can then be interpreted as the change in μ_i associated with moving from a low to high value of the observed input variable. For example, if this transformation were to be imposed on an indicator then the coefficient would correspond to a change from 0 to 1.

In the House, each of the input variables has a relationship with μ_i that is distinguishable from zero.[12] These are consistent with results found in Cragg et al. (2013), Jacobsen (2013), and Kahn (2002). Being a member of the Republican party, log per capita carbon emissions, average unemployment, and percentage employed in industry are all positively associated with μ_i. The last specification in Table 2.3 shows that the relationship between log per capita carbon emissions and ideology is party dependent when using the additional covariates and is only distinguishable for Republicans Log median income, percentage of the population 65 or older, percentage of the population that is black, the percentage of the population that is Hispanic, and the percentage of the population with a college degree are all negatively associated with μ_i.

Similar results hold for the Senate with the exception that only being a mem-

[12] Distinguishable in this case means the 95% HPD interval of the parameter does not include zero.

Table 2.3: Estimates of the hierarchical model in the House

	(1)	(2)	(3)	(4)	(5)
(Intercept)	-0.96^{***}	-0.97^{***}	-0.97^{***}	-0.93^{***}	-0.93^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Republican	1.74^{***}	1.76^{***}	1.76^{***}	1.69^{***}	1.69^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Log production-based emissions		0.28^{***}		0.13^{***}	
		(0.05)		(0.05)	
D x Log production-based emissions			0.23^{***}		0.09
			(0.06)		(0.06)
R x Log production-based emissions			0.31^{***}		0.16^{***}
			(0.06)		(0.06)
Log median income (household)				-0.27^{***}	-0.28^{***}
				(0.08)	(0.08)
Avg. unemployment rate				0.08^{*}	0.09^{*}
				(0.05)	(0.05)
Pct. 65 or older				-0.17^{***}	-0.17^{***}
				(0.05)	(0.05)
Pct. black				-0.16^{***}	-0.15^{***}
				(0.05)	(0.05)
Pct. Hispanic				-0.19^{***}	-0.19^{***}
				(0.05)	(0.05)
Pct. college degree				-0.23^{***}	-0.22^{***}
				(0.08)	(0.08)
Pct. employed in industry				0.14^{***}	0.14^{***}
				(0.05)	(0.05)

Notes: Continuous input variables are standardized by subtracting their means and dividing by two times their standard deviations. $^{*}0 \notin 90\%$ HPD; $^{**}0 \notin 95\%$ HPD; $^{***}0 \notin 99\%$ HPD.

ber of the Republican party, log per capita carbon emissions, log median income, and percentage of the population 65 or older are distinguishable from zero and have the expected sign. The percentage of the population that is black is also distinguishable from zero but is positively associated with μ_i in this case. In addition, the party dependence of log per capita carbon emissions is now distinguishable for both Democrats and Republicans when using the additional covariates

Figures 2.2a and 2.2b illustrate how the estimated ideal points of each legislator compare with their average first dimension DW-NOMINATE scores using the specification in column four of Tables 2.3 and 2.4. Overall, the estimates have a

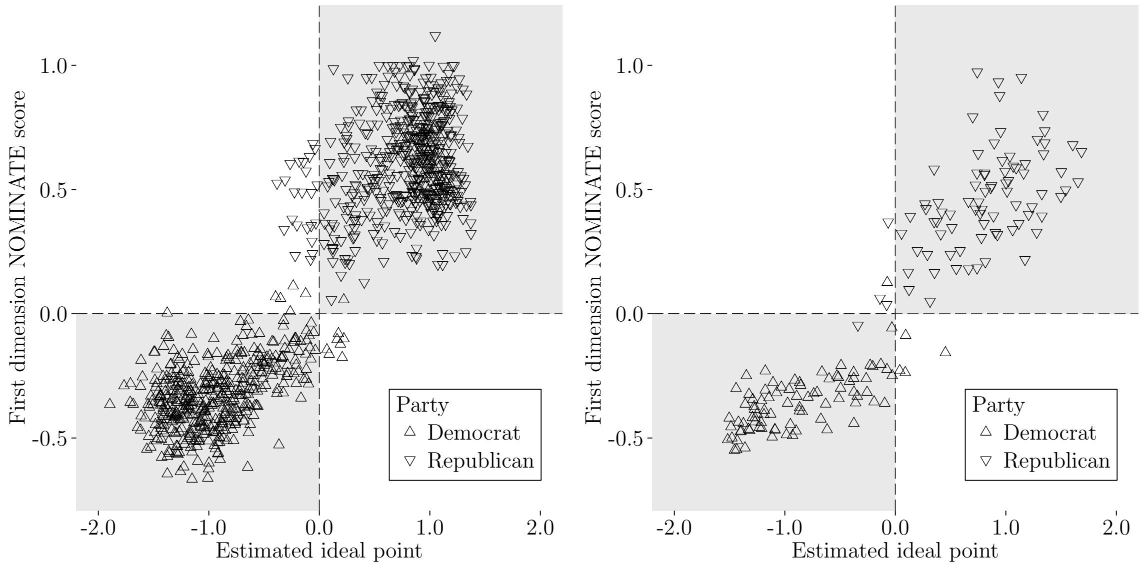
Table 2.4: Estimates of the hierarchical model in the Senate

	(1)	(2)	(3)	(4)	(5)
(Intercept)	-0.87^{***}	-0.77^{***}	-0.76^{***}	-0.70^{***}	-0.70^{***}
	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)
Republican	1.71^{***}	1.52^{***}	1.52^{***}	1.38^{***}	1.38^{***}
	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)
Log production-based emissions		0.71^{***}		0.49^{***}	
		(0.07)		(0.10)	
D x Log production-based emissions			0.75^{***}		0.51^{***}
			(0.10)		(0.13)
R x Log production-based emissions			0.63^{***}		0.46^{***}
			(0.14)		(0.14)
Log median income (household)				-0.46^{***}	-0.46^{***}
				(0.14)	(0.15)
Avg. unemployment rate				-0.08	-0.08
				(0.09)	(0.09)
Pct. 65 or older				-0.23^{**}	-0.23^{**}
				(0.09)	(0.09)
Pct. black				0.21^{**}	0.21^{**}
				(0.09)	(0.09)
Pct. Hispanic				-0.05	-0.05
				(0.09)	(0.09)
Pct. college degree				0.09	0.09
				(0.13)	(0.14)
Pct. employed in industry				0.08	0.08
				(0.09)	(0.09)

Notes: Continuous input variables are standardized by subtracting their means and dividing by two times their standard deviations. $^{*}0 \notin 90\%$ HPD; $^{**}0 \notin 95\%$ HPD; $^{***}0 \notin 99\%$ HPD.

Spearman rank order correlation of 0.82 in the House and 0.91 in the Senate. However, comparing the two methods within party illustrates how they differ. In the House, the correlation decreases to 0.45 and 0.17 when comparing only Democrats or only Republicans respectively; the corresponding values in the Senate are 0.69 and 0.57. These differences are apparent in the figures by noting that the clusters of points in the positive and negative portions of the dimensions – corresponding to the shaded regions – have a less discernible relationship than when comparing all the points together.

Importantly, the differences appear to be consistent with the notion that the



(a) House (b) Senate

Figure 2.2: Comparison of estimated ideal points and DW-NOMINATE scores

estimates are recovering ideology specific to climate change. For example, John McCain (R-AZ) – who has a history of being involved with climate legislation[13] – ranks 17th using the estimated ideal points and 29th using DW-NOMINATE scores among Republicans. Furthermore, McCain's estimated ideal point of 0.38 differs from his colleague Jon Kyl (R-AZ) who has identical covariates in equation (2.23) but an estimated ideal point of 0.99. Similarly, Joe Lieberman (D-CT) – co-sponsor of two major efforts to regulate carbon – ranks 16th using the estimated ideal points and 76th using DW-NOMINATE scores among Democrats. Finally, Lindsey Graham (R-SC) – who attempted to pass comprehensive carbon legislation in 2009 – ranks 11th using the estimated ideal points and 39th using DW-NOMINATE scores among Republicans.

[13] McCain co-sponsored the Climate Stewardship Act of 2003 (S. 139) and the Climate Stewardship and Innovation Acts of 2005 and 2007 (S.1151 and S. 280). The vote that defeated the former bill – Senate roll call 420 on October 30th 2003 – is included in this analysis. In his 2013 State of the Union Address, President Obama referenced McCain and these bills explicitly while discussing climate change legislation.

One way to assess model fit is with the classification rates. This value reflects the percentage of votes that are correctly predicted by the model using the assumption that a predicted probability of 0.5 represents the cutoff between voting one way or the other. Regardless of the specifications listed in Tables 2.3 and 2.4, the correct classification rates for the House and Senate are 96% and 94% respectively. Such high rates are consistent with Poole and Rosenthal (1997) who find that a single policy dimension fits most Congresses in the U.S. very well.

Jackman (2001) also suggests using the percentage of β_j's distinguishable from zero as a means for accessing fit since it indicates to what extent the roll calls are supplying information about the underlying policy dimension. For instance, looking back at (2.21), a β_j equal to zero implies that the θ_i's do not provide any information regarding how roll call j was voted on. Once more regardless of the specifications listed in Tables 2.3 and 2.4, all of the β_j's are distinguishable from zero in the House while in the Senate 89% of them are.

Finally, Bafumi et al. (2005) propose using the excess errors observed in individual samples of the posterior as a way to access fit. This error is defined as:

$$\mathrm{EX}_{ij}^k = \mathrm{PE}_{ij}^k - \mathrm{EE}_{ij}^k \tag{2.40}$$

where PE_{ij}^k is the prediction error:

$$\mathrm{PE}_{ij}^k = \begin{cases} 1 & \text{if} \quad \mathrm{logit}^{-1}(\beta_j^k \theta_i^k - \alpha_j^k) < 0.5 \quad \text{and} \quad v_{ij} = 1 \\ 1 & \text{if} \quad \mathrm{logit}^{-1}(\beta_j^k \theta_i^k - \alpha_j^k) > 0.5 \quad \text{and} \quad v_{ij} = 0 \\ 0 & \text{otherwise} \end{cases} \tag{2.41}$$

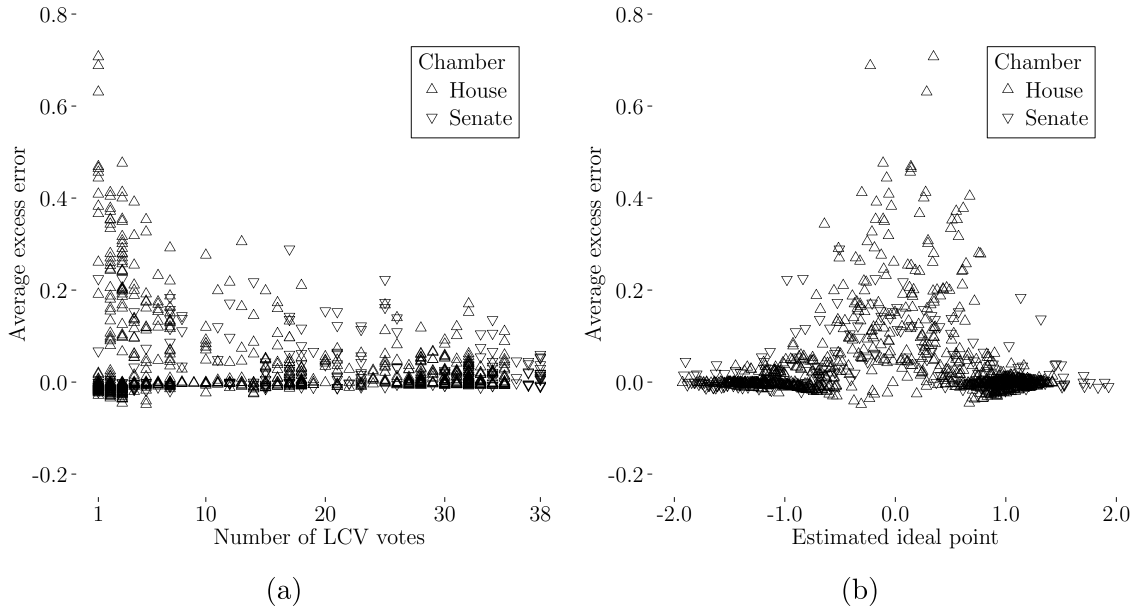


Figure 2.3: Average excess error rates

Notes: A total of 35 votes were analyzed in the House and 38 in the Senate.

and EE_{ij}^k is the expected error:

$$\mathrm{EE}_{ij}^k = \min\left\{\mathrm{logit}^{-1}(\beta_j^k\theta_i^k - \alpha_j^k), 1 - \mathrm{logit}^{-1}(\beta_j^k\theta_i^k - \alpha_j^k)\right\} \tag{2.42}$$

assuming the model is true.

Using the specification in column four of Tables 2.3 and 2.4 once again, the average excess errors for each legislator are plotted by number of observed roll calls and by estimated ideal point in Figures 2.3a and 2.3b respectively. For the majority of legislators, excess error generally differs by less than 10% of what would be expected if the model were true. Not surprisingly, the highest rates are more common among legislators who made less than five votes; fewer votes make ideal points harder to estimate. For example, the highest error rate belongs to Martin Hoke (R-OH) who cast just a single vote. The posterior mean for Hoke's ideal point is 0.35 but the 95%

HPD is bounded by -0.32 and 1.01. Thus, Hoke's apparent moderateness should more appropriately be attributed to the uncertainty of his position rather than his actual politics.

