Climate Politics in the United States*

Matilde Bombardini
UC-Berkeley

Frederico Finan
UC-Berkeley

Nicolas Longuet-Marx
Columbia University

Suresh Naidu
Columbia University

Francesco Trebbi
UC-Berkeley

March 21, 2025

Abstract

We study the effects of climate change and mitigation on U.S. politics. We combine 2000-2020 precinct-level voting information and congressional candidate positions on environmental policy with high-resolution temperature and precipitation data and census block-group level measures of "green" and "brown" employment shares. Holding politician positions fixed within a district, we find that Democratic vote share increases with exogenous changes in local climate and green transition employment. We embed these estimates into a structural model of political competition, including both direct and demand-driven effects of shocks on candidate policy platform supply. Incorporating our model estimates into 2025-2050 projections of climate change and green employment transition, we find that voting for the Democrats increases, while both parties move slightly to the *right* on climate policy. Under worst-case climate projections and current mitigation trajectories, the median 2050 Congressperson has roughly the same environmental ideology as the median 2010 Democrat—for instance supporting carbon pricing.

*Bombardini: UC Berkeley and National Bureau of Economic Research (mbombardini@berkeley.edu). Finan: UC Berkeley and National Bureau of Economic Research (ffinan@berkeley.edu). Longuet-Marx: Columbia University (nkd2120@columbia.edu). Naidu: Columbia University and National Bureau of Economic Research (sn2430@columbia.edu). Trebbi: UC Berkeley and National Bureau of Economic Research (ftrebbi@berkeley.edu). Aidan Wang, Ming-Yen Ho, and Ziyi Liu provided exceptional research assistance. We thank Judd Boomhower, Bard Harstad, Kelsey Jack, Andrea Prat, Reed Walker, seminar and conference participants at Columbia, BFI-IOG meeting Summer 2024, Stanford, and CEMFI for comments and suggestions.

1 Introduction

Climate change is recognized as having large effects on economic well-being. A substantial and growing literature shows effects of temperature, weather, and extreme environmental events on mortality, GDP, health, crime, schooling, job quality, and civil strife (Dell, Jones and Olken, 2012; Carleton et al., 2022; Burke et al., 2023). Scientists and economists have proposed many policies, from carbon pricing to green technology subsidies, that could potentially slow global warming (Hahn et al., 2024). Yet many of these policies have not been widely implemented, or have been passed and subsequently rejected by voters in democratic elections (Doyle, McEachern and MacGregor, 2015; Rowan, 2023). Climate adaptation also remains limited (Burke et al., 2024). It has become increasingly clear that understanding voting and endogenous policy-setting is important for successfully tackling climate change in democratic countries (Dechezleprêtre et al., 2022). Politics, rather than just technology, appears to be a fundamental barrier to climate action.[1] But there is surprisingly little study of the effects of climate change on democratic politics, and few models projecting future impacts incorporate political economy.

With this motivation, our paper focuses on the political economy of climate. We empirically document the effects of temperature and precipitation changes and mitigation on partisan voting and political competition over environmental policy in the U.S. We construct a new panel of precinct-level voting data to estimate effects of weather shocks and green transition employment on vote shares, and use the data to estimate the effect of historical changes in climate and "green" and "brown" jobs changes U.S. electoral patterns. We then combine these within-district estimates with new data on candidate positions on environmental issues to build and estimate a demand and supply system of electoral competition over climate policy at the congressional district level. Armed with this structural model of politics and climate, we then consider the effect of projected scenarios of climate change on electoral politics and congressional policy-making for the years 2025-2050. We find that in the most extreme climate change scenario, voting for the Democrats increases, even as both parties move slightly to the *right* on climate policy. The composition of Congress changes sufficiently towards the Democrats that the environmental roll-call voting of the median *Congressperson* in

[1] Some scholarship has even questioned whether democratic institutions may be suitable to tackle such a complex, forward-looking task given their many veto points. In the words of Lazar and Wallace (2025) *"Governments have been slow to respond to climate change, slow to prevent further damage to our atmosphere, and slow to prepare for what is coming. Democratic governments, it is sometimes said, are worst of all at these tasks."* (p.135)