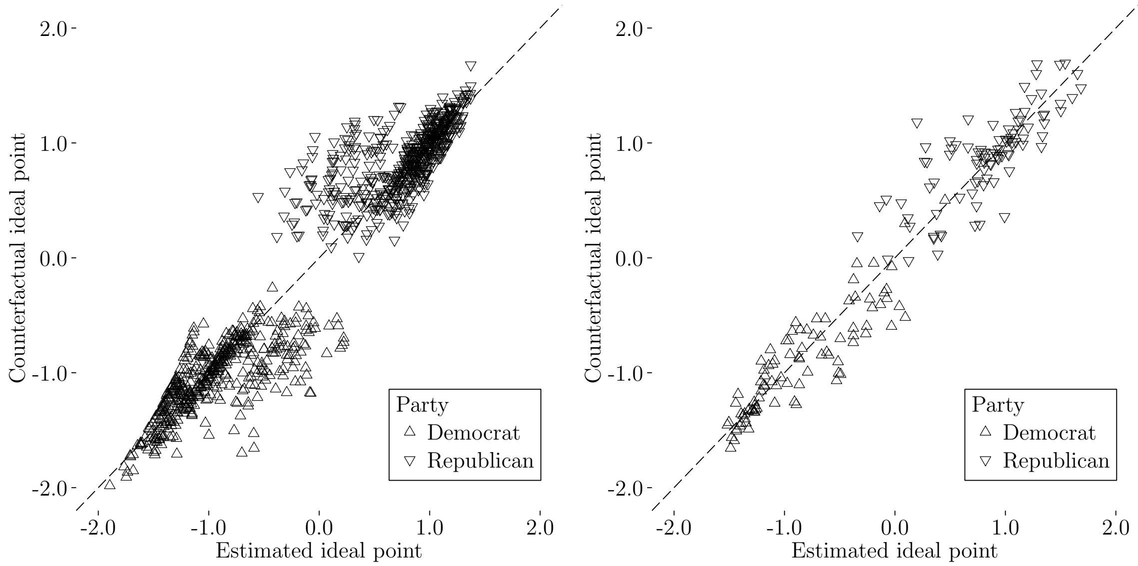
Higher excess error is also more common in the Senate which has fewer legislators and thus fewer observations to use in fitting the hierarchical model. Several of these higher rates belong to senators such as Robert Byrd (D-WV), Kent Conrad (D-ND), Mary Landrieu (D-LA), and Jay Rockefeller (D-WV) who each have high vote percentages but also represent states with higher average per capita carbon emissions. Excess error would be expected in these cases since the model has difficultly resolving the voting implied by their party affiliation with the voting implied by the emissions in their states. John McCain – who cast 34 of the 38 votes considered – is another senator with higher excess error; this would also be expected given that his support of climate change legislation runs counter to his party affiliation.[14]

2.5 Counterfactual results

To further explore the relationship between carbon emissions and voting I calculated each legislator's ideal point after replacing the production-based measure of emissions in the hierarchical model with its consumption-based counterpart. Once again I used the specification in column four of Tables 2.3 and 2.4. Specifically, for each sample k of the parameters γ_0, γ_1, and $\boldsymbol{\delta}$ I also calculated the counterfactual ideal point:

$$\zeta_i^k = \gamma_0^k + \gamma_1^k \, \mathcal{I}_i^R + \boldsymbol{\bar{x}_i' \delta^k} \tag{2.43}$$

[14] See supra note 13.



(a) House (b) Senate

Figure 2.4: Comparison of estimated ideal points and counterfactual ideal points

Notes: The dashed lines are at 45 degrees.

where $\bar{\boldsymbol{x}}_{\boldsymbol{i}}$ contains log per-capita consumption-based carbon emissions.

Figures 2.4a and 2.4b show the counterfactual ideal points compared to the originals for each chamber separately. In the House, there are two patterns that can be seen. First, most moderate representatives who are either slightly left or slightly right of center move further in that same direction. Second, representatives with more extreme ideal points are relatively stable. In the Senate, the result is mixed all along the dimension with Democrats and Republicans moving in both directions. Overall, the consumption-based inventories seem to have a polarizing effect in the House and a reshuffling effect in the Senate.

To determine what effect consumption-based inventories would have had on the outcome of each roll call I used the posterior means to calculate each legislator's predicted vote using the production-based inventory:

$$v_{ij}^{\theta} = \begin{cases} 1 & \text{if} \quad \text{logit}^{-1}(\bar{\beta}_j\bar{\theta}_i - \bar{\alpha}_j) \geq 0.5 \\ 0 & \text{otherwise} \end{cases} \tag{2.44}$$

and the predicted counterfactual vote using the consumption-based inventory:

$$v_{ij}^{\zeta} = \begin{cases} 1 & \text{if} \quad \text{logit}^{-1}(\bar{\beta}_j\bar{\zeta}_i - \bar{\alpha}_j) \geq 0.5 \\ 0 & \text{otherwise} \end{cases} \tag{2.45}$$

Using the votes defined by (2.44), none of the predicted outcomes change. Recall, that in both chambers the correct classfication rates were quite high so this would be expected. Using (2.45) instead, five votes have predicted outcomes that differ from their actual ones: two in the House and three in the Senate. In what follows I paraphrase the LCV's descriptions of these roll calls. First is House roll call 332 in the 105th Congress. This was an amendment to override language that would have prevented the EPA from conducting educational programs on climate change. This vote actually passed but is predicted to fail. Second is House roll call 323 in the 106th Congress. This was an amendment to clarify language that would have prevented the EPA from engaging in already authorized activities that reduced global warming pollution. This vote also actually passed but is predicted to fail. Third is Senate roll call 149 in the 109th Congress. This was a motion to kill a "Sense of the Senate" resolution aimed at putting senators on the record that global warming is real and that mandatory limits are necessary to curb global warming pollution. This vote actually failed but is predicted to pass.[15] Fourth is Senate roll call 142 in the

[15] The resolution was eventually agreed to by voice vote on June 22nd, 2005.

111th Congress. This was an amendment to provide a point of order against climate change legislation that would result in significant job losses in manufacturing- and coal-dependent regions. This vote actually passed but is predicted to fail.[16] Last is Senate roll call 115 in the 114th Congress. This was an amendment to create a reserve fund to respond to economic and national security threats posed by climate change. This vote actually passed but is predicted to fail.

Comparing the models based on just these predicted outcomes has the limitation that it ignores the uncertainty inherent in the estimates of the parameters. For example, I noted earlier the variability associated with legislators who only voted on a small subset of the roll calls considered.[17] To account for this, I calculated the predicted probabilities of a legislator voting "yea" on each of the roll calls using the two sets of ideal points:

$$\rho_{ij}^k = \text{logit}^{-1}(\beta_j^k \theta_i^k - \alpha_j^k) \tag{2.46}$$

$$\pi_{ij}^k = \text{logit}^{-1}(\beta_j^k \zeta_i^k - \alpha_j^k) \tag{2.47}$$

for each sample k. These were used to generate two sets of 100 simulated votes:

$$V_{ij}^k = \left\{ v_{ij}^{k(1)}, ..., v_{ij}^{k(100)} \right\} \quad v_{ij}^k \sim \text{Bernoulli}(\rho_{ij}^k) \tag{2.48}$$

$$\tilde{V}_{ij}^k = \left\{ \tilde{v}_{ij}^{k(1)}, ..., \tilde{v}_{ij}^{k(100)} \right\} \quad \tilde{v}_{ij}^k \sim \text{Bernoulli}(\pi_{ij}^k) \tag{2.49}$$

which corresponds to a total of 200,000 simulated outcomes for each of the roll calls

[16] This is one of the votes that I added and was not considered by the LCV.

[17] Alternatively, consider the American Clean Energy and Security Act vote which corresponds to House roll call 477 in the 111th Congress. This vote is predicted to pass using either emissions measure. However, using production-based emissions there are 231 predicted "yea" votes while using consumption-based there are 255. Clearly, something is different.

Table 2.5: Simulated results of roll call votes on climate change legislation

Legislation	Type	Production-based		Consumption-based	
		P("pro")	Margin	P("pro")	Margin
Waxman-Markey bill[a]	Passage	0.89	7.05	1.00	30.27
Keystone XL pipeline[a]	Passage	0.00	-42.89	0.00	-26.61
CPP standards for new plants[a]	Passage	0.00	-29.72	0.00	-28.04
CPP standards for existing plants[a]	Passage	0.00	-24.53	0.00	-28.59
Lieberman-McCain bill[b]	Amendment	0.02	-7.18	0.00	-8.08
Lieberman-Warner bill[b]	Cloture	0.20	-2.91	0.07	-4.34
Keystone XL pipeline[b]	Passage	0.70	1.49	0.88	4.64
CPP standards for new plants[b]	Passage	0.04	-2.06	0.01	-1.87
CPP standards for existing plants[b]	Passage	0.04	-2.04	0.01	-1.87

Notes: [a] House vote. [b] Senate vote. Based on 200,000 simulations. The P("pro") columns show the percentage of simulations where the pro-climate outcome occurs. The Margin columns show the average difference between the total "pro" votes and the number of votes required for the pro-climate outcome.

using each measure.

Overall, switching from the production-based to the consumption-based inventory lowers the average probability of pro-climate outcomes occurring. In the House, the value falls from 16.8% to 12.8% while in the Senate it falls by a much smaller amount. Table 2.5 provides a more detailed summary of the simulated outcomes of several major votes from each chamber; these include the votes on bills seeking to directly regulate carbon emissions, votes to automatically approve the Keystone XL pipeline, and votes of disapproval of the EPA's Clean Power Program.

In the House, the consumption-based measure of emissions leads to an increase in the probability of the Waxman-Markey bill passing from 89.0% to 100.0%. The average margin – measured as the difference between the total number of "pro" votes and the number of votes required for the pro-climate outcome – also increases from 7.0 to 30.3. The Keystone XL pipeline is automatically approved using either inventory although the vote is less secure using the consumption-based measure since the average losing margin increases from -42.9 to -26.6. With respect to the Clean Power

Program, there is effectively no difference between the two inventories.

In the Senate, using the consumption-based inventory has roughly the opposite effect on bills seeking to directly regulate carbon emissions. The probability of the Lieberman-McCain bill passing falls from 1.8% to 0.1% with the average margin decreasing from -7.2 to -8.1 votes. The probability that the Lieberman-Warner bill passes also falls from 20.3% to 6.7% with the average margin decreasing from -2.9 to -4.3 votes. The probability that the Keystone XL pipeline is automatically approved decreases slightly when switching to the consumption-based measure but in both cases this outcome is quite unlikely. Finally, the consumption-based measure makes congressional disapproval of the Clean Power Plan more likely although using either measure this outcome is all but certain.

2.6 Cross-chamber predictions

I also estimated the hierarchical model treating the House and Senate as a single legislature. Voteview.com, for example, provides such "common space" DW-NOMINATE scores. The idea is to use the legislators that have served in both the House and Senate as so-called "bridges" between the chambers. This allows all the legislators to be compared – either directly or indirectly – to one another. This approach is used in: Bertelli and Grose (2009) who use the congressional testimony by cabinet secretaries to compare them with members of Congress, Bailey (2007) who links members of Congress and Presidents with the Supreme Court by using public positions taken on court cases, and Gerber and Lewis (2004) who treat interest groups that took positions in the California Assembly, the California Senate, and the U.S. House as pseudo legislators and use them as "bridges" to compare the actual legislators across these bodies.

For the case considered here, 52 of the legislators served in both the House and Senate during the period analyzed and together these legislators cast at least one vote on all but 7 of the roll calls considered. Note that this latter point is not an issue since the "bridges" can still be compared to legislators who did cast votes on these missing roll calls. In fact, I strengthened the link between the chambers by also using four of the roll calls as "bridges." The Keystone XL pipeline and the Clean Power Plan votes shown in Table 2.5 represent each chamber's own version of the same legislation. The House and Senate also voted on identical versions of the Homeowner Flood Insurance Affordability Act of 2014. I restricted the model so that the α_j's and β_j's corresponding to these roll calls were equal.[18]

Table 2.6 shows the posterior means and standard deviations of the parameters in (2.23) after using the combined observations from the House and Senate. Comparing these values with those in Tables 2.3 and 2.4 one can see that they closely match the results for the House alone. This would be expected given that the House represents the majority of observations. Two of the assessments of fit are also consistent with previous results: 96% of the votes are correctly classified and 94% of the β_j's are distinguishable from zero.

A nice feature of the "common space" method is that it not only allows the θ_i's to be compared across chambers but also the α_j's and the β_j's. Thus, inferences can be made as to how representatives (senators) might have voted on roll calls that occurred in the Senate (House). For example, one can predict how the House might have voted on the roll calls related to the Lieberman-McCain and the Lieberman-

[18] Although not done, there may be additional roll calls from each chamber that could be linked in this fashion by carefully examining differences between individual House and Senate votes.

Table 2.6: Estimates of the hierarchical model in both chambers

	(1)	(2)	(3)	(4)	(5)
(Intercept)	-0.93^{***}	-0.95^{***}	-0.95^{***}	-0.91^{***}	-0.91^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Republican	1.73^{***}	1.75^{***}	1.75^{***}	1.68^{***}	1.68^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Log production-based emissions		0.34^{***}		0.17^{***}	
		(0.04)		(0.04)	
D x Log production-based emissions			0.34^{***}		0.17^{***}
			(0.06)		(0.06)
R x Log production-based emissions			0.34^{***}		0.18^{***}
			(0.06)		(0.06)
Log median income (household)				-0.27^{***}	-0.28^{***}
				(0.07)	(0.07)
Avg. unemployment rate				0.07	0.07^{*}
				(0.04)	(0.04)
Pct. 65 or older				-0.17^{***}	-0.17^{***}
				(0.04)	(0.04)
Pct. black				-0.14^{***}	-0.15^{***}
				(0.04)	(0.05)
Pct. Hispanic				-0.18^{***}	-0.18^{***}
				(0.04)	(0.04)
Pct. college degree				-0.20^{***}	-0.20^{***}
				(0.07)	(0.07)
Pct. employed in industry				0.14^{***}	0.14^{***}
				(0.05)	(0.04)

Notes: Continuous input variables are standardized by subtracting their means and dividing by two times their standard deviations. $^{*}0 \notin 90\%$ HPD; $^{**}0 \notin 95\%$ HPD; $^{***}0 \notin 99\%$ HPD.

Warner bills. Similarly, one can predict how the Senate might have voted on the Waxman-Markey bill had such companion legislation actually reached the Senate floor.[19]

Cross-chamber votes were simulated for the three major climate legislation roll calls listed in Table 2.5 in a manner identical to the one characterized by (2.46), (2.47), (2.48), and (2.49). In order to ensure that these simulated votes made sense, two assumptions were made. First, the votes in the House were assumed to pass with a simple majority while the vote in the Senate was assumed to pass with a 3/5

[19] Johnson (2015) provides some background and references on why an actual vote did not take place in the Senate.

Table 2.7: Simulated results of cross-chamber roll call votes on climate change legislation

Legislation	Date	Production-based		Consumption-based	
		P("pro")	Margin	P("pro")	Margin
Lieberman-McCain bill[a]	October 30, 2003	0.02	-27.73	0.01	-27.86
Lieberman-Warner bill[a]	June 06, 2008	0.99	40.96	1.00	40.86
Waxman-Markey bill[b]	June 26, 2009	0.00	-9.92	0.00	-6.23

Notes: [a] House vote. [b] Senate vote. Based on 200,000 simulations. The P("pro") columns show the percentage of simulations where the pro-climate outcome occurs. The Margin columns show the average difference between the total "pro" votes and the number of votes required for the pro-climate outcome.

majority. Second, the simulated cross-chamber votes were assumed to take place on the same date as the actual vote. This ensures that the appropriate total number of legislators were simulated: 435 representatives and 100 senators.[20] This latter assumption also implies that none of the legislators missed the vote either by chance or strategically.

Table 2.7 summarizes the simulated outcomes. Using the production-based measure, the probability that the Lieberman-McCain bill passes in the House is 1.83% with an average margin of -27.7; these values change slightly to 0.6% and -27.9 respectively when using the consumption-based measure. The probability that the House's version of the Lieberman-Warner bill passes is 99.46% with an average margin of approximately 41.0 using the production-based inventory; these values are essentially the same when using the consumption-based inventory. Finally, the probability that the Waxman-Markey bill passes in the Senate is 0.07% using the production-based measure and 0.2% using the consumption-based alternative. In essence, it would appear that at least in 2008 and 2009 the House was in a position to pass climate change legislation with the Senate continually being the roadblock.

[20] In the case of the simulated Lieberman-Warner vote in the House there were only 434 representatives since one seat was vacant when the actual Senate vote occurred.

2.7 Conclusion

Previous research generally takes an international view toward the carbon emissions embodied in trade with a focus on the degree of "carbon leakage" that may occur due to incomplete coverage of regulations across nations. While there is no national level counterpart to this issue, the distinction between where carbon is produced and where it is consumed may still important in that in may influence legislative outcomes. Prior research also typically takes estimates of ideology as an exogenous input and only considers carbon's role in congressional voting from the production side. This analysis demonstrates how estimates of ideology and the determinants of voting on climate change can be recovered in one step. Moreover, by accounting for trade in electricity I am able to uncover how a shift to consumption-based emissions impacts voting behavior.

My results show that switching from the traditional production-based measure to a consumption-based measure can significantly impact the probability of climate legislation passing. Although these effects can be small in some cases, it is important to note that in an increasingly polarized Congress the loss or gain of even one vote may be pivotal. Furthermore, congressional action at some point is likely to be crucial. The Clean Power Program is currently vulnerable both to the presidential election and the Supreme Court. In addition, should the Paris Accords evolve into a binding treaty congressional approval is required. In the case of formal treaty ratification, Senate 67 votes in the Senate would be necessary.

2.A The Clean Power Plan

The Clean Power Plan's main impact on emissions is through the carbon intensity rules established for both new and existing electricity generating units. The latter rule establishes gradually declining intensities for fossil fuel-fired generators and natural gas-fired combined cycle generators which are listed in Table 2.8.

The EPA defines state s's rate-based carbon intensity goal in year t as:

$$i_{st} = \lambda_s^f \, i_t^f + \lambda_s^n \, i_t^n \tag{2.50}$$

where i_t^f and i_t^n denote the fossil fuel and natural gas intensities listed in Table 2.8 and λ_s^f and λ_s^n denote the share of state s's electricity from impacted fossil fuel and natural gas generators in 2012 repsectively. Alternatively, the EPA also allows states to comply with the rule using a mass-based goal. This is defined as:

$$m_{st} = i_{st} \, (g_s^f + g_s^n) + 2 \, i_{st} \, \lambda_s^g \, BB3 \tag{2.51}$$

where g_s^f and g_s^n denote state s's electricity generation from fossil fuel and natural gas in 2012, λ_s^g denotes state s's share of total generation from fossil fuel and natural gas in 2012, and $BB3$ denotes the Building Block 3 generation shown in Table 2.8. This is the amount of generation from zero-carbon sources that the EPA assumes will be available each year that is not already being used to meet current rate- or mass-based goals.[21]

[21] Note that if a state adds one GWh from a zero-carbon source then it can also add one GWh from a source that emits $2 \times i_{st}$ since its average carbon intensity remains i_{st}. If a state were to add all of the zero-carbon generation available to it – assumed to equal $\lambda_s^g \times BB3$ – then it can also add an equal amount of generation that emits $2 \times i_{st} \times \lambda_s^g \times BB3$.

Table 2.8: Reduction goals and assumptions for existing generators

	2022	2023	2024	2025	2026	2027	2028	2029	2030
Fossil fuel-fired carbon intensity[a]	215	208	197	191	186	180	174	168	161
Combined cycle carbon intensity[a]	111	108	106	103	101	99	98	96	95
Building Block 3 generation[b]	95	91	93	103	111	113	132	150	166

Notes: [a] MtC/GWh. [b] 1000 GWh.

Importantly, because the above calculations are derived solely from the performance of individual generators in 2012 the same procedure can be used to define the goals at the district level. The corresponding λ_d^f, λ_d^n, λ_d^g, g_d^f, and g_d^n are found by combining the generator data found in the EPA Clean Power Plan State Goal Visualizer, the geographic data found in EIA form 860, and the congressional district boundaries taken from Lewis et al. (2013).

2.B League of Conservation Voters roll calls

Tables 2.9 and 2.10 provide summary information of the roll calls used in the above analysis. Each vote was either categorized as related to climate change by the LCV or deemed relevant to the climate change issue after examining its description on THOMAS.

Table 2.9: Climate change roll calls in the House

Year	Rollcall	Type	Description	Result
1996	207	Amendment	Climate Change Research	Rejected
1998	332	Amendment	Global Warming Gag Rule	Agreed to
2000	323	Amendment	Global Climate Change	Agreed to
2007	337	Amendment	Global Warming and National Security	Rejected
2007	555	Amendment	Reducing Global Warming	Rejected
2009	477	Passage	Climate Change and Clean Energy	Passed
2009	558	Amendment	Defunding Environmental and Energy Staff	Rejected
2011	230[b]	Procedural		Agreed to
2011	231[b]	Passage		Passed
2011	249	Passage	Global Warming Pollution	Passed
2011	448	Amendment	Climate Change Adaption	Agreed to
2011	650	Passage	Keystone XL Tar Sands Pipeline	Passed
2012	170	Passage	Environmental Assault in the Transportation Bill	Passed
2012	241	Amendment	Climate Change Education	Agreed to
2012	292	Procedural	Keystone XL Tar Sands Pipeline	Agreed to
2012	593	Amendment	Carbon Pollution Endangerment Finding	Rejected
2012	71	Passage	Drilling Everywhere to Fund Transportation	Passed
2013	179	Passage	Keystone XL Tar Sands Pipeline	Passed
2013	430	Amendment	Social Cost of Carbon	Agreed to
2013	601	Amendment	Methane Emissions	Rejected
2014	103	Amendment	Climate Change Science	Rejected
2014	106	Passage	Carbon Pollution	Passed
2014	267	Amendment	Blocking Climate Action in Trade Agreements	Agreed to
2014	389	Amendment	Social Cost of Carbon	Agreed to
2014	39	Amendment	Climate Change and Public Lands	Rejected
2014	397	Amendment	Impacts of Climate Change	Agreed to
2014	519	Passage	Keystone XL Tar Sands Pipeline	Passed
2014	91	Passage	Undermining Flood Insurance Reform	Passed
2015	209[a]	Amendment	Blocking Climate Research	Agreed to
2015	381[a]	Amendment	Climate Science and Benefits of Action	Rejected
2015	384[a]	Passage	Carbon Pollution Limits for Power Plants	Passed
2015	400[a]	Amendment	Social Cost of Carbon	Rejected
2015	513[a]	Amendment	Considering the Social Cost of Carbon	Rejected
2015	650[a]	Passage	Attack on Carbon Pollution Standards for Existing Power Plants	Passed
2015	651[a]	Passage	Attack on Carbon Pollution Standards for New Power Plants	Passed

Notes: [a] Recent votes identified by the LCV. [b] Manually added votes identified using THOMAS.

Table 2.10: Climate change roll calls in the Senate

Year	Rollcall	Type	Description	Result
2003	420	Amendment	Global Warming	Rejected
2005	148[b]	Amendment		Rejected
2005	149	Procedural	Global Warming	Rejected
2005	151[b]	Amendment		Rejected
2007	166	Amendment	Water Resources – Global Warming	Rejected
2008	117	Amendment	Wind Insurance	Rejected
2008	141[b]	Cloture		Rejected
2008	145	Cloture	Global Warming	Rejected
2009	117[b]	Amendment		Agreed to
2009	126[b]	Amendment		Agreed to
2009	141[b]	Amendment		Agreed to
2009	142[b]	Amendment		Agreed to
2009	295	Procedural	Defunding Environmental and Energy Staff	Rejected
2009	307	Amendment	National Security and Climate Change	Rejected
2010	184	Procedural	Dirty Air Act	Rejected
2011	51[b]	Amendment		Rejected
2011	52[b]	Amendment		Rejected
2011	53[b]	Amendment		Rejected
2011	54	Amendment	Global Warming Pollution	Rejected
2012	34	Amendment	Keystone XL Tar Sands Pipeline	Rejected
2012	38	Amendment	Arctic Refuge, Offshore Drilling, and Keystone XL	Rejected
2013	59	Procedural	Pricing Carbon Pollution	Rejected
2013	61	Amendment	Keystone XL Tar Sands Pipeline	Agreed to
2013	76	Amendment	Climate Change Safeguards	Rejected
2014	280	Passage	Keystone XL Tar Sands Pipeline	Failed
2014	78	Passage	Undermining Flood Insurance Reform	Passed
2015	103[a]	Amendment	Blocking Climate Action	Agreed to
2015	115[a]	Amendment	Responding to the Threat of Climate Change	Agreed to
2015	116[a]	Amendment	Attack on the Clean Power Plan	Agreed to
2015	12[a]	Amendment	Climate Change Science	Rejected
2015	123[a]	Procedural	Lifting the Climate Change Gag Order	Rejected
2015	20[a]	Amendment	International Climate Action	Rejected
2015	238[a]	Amendment	Climate Change Science Education	Rejected
2015	306[a]	Passage	Attack on Carbon Pollution Standards for Existing Power Plants	Passed
2015	307[a]	Passage	Attack on Carbon Pollution Standards for New Power Plants	Passed
2015	38[a]	Amendment	Climate Resiliency	Rejected
2015	46[a]	Amendment	Keystone XL Environmental Impact Analysis	Rejected
2015	89[a]	Amendment	Acknowledging Climate Change	Rejected

Notes: [a] Recent votes identified by the LCV. [b] Manually added votes identified using THOMAS.

2.C Electricity generation and emissions embodied in trade

Table 2.11: Estimates of state-level per capita electricity use

	(1)	(2)	(3)
Pct. employed in industry	0.151^{***}	-0.060	4.842^{***}
	(0.032)	(0.056)	(0.966)
Pct. employed in trade	0.075^{**}	-0.121	-17.050^{***}
	(0.031)	(0.190)	(3.282)
Pct. 65 or older	0.145	2.602^{***}	17.090
	(0.101)	(0.749)	(16.800)
Pct. homes w/ electric heat	0.116^{***}	0.295^{***}	0.912^{***}
	(0.012)	(0.030)	(0.135)
Log median income (household)	8.363^{***}	5.679	$-4{,}671.000^{***}$
	(1.525)	(12.680)	(1,764.000)
Cooling degree days	0.001^{*}	0.000	0.003
	(0.000)	(0.001)	(0.002)
Heating degree days	-0.000^{***}	0.001	-0.000
	(0.000)	(0.000)	(0.001)
Coal price	0.316	0.597	9.662^{***}
	(0.223)	(0.622)	(2.122)
Electricity price	-0.325^{***}	-1.139^{***}	4.398^{***}
	(0.034)	(0.116)	(1.515)
Natural gas price	-0.109	-1.398^{***}	5.159
	(0.106)	(0.292)	(3.280)
Oil price	-0.047	0.432	-7.964^{**}
	(0.128)	(0.371)	(3.095)
Observations	1,008	1,008	1,008
R^2	0.995	0.996	0.997
Adjusted R^2	0.995	0.996	0.996
Residual Std. Error	1.127 (df = 929)	1.033 (df = 918)	0.970 (df = 907)

Notes: Model 1 corresponds to equation (2.9). Model 2 includes the squares of each of the regressors. Model 3 includes the squares and the square roots of each of the regressors.