2050 is comparable to the median *Democrat* in our 2000-2020 sample.[2]

Analyzing the political economy of climate presents complex econometric challenges. Primarily, it is difficult to pinpoint what drives voter demand for climate action and how much demand quantitatively matters in equilibrium. Indeed, the lack of strong climate policy may be the result of low voter demand, perhaps due to a lack of awareness, misinformation, or uncertainty about climate change's costs. Alternatively, voters might fear the economic burden of transitioning to a low-carbon society. Or low demand could be due to growing ideological and partisan polarization, making climate policy subject to the same gridlock common to other policy domains (Voorheis, McCarty and Shor, 2015; Binder, 2004). A fairly large literature in economics and political science has empirically investigated voters' climate beliefs and environmental policy preferences, including in response to climate and weather shocks. Examples include Deryugina (2013), Egan and Mullin (2012), Egan and Mullin (2017), Bergquist and Warshaw (2019), Hazlett and Mildenberger (2020), Kahn and Matsusaka (1997), Hoffmann et al. (2022), Zaval et al. (2014), Choi, Gao and Jiang (2020), Druckman and McGrath (2019). But little has examined actual electoral behavior in response to climate shocks, with important exceptions including Boomhower (2024); Stokes (2016); Pahontu (2020), and a few papers focused on Green Party voting in Europe (Hoffmann et al., 2022; Hilbig and Riaz, 2024).

Canonical models of competitive electoral equilibrium, like the one we present in Appendix C, imply that identification of voter demand parameters requires controlling for the (endogenous) policy platforms supplied by each candidate. Such platforms directly affect voter choice and vote shares, and are in turn functions of the expected vote shares of candidates. To hold platform supply constant in the demand equation, we focus on variation within a congressional race (i.e., congressional district $\times$ election year), using disaggregated geographical information on both vote outcomes and demand shifters. Using the 20-year panel of precinct-level data first presented in Longuet-Marx (2024), we estimate the effect of extreme local temperature and rainfall shocks on voting patterns. In order to capture the effects of adaptation/mitigation efforts, we construct measures of "brown" and "green" jobs at the precinct level and estimate the causal effect of shifting climate-related employment patterns on voting outcomes. We find that climate change and mitigation-related employment changes shift voter demand for parties (without loss we focus on Democratic vote share as our

[2]For context, the 2009 Waxman-Markey bill, that would have set up tradable emissions in the United States, was passed with 211 out of 255 Democrat congresspeople (83%) voting yes, and only 8 Republicans. This bill would have reduced emissions by 83% by 2050. `https://www.nytimes.com/2009/06/27/us/politics/27climate.html`

outcome variable). We follow approaches widely used in the climate literature, controlling for cross-sectional and geography-by-time fixed effects and show robustness to many alternative specifications, importantly including spatial autocorrelation, a set of time-varying controls, and multiple sets of fixed effects. Our proxies for climate damages and for sectoral exposure to the green transition affect vote shares and turnout within a congressional race.

Our extreme local temperature and rainfall shock results are quantitatively consistent with previous research on climate effects on voter preferences, and the employment results are comparable in magnitude to the literature on employment shocks and electoral outcomes (Choi et al., 2021; Bombardini, Li and Trebbi, 2023). An additional day with temperatures two standard deviations above the local historical mean increases the Democratic vote margin by 0.08 to 0.47 percentage points, while a one-percentage-point decrease in brown jobs raises the Democratic vote share by 0.17 points. A comparable increase in green jobs raises Democratic shares by 0.45 points, although less precisely estimated. In terms of their relative importance in driving voter demand for pro-environment candidates, we find that a one standard-deviation increase in extreme local temperature and rainfall have a roughly 80% larger effect in the OLS specification than a one standard-deviation change in brown and green employment. To address endogeneity in local job variation, we additionally develop a shift-share design, using national employment growth reweighted by local employment shares (Borusyak, Hull and Jaravel, 2022).