Recall that equation (2.9) defines the model for determining state-level per capita electricity use:

$$q_{st} = \alpha_s + \gamma_t + \boldsymbol{c'_{st}\beta} + +\boldsymbol{w'_{st}\delta} + \boldsymbol{p'_{st}\eta} +$$

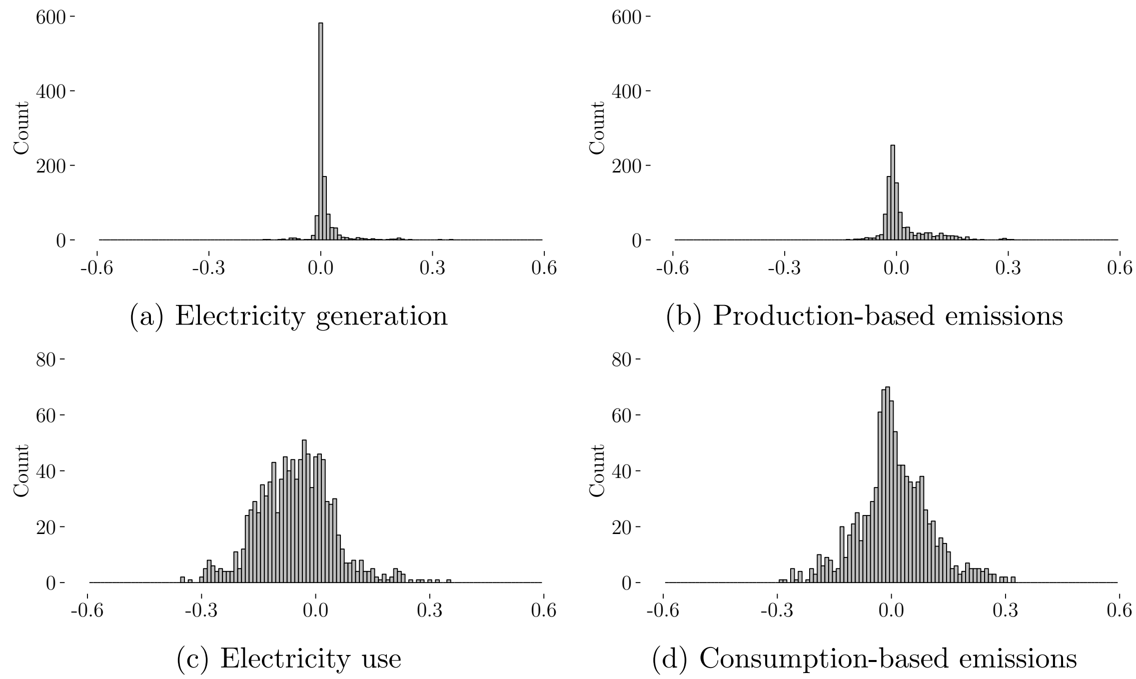


Figure 2.5: Aggregated congressional district data compared with state data

Notes: The x-axis shows the percentage difference between estimated congressional district data aggregated by state and the actual state data provided by the Energy Information Administration.

which is used to derive district-level consumption-based emissions. Table 2.11 reports the estimated values for the coefficients of this model. Perhaps the only surprising result is the negative coefficient on heating degree days; *a priori* one would expect both cooling and heating degree days to lead to increased electricity use. The adjusted R^2 indicates that the models fit the data well and are likely to yield reasonable out-of-sample predictions which is their main purpose.

In order to assess the plausibility of the district-level data I calculated:

$$\hat{g}_{st} = \frac{\sum_{d \in D_s} g_{dt}}{g_{st}} - 1 \tag{2.52}$$

$$\hat{e}^p_{st} = \frac{\sum_{d \in D_s} e^p_{dt}}{e^p_{st}} - 1 \tag{2.53}$$

$$\hat{q}_{st} = \frac{\sum_{d \in D_s} q_{dt}}{q_{st}} - 1 \tag{2.54}$$

$$\hat{e}^c_{st} = \frac{\sum_{d \in D_s} e^c_{dt}}{e^c_{st}} - 1 \tag{2.55}$$

where D_s is the set of districts in state s. Recall that the values of g_{st}, e^p_{st}, q_{st}, and e^c_{st} are based on data taken directly from the EIA. Aggregating the district-level data and comparing it to the state-level data provides one way of determining if the district-level estimates are reasonable.

The values of $\hat{g}_{st}, \hat{e}^p_{st}, \hat{q}_{st}$, and $\hat{e}^c_{st}$ are presented in Figure 2.5. Figure 2.5a shows that aggregated electricity generation – derived by spatially combining plant-level generation with congressional district boundaries – closely matches the state-level data. Figure 2.5b shows the same is true for aggregated production-based emissions derived by using plant-level fuel combustion data and the allocation procedure described by equations (2.4), (2.5), (2.6), and (2.7). Figure 2.5c shows that aggregated electricity use – derived using out-of-sample predicted values of the model above – is less accurate. However, the errors appear to be normally distributed around zero and are generally within 10% of the state value. Figure 2.5d shows a similar pattern for aggregated consumption-based emissions; this is to be expected since the error in electricity use propagates directly into these values. Importantly, for those states with only one congressional district – Delaware, Montana, North Dakota, South Dakota, Vermont, and Wyoming – the same four patterns are observed.

2.D MCMC convergence

MCMC simulation was done using `Stan` – an increasingly popular programming language which implements Bayesian inference using the No-U-Turn Sampler introduced by Hoffman and Gelman (2014). Gelman and Shirley (2011) note that two of the main difficulties with using MCMC methods – regardless of sampler – are ensuring that the chains run long enough to converge and that the samples accurately reflect the target distribution. `Stan` conveniently outputs two statistics which can help diagnosis whether these difficulties have been overcome.

The first statistic is the "potential scale reduction factor" originally proposed by Gelman and Rubin (1992). Generally denoted $\hat{R}$, this value measures the ratio of the average variance of the samples within each MCMC chain to the variance of the pooled samples between all the MCMC chains. If the chains were sampling from the same distribution – suggesting convergence – then this value would equal one. Gelman and Rubin (1992) recommend that each of the chains be initialized with diffuse starting values and to continue sampling until $\hat{R}$ is less than 1.1 for all of the model parameters.

The second statistic is the effective sample size n_{eff} which estimates the number of independent samples within each chain after correcting for autocorrelation. `Stan` uses a variogram-based approach – see Stan Development Team (2015c) for a more detailed discussion – to provide these estimates. The value of n_{eff} is important since having more samples yields more precise estimates of the parameters and it also indicates the sampler is providing accurate information about the target distribution.

Table 2.12 provides a summary of the two statistics using the specification in column four of Tables 2.3, 2.4, and 2.6. The $\hat{R}$'s across all parameters are equal to

Table 2.12: MCMC convergence diagnostics

Parameter	House			Senate			Common		
	$\hat{R}$		n_{eff}	$\hat{R}$		n_{eff}	$\hat{R}$		n_{eff}
	Mean	SD	Mean	Mean	SD	Mean	Mean	SD	Mean
α_j	1.0	0.0	180.7	1.0	0.0	757.3	1.0	0.0	556.6
β_j	1.0	0.0	1572.3	1.0	0.0	1508.3	1.0	0.0	1632.6
$\boldsymbol{\gamma}$, $\boldsymbol{\delta}$	1.0	0.0	433.4	1.0	0.0	786.9	1.0	0.0	516.7
θ_i	1.0	0.0	1822.6	1.0	0.0	1642.9	1.0	0.0	1853.7

one suggesting the chains converged. Furthermore, the table shows that of the 2,000 samples stored from the simulation provide – on average – a minimum of 200 effective samples for each of the parameters.

2.E Heteroskedastic extension

As a robustness check I also estimated a heteroskedastic model of climate change voting using an approach similar to one implemented in Lauderdale (2010). In this case, the error terms in the spatial model are assumed to be distributed:

$$\epsilon_{ijy} \sim \text{GEV}(\mu, \sigma_i \sigma_j, 0) \tag{2.56}$$

$$\epsilon_{ijn} \sim \text{GEV}(\mu, \sigma_i \sigma_j, 0) \tag{2.57}$$

so that they now depend on both roll call j and legislator i. The σ_i's characterize to what extent the legislator's voting behavior is not related to the underlying policy dimension. In other words, it captures the variation in the degree to which individual legislators vote on the basis their ideal point θ_i. Lauderdale (2010) argues that "particularistic constituency concerns, idiosyncratic views held by only a small number of legislators, or other factors that are not broadly influential" might serve as situations in which this estimator is useful. It is not unreasonable to think that climate change action might fall into this category. For example, Lauderdale (2010) shows that high σ_i's are observed for senators considered to be "mavericks" such as John McCain (R-AZ) who's maverick status is partially related to his position on climate change.[22]

[22] See supra note 13.

The formal model now becomes:

$$\text{P(“yea” on roll call } j) = \text{logit}^{-1}((\beta_j \theta_i - \alpha_j)/\sigma_i) \tag{2.58}$$

$$\theta_i \sim \mathcal{N}(\mu_i, 1) \tag{2.59}$$

$$\mu_i = \gamma_0 + \gamma_1 \, \mathcal{I}_i^R + \bar{\boldsymbol{x}}_{\boldsymbol{i}}' \boldsymbol{\delta} \tag{2.60}$$

$$\alpha_j \sim \mathcal{N}(0, 25) \tag{2.61}$$

$$\beta_j \sim \mathcal{N}(0, 25) \tag{2.62}$$

$$\gamma_0 \sim \mathcal{N}(\text{-}1, 1) \tag{2.63}$$

$$\gamma_1 \sim \mathcal{N}(2, 1) \tag{2.64}$$

$$\boldsymbol{\delta} \sim \mathcal{N}(0_k, 25 \times I_k) \tag{2.65}$$

$$\sigma_i \sim \Gamma(\nu, \nu) \tag{2.66}$$

$$\nu \sim \mathcal{U}(0, 1000) \tag{2.67}$$

where the additional priors for σ_i and ν are taken directly from code provided by Lauderdale and the random draws:

$$\sigma_i^0 \sim \Gamma(\nu^0, \nu^0) \tag{2.68}$$

$$\nu^0 \sim \mathcal{U}(0, 1000) \tag{2.69}$$

serve as additional initial values. To accommodate for the increased complexity of the model, each MCMC chain was simulated for 1,000 iterations after an initial 1,000 iterations were used as “warm-up” and only every other iteration was stored for analysis.

Tables 2.13 and 2.14 provide the posterior means and standard deviations of

Table 2.13: Estimates of the robust model in the House

	(1)	(2)	(3)	(4)	(5)
(Intercept)	-0.96^{***}	-0.97^{***}	-0.96^{***}	-0.93^{***}	-0.93^{***}
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Republican	1.74^{***}	1.76^{***}	1.74^{***}	1.69^{***}	1.69^{***}
	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)
Log production-based emissions		0.28^{***}		0.13^{***}	
		(0.04)		(0.05)	
D x Log production-based emissions			0.23^{***}		0.09
			(0.06)		(0.07)
R x Log production-based emissions			0.30^{***}		0.16^{***}
			(0.06)		(0.06)
Log median income (household)				-0.27^{***}	-0.28^{***}
				(0.08)	(0.08)
Avg. unemployment rate				0.08^{*}	0.09^{*}
				(0.05)	(0.05)
Pct. 65 or older				-0.17^{***}	-0.17^{***}
				(0.05)	(0.05)
Pct. black				-0.16^{***}	-0.15^{***}
				(0.05)	(0.05)
Pct. Hispanic				-0.19^{***}	-0.18^{***}
				(0.05)	(0.05)
Pct. college degree				-0.22^{***}	-0.22^{***}
				(0.08)	(0.08)
Pct. employed in industry				0.15^{***}	0.14^{***}
				(0.05)	(0.05)

Notes: Continuous input variables are standardized by subtracting their means and dividing by two times their standard deviations. $^{*}0 \notin 90\%$ HPD; $^{**}0 \notin 95\%$ HPD; $^{***}0 \notin 99\%$ HPD.

the parameters in (2.60). One can see that the estimates are nearly identical to those found in Tables 2.3 and 2.4. Futhermore, the classification rates, the number of distinguishable β_j's, and the average excess error rates – as seen in 2.6 – are also comparable to the homoskedastic model.

Of course, the σ_i's are of direct interest since they point to those legislators that are seemingly less predictable when voting on climate change. In the House, the posterior means range from 0.995 to 1.012 showing no discernible difference from the homoskedastic model. In the Senate, the posterior means for some senators are noticeably greater than one. The ten senators with the highest observed σ_i's are

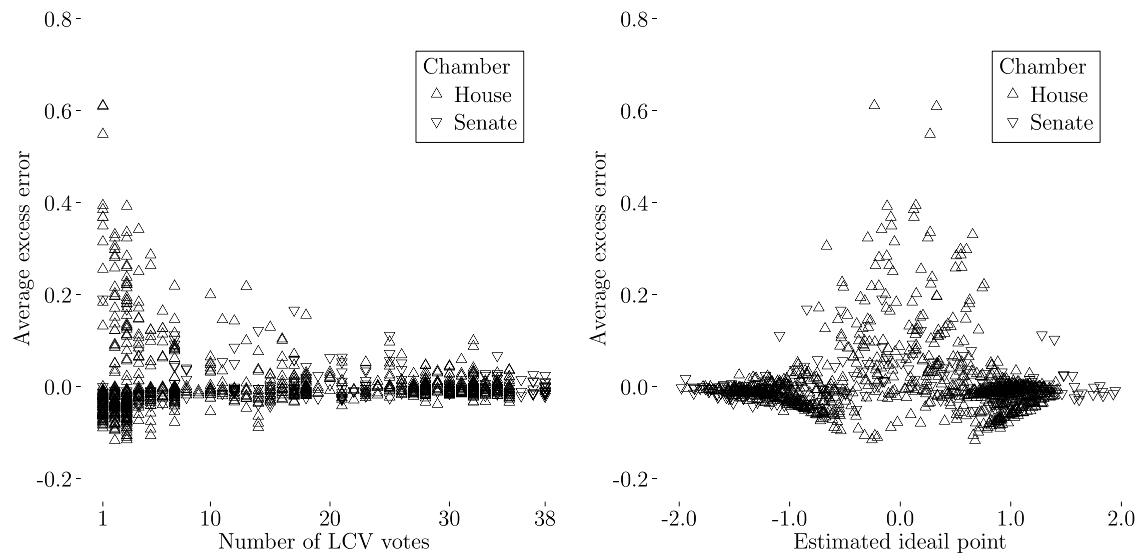
Table 2.14: Estimates of the robust model in the Senate

	(1)	(2)	(3)	(4)	(5)
(Intercept)	-0.88^{***}	-0.78^{***}	-0.77^{***}	-0.70^{***}	-0.70^{***}
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Republican	1.72^{***}	1.54^{***}	1.54^{***}	1.39^{***}	1.39^{***}
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Log production-based emissions		0.67^{***}		0.46^{***}	
		(0.08)		(0.10)	
D x Log production-based emissions			0.73^{***}		0.48^{***}
			(0.11)		(0.14)
R x Log production-based emissions			0.58^{***}		0.43^{***}
			(0.14)		(0.14)
Log median income (household)				-0.46^{***}	-0.44^{***}
				(0.14)	(0.14)
Avg. unemployment rate				-0.07	-0.08
				(0.09)	(0.08)
Pct. 65 or older				-0.25^{***}	-0.24^{***}
				(0.09)	(0.09)
Pct. black				0.18^{**}	0.19^{**}
				(0.09)	(0.09)
Pct. Hispanic				-0.08	-0.08
				(0.09)	(0.09)
Pct. college degree				0.06	0.05
				(0.13)	(0.14)
Pct. employed in industry				0.05	0.05
				(0.09)	(0.09)

Notes: Continuous input variables are standardized by subtracting their means and dividing by two times their standard deviations. $^{*}0 \notin 90\%$ HPD; $^{**}0 \notin 95\%$ HPD; $^{***}0 \notin 99\%$ HPD.

Timothy Johnson (D-SD), Kent Conrad (D-ND), Bob Corker (R-TN), John McCain (R-AZ), Robert Byrd (D-WV), Mary Landrieu (D-LA), Jay Rockefeller (D-WV), Ben Nelson (D-NE), Judd Gregg (R-NH), and Mark Pryor (D-AR). The σ_i's in this group range from 1.647 to 2.223. However, only Johnson and Conrad have values distinguishable from one using the 95% HPD intervals. Notably, several of these senators have high observed average excess error rates; this is consistent with the notion that the σ_i's capture the degree to which the one dimensional model fails to predict the observed votes.

Finally, using the new estimated ideal points and counterfactual ideal points, I



(a) (b)

Figure 2.6: Average excess error rates

Notes: A total of 35 votes were analyzed in the House and 38 in the Senate.

performed the same vote simulation as described by (2.48), (2.49), (2.48), and (2.49). Once again, switching from the production-based to the consumption-based inventory lowers the average probability of pro-climate outcomes occurring. In the House, the value falls from 16.5% to 15.8% while in the Senate it again falls by a much smaller amount. A more detailed summary of the simulated outcomes of several major votes from each chamber are provided in Table 2.15 and one can see that they are very similar to those found in 2.5.

The results in this section provide some supporting evidence that the simpler model is able to fit the data well. However, some caution is warranted. For instance, Lauderdale (2010) finds via simulation that the heteroskedastic model has some diffculty in resolving the σ_i's when the number of roll call votes is small or when the range of true legislator-specific variances is also small.

Table 2.15: Simulated results of roll call votes on climate change legislation

Legislation	Type	Production-based		Consumption-based	
		P("pro")	Margin	P("pro")	Margin
Waxman-Markey bill[a]	Passage	0.69	3.04	0.99	18.27
Keystone XL pipeline[a]	Passage	0.00	-44.84	0.00	-30.94
CPP standards for new plants[a]	Passage	0.00	-30.00	0.00	-28.25
CPP standards for existing plants[a]	Passage	0.00	-23.06	0.00	-27.63
Lieberman-McCain bill[b]	Amendment	0.04	-6.29	0.01	-7.80
Lieberman-Warner bill[b]	Cloture	0.26	-2.59	0.15	-3.80
Keystone XL pipeline[b]	Passage	0.60	0.98	0.80	3.29
CPP standards for new plants[b]	Passage	0.05	-2.09	0.03	-1.92
CPP standards for existing plants[b]	Passage	0.06	-2.07	0.03	-1.89

Notes: [a] House vote. [b] Senate vote. Based on 200,000 simulations. The P("pro") columns show the percentage of simulations where the pro-climate outcome occurs. The Margin columns show the average difference between the total "pro" votes and the number of votes required for the pro-climate outcome.

Chapter 3

Self-enforced international environmental agreements: A role for bargaining power

3.1 Introduction

A large literature exists on game theoretic analysis of international environmental agreements (IEAs) and not surprisingly a considerable amount of attention has been devoted specifically to agreements seeking to curb carbon emissions. The usefulness of game theory in this setting can be justified based on three observations. First, because benefits from a carbon IEA are non-rival and non-excludable each country has an incentive to free-ride; they stand to gain by forgoing the cost of action while benefiting from the actions taken by others. Second, IEAs must be negotiated and so problems of coordination exist; indeed, the debate on who should abate, by how much, and what should happen if they do not comply all remain contentious issues in current climate negotiations. Third, countries are sovereign and there is currently no supranational authority which can enforce an IEA; thus, an agreement must be self-enforced in that it must be in the best interest of each country to participate. These three aspects roughly characterize the strategic tensions that exists in current models of international cooperation.

Caparrós (2016) and Finus (2008) note that within the literature on game theory and IEAs, models can be broadly separated into three groups based on which of the three strategic aspects is more important. First are static models where each country's decision to participate in an IEA is the main focus (examples include Barrett (1994), Chander and Tulkens (1997, 1995), Eyckmans and Tulkens (2003), Finus et al. (2006), Helm (2001), Germain et al. (2010, 2003), Nagashima et al. (2009), and Weikard et al. (2006)).[1] Second are static models where the negotiation process and bargaining are of central interest (examples include Beccherle and Tirole (2011), Konrad and Buchholz (1994), Segendorff (1998)). Third are repeated models where the ability of countries to credibly enforce an agreement's obligations over time is the main focus (examples include Asheim and Holtsmark (2008), Asheim et al. (2006), Barrett (2005, 2002, 1994), Dutta and Radner (2009), Froyn and Hovi (2008), Heitzig et al. (2011), and Kratzsch et al. (2012)).

Interestingly, four equilibrium concepts have dominated the three groups of models. The first group typically relies on either the non-cooperative notion of internal and external stability defined by D'Aspremont et al. (1983) or the cooperative

[1] The major distinction between internal and external stability and the γ-core is that the former leaves open the possibility of no or partial cooperation while the latter singularly looks at efficient cooperation. One way to understand the difference is to consider how a free-rider is treated. In the non-cooperative case, free-riding is ignored; any group that is cooperating simply maximizes their joint utility even with free-riders present. In the cooperative case, free-riding is not tolerated; any cooperating group dissolves if free-riders are present (even if the group's members are worse off by doing so).

notion of the γ-core defined by Chander and Tulkens (1997, 1995). The second group relies on the bargaining solution defined by Nash (1950). The third group generally uses the notion of renegotiation-proofness defined by Farrell and Maskin (1989).

This paper presents a new approach by applying the concept of contractual equilibrium defined by Miller and Watson (2013) to an infinitely repeated abatement game. In a sense, this type of equilibrium represents a hybrid of those just mentioned. A contractual equilibrium considers cooperative outcomes during negotiation phases similar to concepts like the γ-core and Nash (1950) bargaining[2] while also considering strategic incentives during action phases similar to concepts like internal and external stability and renegotiation-proofness.

The application makes several contributions to the existing literature. First, the cooperative models lack any notion of how the agreement is to be enforced over time. Standard cooperative approaches – like the γ-core – also make strong assumptions on how agreements enforce compliance and focus exclusively on the most efficient outcome. In contrast, contractual equilibrium relies on self-enforcement more common in the non-cooperative literature. Cooperative actions are sustained in equilibrium under threat of specific punishments. Contractual equilibrium also allows for potentially inefficient agreements to emerge even when all countries participate.

Second, the repeated models lack a mechanism for how countries form an agreement. The focus is typically on outcomes such as participation and efficiency with no consideration given to the "process" that generates the IEA.[3] Indeed, renegotiation-proofness by definition rules out the possibility of negotiation. This implicitly ignores

[2] In fact, it utilizes the Nash (1950) bargaining solution explicitly.

[3] Barrett (1998) notes: "International cooperation can be looked at in two different ways: as a process and as an outcome. Ultimately, it is the outcome that we will be most interested in. But the outcome may depend on the process that gave rise to it. So we may want to model the process, too."

the third strategic tension arising from problems of coordination. Contractual equilibrium considers negotiation explicitly thus extending notions of bargaining from existing static models to a repeated setting.

Finally, many of the existing models rely on symmetry; furthermore, when asymmetry is present it is usually only in two country settings. This paper provides an equilibrium characterization for an n country model with heterogeneous benefits and costs. This extends the two player characterization presented in Miller and Watson (2013) to more general settings and also makes the model well suited for "real-world" numerical applications.

The reminder of the paper is organized as follows. Section 3.2 develops the model which contractual equilibrium is applied to. Section 3.3 provides a numerical application. Section 3.4 concludes.

3.2 The model

Consider a repeated game involving $i = 1, \ldots, n$ countries. Each period of the game includes three phases. First, is the bargaining phase where the countries can make transfers and coordinate their abatement levels. Second, is the action phase where abatement actually occurs. Third, is a voluntary transfer phase. The payoffs to each country in the action phase of period t is given by:

$$u_{it}(a^t) = \sum\nolimits_{j=1}^{n} b_{ij} a_{jt} - \frac{c_i}{2} a_{it}^2 + d_i \tag{3.1}$$

where $a^t = (a_{1t}, \ldots, a_{nt})$, a_{it} is the abatement level chosen by country i, b_{ij} denotes the benefit country i receives from country j's abatement, c_i is a country-specific abatement cost parameter, and d_i is a country-specifc constant. The unique stage game Nash equilibrium is given by:

$$\hat{a}_{it} = \frac{b_{ii}}{c_i}$$

while the social optimum is given by:

$$a^*_{it} = \frac{\sum_{j=1}^{n} b_{ji}}{c_i}$$

For simplicity, it is assumed that countries use pure strategies when choosing abatement.

Let V denote the compact set of payoff vectors available to the countries when they agree and let L denote the highest attainable joint payoff:

$$V \subset \left\{(v_1, \ldots, v_n) : \sum\nolimits_{j=1}^{n} v_j = L\right\} \tag{3.2}$$

Let Z^i denote the subset of V with vectors that yield the lowest payoff to country i. Thus, for each vector $z^i \in Z^i$ the payoff to country i is defined as:

$$z^i_i = \min_{v \in V} \ v_i \tag{3.3}$$

Finally, let Y denote the set of payoff vectors available to the countries after the voluntary transfer phase:

$$Y = \left\{(y_1, \ldots, y_n) : y_i \geq z^i_i \ \forall \ i \ , \ \sum\nolimits_{j=1}^{n} y_j = L\right\} \tag{3.4}$$

Thus, in each period of the game – and when the countries agree – the countries receive some payoff vector in Y.