We then proceed to identify the effects of these same climate and employment shocks on the environmental platforms supplied by politicians competing in the election, controlling for voter demand. One reason it is difficult to make long-term projections involving politics and climate is that the electoral arena does not stay fixed (Calvo, Pons and Shapiro, 2024). Electoral politics is an interaction between the demands of voters and the supply of policies by candidates, making it important to model the choice of environmental policy. Indeed, lack of climate policy may stem from limited supply of climate policies, despite high demand on the part of the electorate. For instance, climate issues could be "bad politics" given the structure of electoral competition (e.g. due to the location of swing districts, donor or concentrated electoral blocs) or other legislative incentives (bargaining over other issues). Little of the literature has considered the supply of environmental policies by political parties, with exceptions including Béland and Boucher (2015), Aklin and Urpelainen (2013), List and Sturm (2006), Fredriksson, Wang and Mamun (2011), (Gagliarducci, Paserman and Patacchini, 2019), and Kaplan, Spenkuch and Yuan (2019). Measuring and modeling the interplay of climate change with both supply and demand forces is a challenge that we

address in this paper and separates us from this literature.

For our supply analysis, we use campaign websites and candidate surveys also collected by Longuet-Marx (2024), and measure environmental policy platforms for both winners and losers of congressional races. We show that these policy platforms are highly correlated with subsequent roll-call voting on climate policy among political winners, suggesting that campaigns are signals of true policy preferences. While multidimensional scaling models in political science and political economy have long engaged in the exercise of measuring policy preferences of politicians (Poole and Rosenthal (1984), Poole and Rosenthal (1985), Poole and Rosenthal (2011), Clinton, Jackman and Rivers (2004), Canen, Kendall and Trebbi (2020), Canen, Kendall and Trebbi (2021)), these approaches typically focus on incumbents, limiting the usefulness of these measures for problems of electoral competition.[3] We flexibly model such competition and identify the effect of weather and employment changes on candidate supply of environmental policies using parameter estimates from the demand equation jointly with party shifters on candidate positions, as well as recovering the sensitivity of voters to environmental platforms of candidates.

Finally, we integrate demand and supply parameters with climate projections for the United States. This allows us to predict the effects of climate change and trends in green/brown employment on congressional elections, congressional composition, and ideology up to 2050. While we recognize that our projections suffer from a substantial amount of forecasting uncertainty, these exercises may be a useful proof of concept in quantitative integrating political economy forces in long-run models of climate change or models aimed at calculating the economic costs of carbon emissions. Extant models, including the majority of the Integrated Assessment Models (IAMs), link climate science projections and economic forces, but typically do not incorporate a political feedback loop. In this sense, our results are most comparable to Moore et al. (2022). The authors augment a climate model with reduced-form parameterizations of political feedback loops (and social conformity and endogenous technology). Moore et al. (2022) posits a threshold function where supporters of climate policy must exceed opponents in order for a policy to happen (and then the policy is a mechanical function of support). In contrast, we take a political economy approach and microfound the policy response as a function of both voter preferences and political competition, interacting in an equilibrium model.

Our paper contributes to several strands of literature. Most directly, we speak to

[3] An exception is the method in Bonica (2013) to estimate ideal points from Political Action Committee contributions. These ideal points can be calculated for all candidates in a race with available political donations data.

the political economy and political science research linking the environment and electoral politics. Both ballot initiatives and elections for state office and legislatures have been studied, but not extensively, and mostly with a focus on the demand side. Kahn and Matsusaka (1997) focuses on 16 ballot initiatives in California and estimates a county voter demand model, finding that environmental policy appears a normal good for most voters. List and Sturm (2006) focuses on single-issue environmental voters in U.S. gubernatorial elections. Stokes (2016) focuses on voter backlash to costly environmental projects (NIMBY wind turbine location) in Canada. Anderson, Marinescu and Shor (2023) studies two failed carbon tax referenda in Washington State' in 2016 and 2018 and emphasizes how ideology explains much of the variation in voting outcomes, a result in sharp contrast with conclusions in Kahn and Matsusaka (1997), where voter ideology is deemed less relevant. Closer to our approach in terms of identifying variation of demand parameters, Hazlett and Mildenberger (2020) focuses on the political consequences of wildfire exposure on voting, showing that wildfires increase support for costly pro-climate ballot initiatives by 5 to 6 percentage points for Californians living within 5 kilometers of a recent wildfire, but finds an asymmetry between Democratic and Republican localities. Boomhower (2024) focuses on the electoral consequences of earthquakes induced by fracking activities in the states of Oklahoma and Texas. The author focuses on environmental regulators, who are elected (not appointed) in those states, and finds compelling causal evidence of lower support for incumbents and higher turnout after a local shock.