The countries begin each period with the intention of abating at some particular level and then have the opportunity to negotiate. An agreement in a given period constitutes immediate transfers among the countries, new coordinated levels of abatement, voluntary transfers, and continuation values for the next period as a function of abatement in the current period. Consider each country's payoff from the beginning of a period as the sum of its payoff within the period and its discounted continuation value from the start of the next period. Each country's value under agreement takes the form:

$$y_{it} = (1 - \delta)(m_{it} + u_{it}(a^t)) + \delta y_{it+1}(a^t) \tag{3.5}$$

where m_{it} denotes the transfer to country i and $y_{it+1}(a^t) \in Y$. If the countries fail to agree they make no transfers and abate as they originally intended. However, the model assumes the countries want to reach an agreement and even if they fail to do so today they anticipate doing so tomorrow. Thus, each country's value under disagreement takes the form:

$$\underline{y}_{it} = (1 - \delta)u_{it}(a^t) + \delta y_{it+1}(a^t) \tag{3.6}$$

where again $y_{it+1}(a^t) \in Y$. Importantly, in equilibrium – whether under agreement or disagreement – the current period's abatement levels a^t must be incentive compatible given the continuation values $y_{it+1}(a^t)$. That is to say, no country should be better off by myopically deviating from a^t in the current period and then getting punished in the next period.

Fully characterizing Y requires finding each country's lowest payoff z_i^i and the highest attainable joint payoff L. Let S denote the difference between the highest joint payoff of agreement and each of these lowest payoffs:

$$S = L - \sum\nolimits_{j=1}^{n} z_j^j \tag{3.7}$$

This slack provides a measure of how much a country might be rewarded (or punished) in equilibrium. Intuitively, as this value increases the joint payoff of the agreement also increases since there exists larger rewards (or larger punishments) to incentivize cooperation.

Negotiation in the model follows the Nash (1950) bargaining solution whereby countries divide surplus from agreement according to fixed weights denoted here by π_i. The payoffs at an agreement point y can be expressed relative to a disagreement point $\underline{y}$ as follows:

$$y_i = \underline{y}_i + \pi_i \left(L - \sum\nolimits_{j=1}^{n} \underline{y}_j \right) = (1 - \pi_i)\underline{y}_i - \pi_i \sum_{k \neq i} \underline{y}_j + \pi_i L \tag{3.8}$$

Note that (3.3) can be rewritten as:

$$z_i^i = \min_{\{a_j, y_j'\}_{j=1}^{n}} (1 - \pi_i)\underline{y}_i - \pi_i \sum_{k \neq i} \underline{y}_j + \pi_i L \tag{3.9}$$

$$\text{s.t.} \begin{cases} \underline{y}_k = (1-\delta)\left(\sum_{j=1}^n b_{kj}a_j - \frac{c_k}{2}a_k^2 + d_k\right) + \delta y'_k \ \forall\, k \\ (1-\delta)\left(\frac{b_{kk}^2}{2c_k} - b_{kk}a_k + \frac{c_k}{2}a_k^2\right) \le \delta(y'_k - z_k^k) \ \forall\, k \\ y' \in Y \end{cases}$$

Hence, the characterization z_i^i amounts to selecting an appropriate disagreement point which is defined by stage game abatement levels $\{a_j\}_{j=1}^n$ and continuation values $\{y'_j\}_{j=1}^n$. Note that the inequality constraints above ensure incentive compatibility of the disagreement point in the continuation game. Should some country j deviate in the current period then a vector of continuation values in the subset Z^j is chosen in the next period.

Define $\eta_k = y'_k - z_k^k$ and note that $\pi_i \sum_{j=i}^n \delta y'_j = \pi_i \delta L$. Substitution and some rearranging implies:

$$z_i^i = \gamma_i(S) + \pi_i L + (1-\pi_i)d_i - \pi_i \sum_{k \neq i} d_k \tag{3.10}$$

where $\gamma_i(S)$ is determined by the optimization problem:

$$\gamma_i(S) = \min_{\{a_j,\eta_j\}_{j=1}^n} (1-\pi_i)\left(\sum\nolimits_{j=1}^n b_{ij}a_j - \frac{c_i}{2}a_i^2\right) - \pi_i \sum_{k\neq i}\left(\sum\nolimits_{j=1}^n b_{kj}a_j - \frac{c_k}{2}a_k^2\right) + \frac{\delta}{1-\delta}\eta_i \tag{3.11}$$

$$\text{s.t.} \begin{cases} (1-\delta)\left(\frac{b_{kk}^2}{2c_k} - b_{kk}a_k + \frac{c_k}{2}a_k^2\right) \le \delta\eta_k \ \forall\, k \\ \sum_{j=1}^n \eta_j = S \\ 0 \le \eta_j \end{cases}$$

Note that when S is sufficiently large there are multiple solutions to the above problem; the abatement levels $\{a_j^i\}_{j=1}^n$ will be unique but there are potentially multiple sets of $\{\eta_j^i\}_{j=1}^n$ that will still preserve incentive compatibility.

Substituting (3.10) into (3.7) yields:

$$S = -\sum_{j=1}^{n} \gamma_j(S) \tag{3.12}$$

It is the fixed point of (3.12) that characterizes equilibrium. Letting S^* denote this fixed point, the highest joint payoff of agreement can be found by solving:

$$L^* = \max_{\{a_j,\eta_j\}_{j=1}^n} \sum_{j=1}^{n} \left(\sum_{l=1}^{n} b_{jl} a_l - \frac{c_j}{2} a_j^2 + d_j \right) \tag{3.13}$$

$$\text{s.t.} \begin{cases} (1-\delta)\left(\frac{b_{kk}^2}{2c_k} - b_{kk}a_k + \frac{c_k}{2}a_k^2\right) \leq \delta\eta_k \ \forall\ k \\ \sum_{j=1}^{n} \eta_j = S^* \\ 0 \leq \eta_j \end{cases}$$

Hence, the set of payoffs giving the lowest value to country i is given by:

$$Z^i = \left\{ (z_1^i, \ldots, z_n^i) : I \wedge II \wedge III \right\} \tag{3.14}$$

where I, II, and III correpsond to the conditions:

$$I : z_i^i = \gamma_i(S^*) + \pi_i L^* + (1-\pi_i) d_i - \pi_i \sum_{k \neq i} d_k \tag{3.15}$$

$$II : z_k^i \geq \frac{1-\delta}{\delta} \left[\frac{b_{kk}}{2c_k} - b_{kk} a_k^i + \frac{c_k}{2}(a_k^i)^2 \right] + z_k^k \ \forall\ k \neq i \tag{3.16}$$

$$III : \sum_{j=1}^{n} z_j^i = L^* \tag{3.17}$$

and the set of payoffs available to the countries after the voluntary transfer phase is given by:

$$Y^* = \left\{ (y_1, \ldots, y_n) : y_i \geq z_i^i \; \forall \, i \;, \; \sum\nolimits_{j=1}^{n} y_j = L^* \right\} \tag{3.18}$$

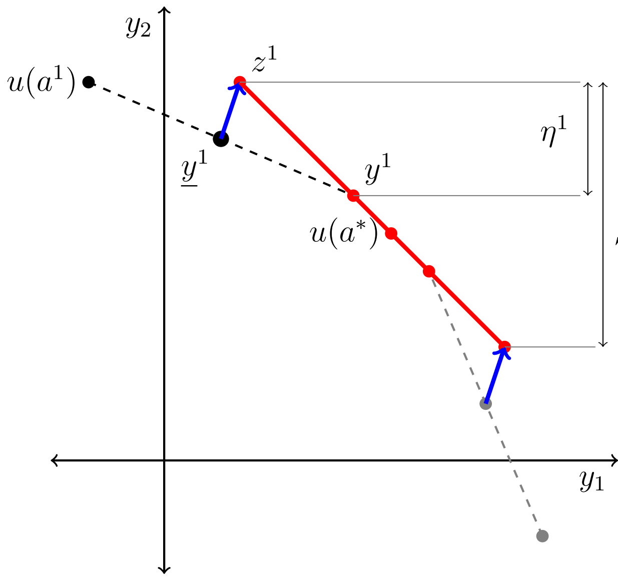
Figure 3.1a provides an illustration of the equilibrium for the case of two countries.[4] The set of payoffs giving the lowest value to country i is just a single point z^i and Y^* is a line segment with slope negative one. Figure 3.1b provides an illustration of the equilibrium for the case of three countries. The set of payoffs giving the lowest value to country i is now a line segment and Y^* is a triangle in a plane with normal vector $(1, 1, 1)$.

A key result in Miller and Watson (2013) is Thereom 7 which states that in the two country model L^* is maximized when one of the players has all the bargaining power. This result is extended to the n country case with the following proposition:

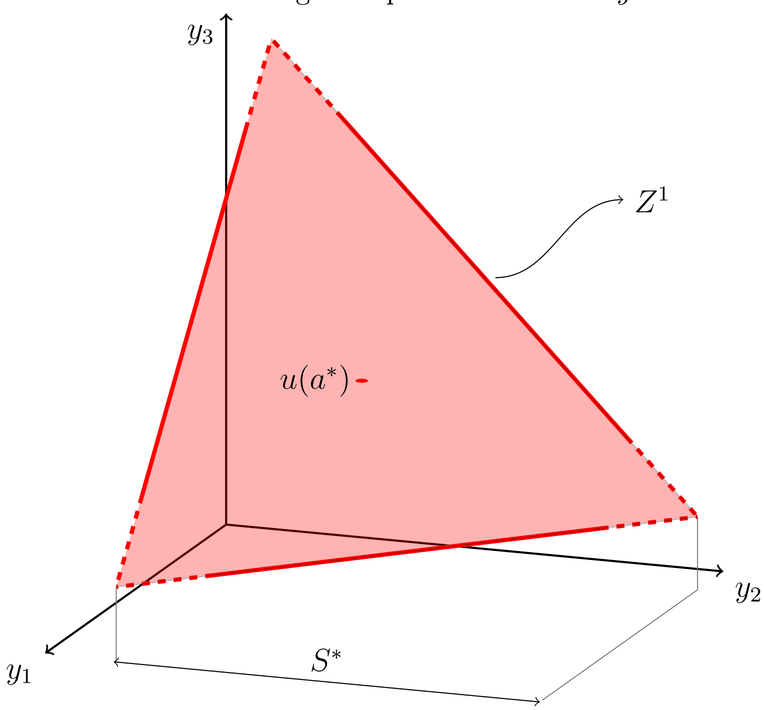
Proposition 1. *Given the stage game described by* (3.1)*, assume that* $b_{ij} = b_{kl}$ *for all* i*,* j*,* k*, and* l*. Let* m *denote the country with the lowest cost parameter* c_m*. The equilibrium slack – S^* – is maximized when* $\pi_m = 1$

Figures 3.2 and 3.3 illustrate this result for six different sets of c_i's. Note that Proposition 1 states that the equilibrium slack S^* is maximized when country m has all the bargaining power and not the level L^*. This is because in some cases S^* is sufficiently large that L^* can be achieved even if country m does not have all the bargaining power. In fact, what Figures 3.2 and 3.3 reveal that S^* is typically increasing as bargaining power becomes more asymmetric.

[4] Figure 3.1a is essentially a copy of Figure 1 in Miller and Watson (2013).

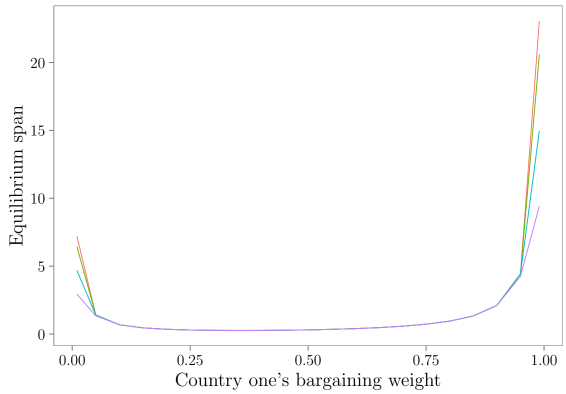


(a) The red line segment corresponds to Y^*. The blue arrows correspond to the bargaining weights. The point z^1 is attained by choosing a^* and then using a transfer to split the surplus relative to the disagreement point $\underline{y}^1$. The point $\underline{v}^1$ is attained by choosing a^1 in the current period and then continuing with promised utilities y^1 in the next period.

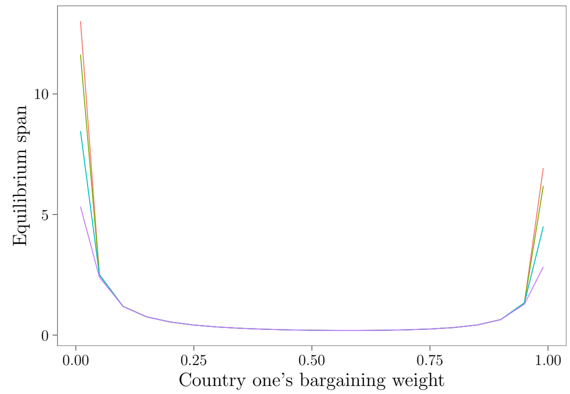


(b) The shaded area corresponds to Y^*. The red line segments correspond to the three subsets Z^i which yield the lowest payoffs to each of the countries.

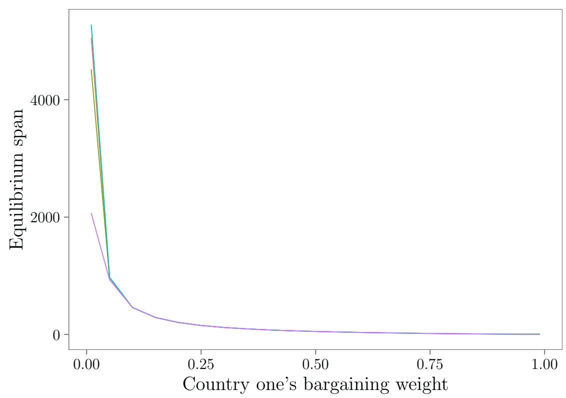
Figure 3.1: Contractual equilibrium with two and three countries



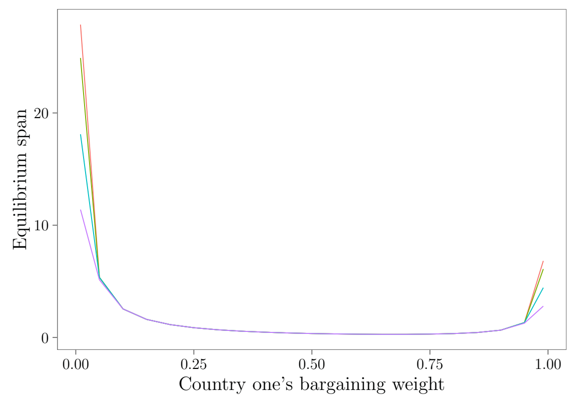
(a) $c_1 < c_2$



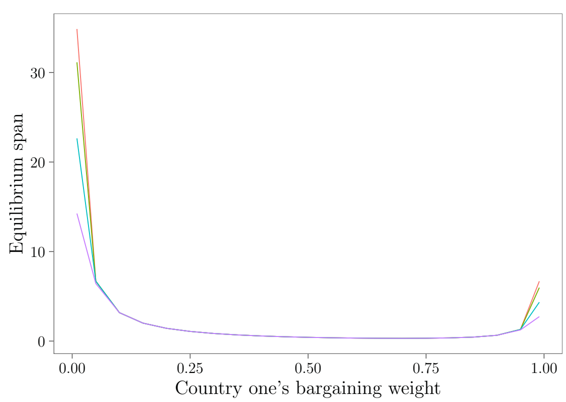
(b) $c_2 < c_1$



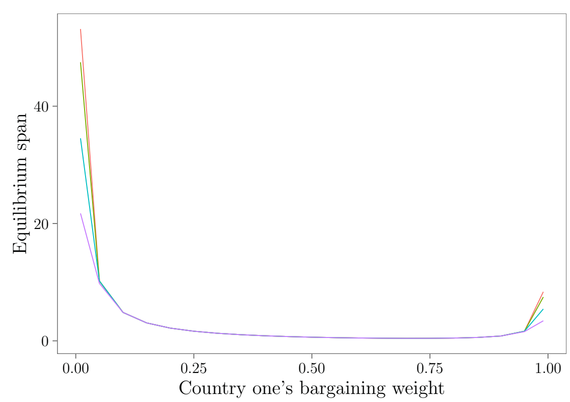
(c) $c_2 < c_1$



(d) $c_2 < c_1$

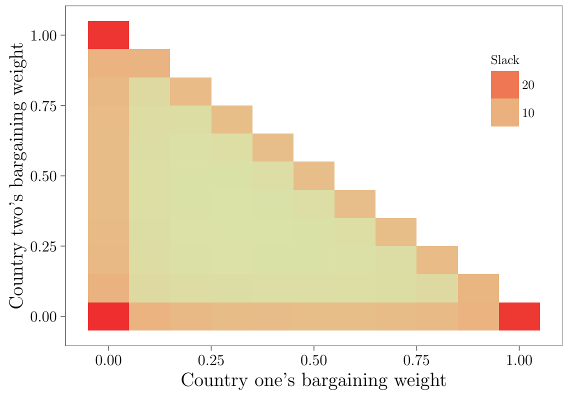


(e) $c_2 < c_1$

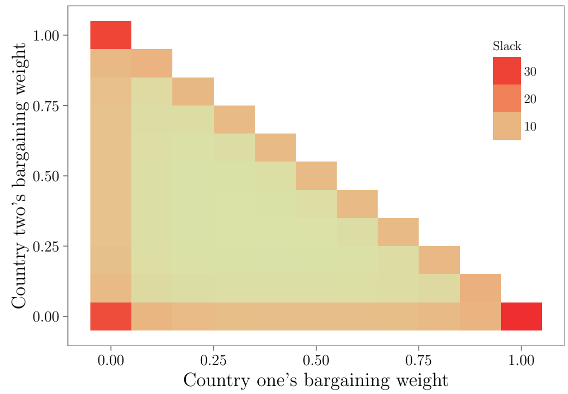


(f) $c_2 < c_1$

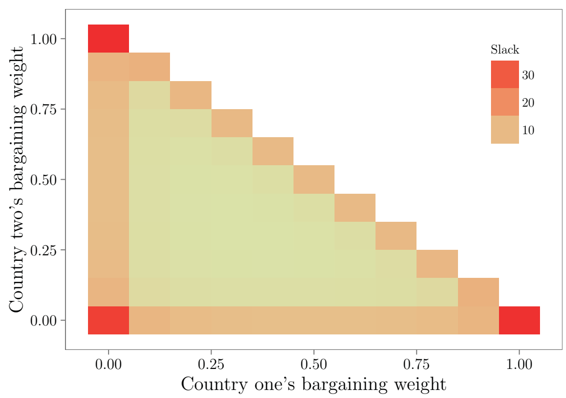
Figure 3.2: Simulations - two countries



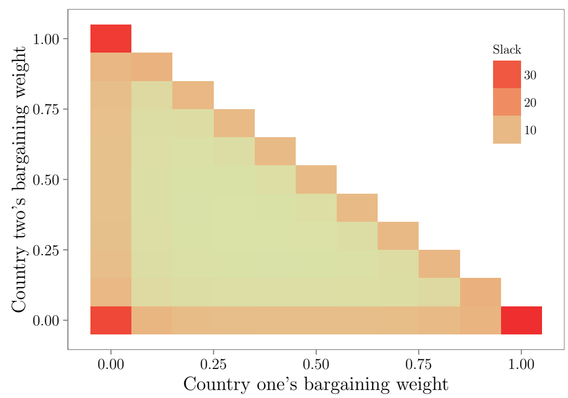
(a) $c_3 < c_2 < c_1$



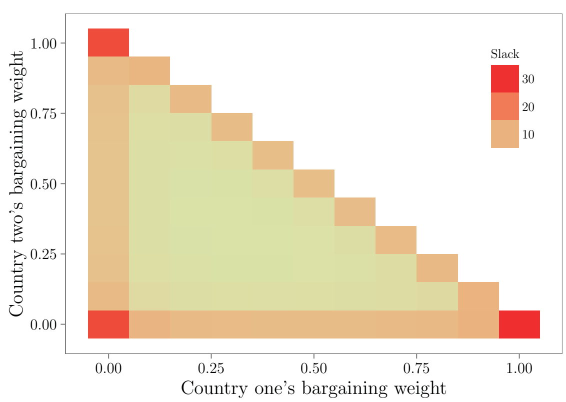
(b) $c_1 < c_2 < c_3$



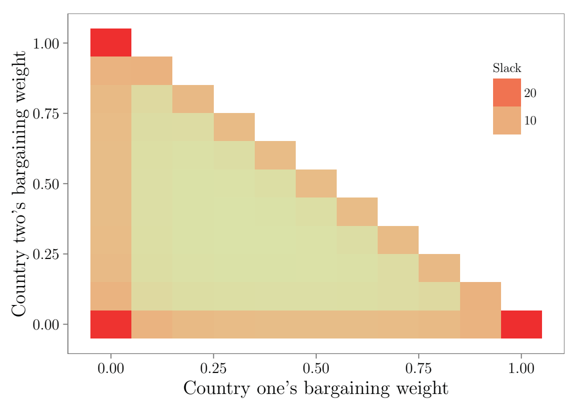
(c) $c_2 < c_1 < c_3$



(d) $c_1 < c_2 < c_3$



(e) $c_1 < c_3 < c_2$



(f) $c_1 < c_2 < c_3$

Figure 3.3: Simulations - three countries

3.3 Numerical application

To illustrate the role bargaining power plays in an agreement to reduce carbon emissions, I analyze a fifteen region game based on the Coalition Dynamic Integrated model of Climate and the Economy (C-DICE) introduced by Nordhaus (2015) as well as a twelve region game based on the STAbility of COalitions model (STACO) introduced by Finus et al. (2006).[5] In both models, the per unit benefit from abating is constant with each region receiving a fixed share. Along with costs, these two components comprise the major policy assumptions of the two models. Following Nordhaus (2015), I consider the case where the global benefit of abating is $25 USD 2011. I assume this value correspond to discount rate of 4%. Regional shares and costs are discussed in the next two subsections.

3.3.1 C-DICE

Nordhaus (2015) considers three sharing schemes: shares which are proportional to output; shares based on the Regional Dynamic Integrated model of Climate and the Economy (RICE) model in Nordhaus (2010); and the averaged shares of the RICE, The Climate Framework for Uncertainty, Negotiation and Distribution (FUND), and the Policy Analysis of the Greenhouse Effect (PAGE) models. Costs in C-DICE are based on a study by the McKinsey Company (2009). C-DICE regions include: Brazil; Canada, China; EU - the European Union; Eurasia; India; Japan; MidEast - the middle east; ROW - the rest of the world; Russia; SEAsia - Southeast Asia; SSA - Sub-Saharan Africa; Safrica - South Africa; and US - the United States.

[5] In fact, STACO is similiar to C-DICE since its benefits component is based on the original DICE model from Nordhaus (1993).

Table 3.1: Coalition Dynamic Integrated model of Climate and the Economy (C-DICE)

Region	Regional data						Control rate	
	y_i	p_i	$\bar{e}_i$	$\sum \bar{e}_i$	g_i	θ_i	$\hat{\mu}_{it}$	μ^*_{it}
Brazil	2,816	197	470	10,854	50.2	3.1	1.08	34.81
Canada	1,419	34	533	27,228	76.1	1.6	0.21	13.37
China	13,496	1,344	9,480	131,795	53.5	14.8	2.60	17.55
EU	16,906	506	4,048	314,979	69.3	18.5	2.88	15.56
Eurasia	1,434	143	997	75,565	53.7	1.6	0.28	17.65
India	5,963	1,221	2,174	33,951	40.9	6.5	0.98	15.14
Japan	4,386	128	1,250	48,547	70.4	4.8	0.68	14.12
LatAm	5,065	394	1,378	38,057	48.7	5.6	1.12	20.00
MidEast	5,954	337	2,182	32,902	49.7	6.5	0.70	10.79
ROW	5,660	893	1,389	24,341	40.0	6.2	1.82	29.28
Russia	3,227	143	1,900	99,275	62.3	3.5	0.54	15.45
SEAsia	6,676	390	2,433	50,379	54.3	7.3	2.00	27.36
SSA	2,096	776	302	4,386	34.3	2.3	0.71	30.70
Safrica	614	52	483	14,116	51.6	0.7	0.17	23.74
US	15,534	312	5,671	355,964	76.9	17.0	2.85	16.77

Notes: Data from Nordhaus (2015), the World Resources Institute's Climate Analysis Indicators Tool, and the Notre Dame Global Adaptation Index. The price of carbon equals \$25 USD 2011. y_i denotes 2011 output in billions USD 2011. p_i denotes 2011 populations in millions. $\bar{e}_i$ denotes 2011 emissions in millions of tons of CO_2. $\sum \bar{e}_i$ denotes cumulative emissions. g_i denotes the region's average global adaption index. θ_i denotes the share of benefits from abatement that accrue to country i using proportional y_i.

The payoff to region i is given by:

$$u_{it}(\mu_{1t}, \ldots, \mu_{15t}) = \gamma\theta_i \sum_{j=1}^{15} \bar{e}_j \mu_{jt} - \alpha_i y_i \mu_{it}^2 + y_i - \gamma\theta_i \sum_{j=1}^{15} \bar{e}_j \tag{3.19}$$

where y_i is Gross Domestic Product, $\bar{e}_i$ is uncontrolled emissions, and μ_{it} is region i's emissions control rate:

$$\mu_{it} = \frac{\bar{e}_i - e_{it}}{\bar{e}_i}$$

Letting $\sigma_i = \bar{e}_i / y_i$, the unique stage game Nash equilibrium is given by:

$$\hat{\mu}_{it} = \theta_i \frac{\gamma\sigma_i}{2\alpha_i}$$

while the social optimum is given by:

$$\mu_{it}^{*} = \frac{\gamma\sigma_i}{2\alpha_i} \sum_{j=1}^{15} \theta_j$$

Table 3.1 provides the benchmark emissions control rates for the C-DICE model using the shares that are proportional to output and when the global benefit of abating is \$25 USD 2011. For example, the United States receives 17% of the benefits from abating, abates 2.9% of it's emissions in the stage game Nash equilibrium, and abates 17% at the social optimum. Globally, 2% of emissions are abated in the stage game Nash equilibrium while 18% is abated in the stage game social optimum.

3.3.2 STACO

Finus et al. (2006) consider two sharing schemes or calibrations: shares based on Frankhauser (2013) and shares based on Tol (1997). Costs are based on the Emissions Prediction and Pollicy Analysis (EPPA) estimates found in Ellerman and Decaux (1998). STACO regions include: Brazil (BRA); China (CHN), dynamic Asian economies (DAE); the European Community (EEC); eastern European countries (EET); energy exporting countries (EEX); the former Soviet Union (FSU); India (IND); Japan (JPN); other OECD countries (OOE); the rest of the world (ROW); and the United States (USA).

The payoff to region i is given by:

$$u_{it}(a_{1t}, \ldots, a_{12t}) = \gamma\psi_i \sum_{j=1}^{12} a_{jt} - \frac{c_{i1}}{3} a_{it}^3 - \frac{c_{i2}}{2} a_{it}^2 \tag{3.20}$$

However, to keep things compatible with the earlier analysis I use second-order Taylor

Table 3.2: STAbility of COalitions model (STACO)

Region	Regional data						Abatement	
	y_i	p_i	$\bar{e}_i$	$\sum \bar{e}_i$	g_i	ψ_i	$\hat{a}_{it}$	a^*_{it}
BRA	774	190	130	10,854	50.2	1.5	2	10
CHN	1,021	1,340	2,360	131,795	53.5	6.2	283	903
DAE	972	207	410	20,083	60.8	2.5	28	112
EEC	9,579	375	1,400	270,120	70.7	23.6	72	144
EET	405	120	510	54,789	58.6	1.3	22	91
EEX	1,650	1,602	1,220	91,798	45.4	3.0	35	135
FSU	501	287	1,000	158,003	52.8	6.8	53	160
IND	458	1,145	630	33,951	40.9	5.0	59	198
JPN	5,584	124	560	48,547	70.4	17.3	21	53
OOE	1,902	142	620	51,429	73.1	3.5	25	86
ROW	1,119	584	700	35,006	42.0	6.7	54	165
USA	8,845	305	2,420	355,964	76.9	22.6	158	320

Notes: Data from Finus et al. (2006), Weikard et al. (2006), the World Resources Institute's Climate Analysis Indicators Tool, and the Notre Dame Global Adaptation Index. The price of carbon equals \$45.85 USD 1985. y_i denotes 2010 output in billions USD 1985. p_i denotes 2010 populations in millions. $\bar{e}_i$ denotes 2010 emissions in millions of tons of CO_2. $\sum \bar{e}_i$ denotes cumulative emissions. g_i denotes the region's average global adaption index. ψ_i denotes the share of benefits from abatement that accrue to country i using STACO's Calibration I.

approximations of each region's cost function:

$$\frac{c_{i1}}{3}a_{it}^3 + \frac{c_{i2}}{2}a_{it}^2 \approx \sigma_{1i} + \sigma_{2i}a_{it} + \frac{\sigma_{3i}}{2}a_{it}^2$$

centered around the midpoint between the stage game Nash equilibrium and the social optimum. The modified payoff to region i is given by:

$$u_{it}(a_{1t}, \dots, a_{12t}) \approx \gamma\psi_i \sum\nolimits_{j=1}^{n} a_{jt} - \sigma_{2i}a_{it} - \frac{\sigma_{3i}}{2}a_{it}^2 - \sigma_{1i} \tag{3.21}$$

The unique stage game Nash equilibrium is given by:

$$\hat{a}_{it} = \frac{\gamma\psi_i - \sigma_{2i}}{\sigma_{3i}}$$

while the social optimum is given by:

$$a_{it}^{*} = \frac{\gamma \sum_{j=1}^{n} \psi_j - \sigma_{2i}}{\sigma_{3i}}$$

Table 3.2 provides the benchmark abatement levels using the first calibration found in Finus et al. (2006). Importantly, the new estimates from the approximations are comparable to those found using the actual cost functions in (3.20). For example, in the original STACO model – when the global benefit of abating is \$37.40 USD 1985 – the stage game Nash equilibrium for the United States is 162 million tons of CO_2 while the social optimum is 380 million tons of CO_2. In this approximated version, these values are 158 and 320 respectively when the price of carbon is \$45.85 USD 1985.[6] Globally, 7% of emissions is abated in the stage game Nash equilibrium while 20% is abated at the social optimum.

3.3.3 Bargaining protocols

How the surplus of an agreement to reduce CO_2 is divided is naturally a contentious issue. Article 3(1) and 3(2) of the United Nations Framework Convention on Climate Change emphasize "common but differentiated responsibilities and respective capabilities" and the "needs and special circumstances of developing country Parties, especially those that are particularly vulnerable to the adverse effects of climate change." This provides some notion of what climate equity should be. The debate over what "differentiated responsibilities" means typically involves current emissions, historical emissions, stage of development, vulnerability, and the ability to act.

[6] This price is used since it is equivalent to \$100 USD 2011 after accounting for inflation.

Table 3.3: Bargaining ranks in C-DICE

Region	Pragmatic			Climate equity					
	y_i	$\bar{e}_i$	$\sum \bar{e}_i$	p_i	$1/g_i$	$(y_i/p_i)^{-0.25}$	θ_i	$1/\bar{e}_i$	$1/\sum \bar{e}_i$
Brazil	11	14	14	10	6	14	12	6	2
Canada	14	12	11	15	14	5	13	1	5
China	3	1	3	1	8	2	1	15	13
EU	1	3	2	5	12	13	3	11	14
Eurasia	13	11	5	12	9	3	11	4	11
India	5	6	9	2	3	8	6	14	7
Japan	9	10	7	13	13	10	10	3	9
LatAm	8	9	8	6	4	11	8	10	8
MidEast	6	5	10	8	5	6	5	8	6
ROW	7	8	12	3	2	12	7	13	4
Russia	10	7	4	12	11	4	9	4	12
Safrica	15	13	13	14	7	1	15	2	3
SEAsia	4	4	6	7	10	9	4	9	10
SSA	12	15	15	4	1	15	14	12	1
US	2	2	1	9	15	7	2	7	15
Min	0.01	0.01	0.00	0.00	0.05	0.05	0.00	0.01	0.00
Max	0.19	0.27	0.28	0.20	0.10	0.08	0.36	0.32	0.36
Mean	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
SD	0.06	0.07	0.09	0.06	0.02	0.01	0.11	0.09	0.09

Notes: Based on data from Nordhaus (2015), Weikard et al. (2006), the World Resources Institute's Climate Analysis Indicators Tool, and the Notre Dame Global Adaptation Index.

Table 3.4: Bargaining ranks in STACO

Region	Pragmatic			Climate equity					
	y_i	$\bar{e}_i$	$\sum \bar{e}_i$	p_i	$1/g_i$	$(y_i/p_i)^{-0.25}$	ψ_i	$1/\bar{e}_i$	$1/\sum \bar{e}_i$
BRA	9	12	12	9	4	7	11	1	1
CHN	7	2	4	2	6	2	6	11	9
DAE	8	11	11	8	8	8	10	2	2
EEC	1	3	2	5	10	10	1	10	11
EET	12	10	6	12	7	6	12	3	7
EEX	5	4	5	1	3	3	9	9	8
FSU	10	5	3	7	5	4	4	8	10
IND	11	7	10	3	1	1	7	6	3
JPN	3	9	8	11	9	12	3	4	5
OOE	4	8	7	10	11	9	8	5	6
ROW	6	6	9	4	2	5	5	7	4
USA	2	1	1	6	12	11	2	12	12
Min	0.01	0.01	0.01	0.02	0.06	0.04	0.01	0.02	0.01
Max	0.29	0.20	0.28	0.25	0.11	0.14	0.24	0.35	0.32
Mean	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
SD	0.10	0.06	0.09	0.08	0.02	0.03	0.08	0.09	0.09

Notes: Based on data from Finus et al. (2006), Weikard et al. (2006), the World Resources Institute's Climate Analysis Indicators Tool, and the Notre Dame Global Adaptation Index.

To explore how these measures impact contractual equilibrium I consider normalized bargaining weights based on: output, current emissions, cumulative emissions, population, vulnerability as measured by the inverse Notre Dame Global Adaptation Index, ability to pay, damages, inverse current emissions, and inverse cumulative emissions. I also consider equal bargaining. The data necessary to calculate these weights are provided in Tables 3.1 and 3.2. Note that the ability to pay protocol is taken directly from Weikard et al. (2006) and is given by:

$$\pi_i = \left(\frac{y_i}{p_i}\right)^{-0.25} \tag{3.22}$$

For the case of bargaining based on damages, the weights are simply the regional benefit shares used in each of the models.

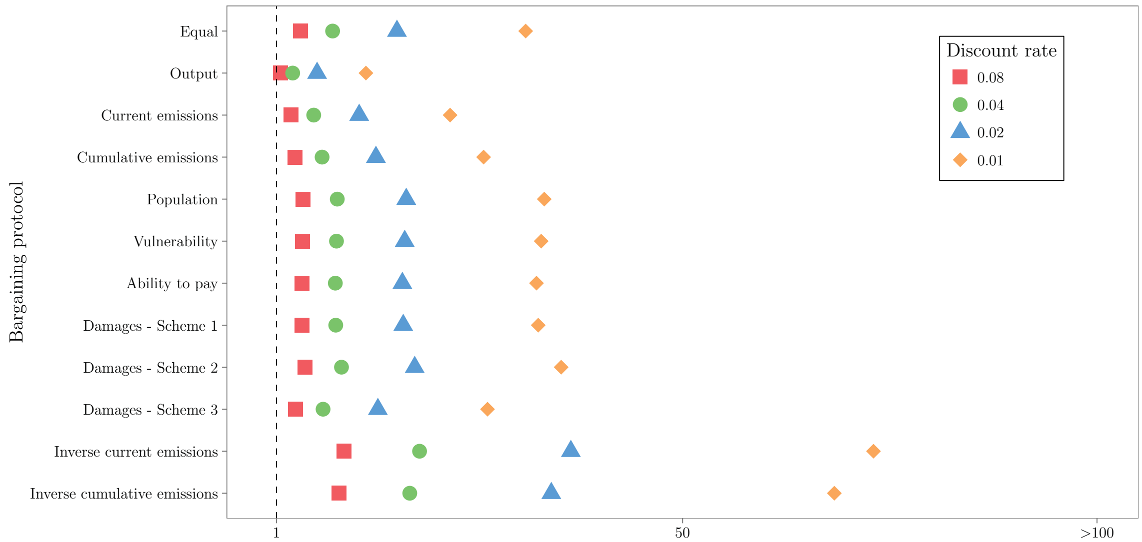
Finus (2008) labels the first three protocols "pragmatic" or "grand fathering" in that they preserve the status quo by favoring rich countries and high emitters. The remaining six are more consistent with some notion of climate equity. Tables 3.3 and 3.4 show each region's rank using these weights. For example, using an output-based scheme the U.S. receives the second highest share (rank 2). On the other hand, using a scheme based on cumulative emissions the U.S. receives the lowest share (ranks of 15 and 12 in C-DICE and STACO respectively). Summary statistics for each scheme are also shown. For the case of C-DICE, the cumulative emissions, inverse emissions, and inverse cumulative emissions protocols have the most variation while the ability to pay protocol has the least. For STACO, the output protocol has the most variation while the adaptability protocol has the least.

3.3.4 Results

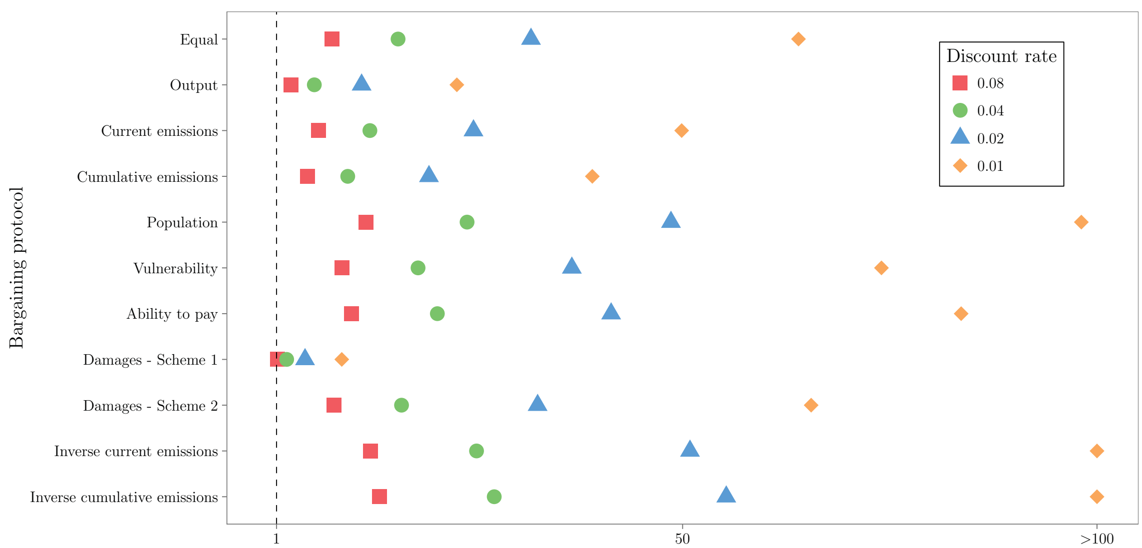
Figures 3.4a and 3.4b illustrates the results of the simulation. Apparent in both figures is that bargaining based on climate equity typically results in higher values of equilibrium slack S^* than those based on "grandfathering." In particular, the protocols based on inverse current emissions and inverse cumulative emissions generate the largest levels of slack.

3.4 Conclusion

This paper has sought to broaden the existing literature which uses game theory to model IEAs. In particular, it introduces the concept of contractual equilibrium to a standard abatement game. This notion of equilibrium provides a means for better understanding the process of agreement formation which in this case is based on Nash (1950) bargaining. The main result of the paper demonstrates that asymmetric bargaining power leads to more effective agreements and that – for one specification of utility – it is best to have the low cost country receive all the surplus from an agreement. Turning to numerical simulation using predefined bargaining power, it is shown that bargaining based on some notion of climate equity – for instance, inverse emissions – leads to more effective agreements than bargaining based on pragmatism such as output.



(a) C-DICE



(b) STACO

Figure 3.4: Equilibrium slack relative to slack required for the social optimum

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