A related literature on environmental shocks and beliefs updating mostly focuses on survey evidence. In an influential contribution, Egan and Mullin (2012) studies public opinion data from Pew Research Center as a response to severe weather shocks. The authors show that "*weather patterns have a significant effect on people's beliefs about the evidence for global warming.*" Similar results are also in Deryugina (2013). The evidence since then has been more mixed (Egan and Mullin, 2017). Hilbig and Riaz (2024) presents precise zeros in estimating the effects of flooding in Germany, focusing on voter beliefs about climate change and electoral support for the Green Party in federal elections. These results appear in contrast with Hoffmann et al. (2022), that also studies Green Parties in Europe, but finds positive effects.[4]

Our paper also speaks to a new and growing literature on the structural estimation of large electoral demand models. Examples include Berry, Cox and Haile (2024), and equilibrium systems of demand and supply such as Longuet-Marx (2024); Cox (2024); Iaryczower, Montero and Kim (2022). We complement these recent papers through a

[4]A recent paper looking at the effect of disasters on roll-call voting in the U.S. Congress finds that only Democrats support more green legislation (Jud and Nguyen, 2024).

specific focus on climate politics, which lends the structural model to novel quantitative applications within the space of climate projections.

Finally, a contribution of this paper is to provide a microfounded, quantitative approach for integrating politico-economic forces in climate forecasting and potentially useful for extending Integrated Assessment Models (IAMs) (Wiliam and Thompson (2017); Geels, Berkhout and Van Vuuren (2016)). IAMs could benefit from incorporating an explicit politico-economic dimension and, as discussed above, our quantitative equilibrium model of climate politics can complement the more reduced-form approaches that have been proposed in the climate science literature.

In the next section we describe the data. We then present our demand estimates using within-congressional district variation, along with heterogeneity and robustness exercises. We then present our empirical model of political competition and endogenous supply of environmental policy, and discuss identification and consistency with the demand estimates. We then present results from the unified model of political equilibrium, with both demand and supply estimates. Finally, we integrate climate projection data with our structural estimates and project various future scenarios for how climate change will change the composition and ideology of the U.S. House of Representatives. The last section concludes.

2 Data

This section presents an overview of the main data sources employed in the paper. All the details of the data construction can be found in the Online Appendix.

Electoral Voting Data: We use precinct-level voting data from Longuet-Marx (2024). Precincts are the smallest level at which election results are reported in the United States. A precinct has on average 1,200 registered voters, that is, on average, 60 times smaller than a county and 400 times smaller than a congressional district. Since precinct boundaries change over time, in order to build a stable panel of geographic subunits of a congressional district, we impute all precinct votes to the 2010 census block-group level, which have approximately the same population size as precincts. A U.S. Census block-group is a geographical unit used by the United States Census Bureau for collecting and reporting demographic data. It is a subdivision of a census tract and is further divided into census blocks. We also obtain block-group-level demographics from the decennial U.S. Census and the American Community Survey (ACS) for each election.

Climate: Our primary data for temperature and precipitation comes from an updated version of Schlenker and Roberts (2009), which reports daily minimum temperature, maximum temperature, and total precipitation on each 2.5 mile $\times$ 2.5 mile grid cell for the contiguous United States. At the grid-cell level, we first construct weather measurements as follows. First, we calculate the mean and standard deviation of average daily temperatures (maximum plus minimum temperature of the day divided by two) and precipitation for each calendar day of the year (January 1st, ... , December 31st) between 1959 and 2000. For each grid cell starting in 2001, a day's average temperature or precipitation is considered to be extreme if the day's temperature or precipitation exceeds the historical average for that day by two historical standard deviations. Aggregating to the year level, we count the total number of days with extreme temperature and precipitation for each year from 2000 to 2022. We also count the number of days that exceeds a number of temperature and precipitation thresholds (e.g., 30 degrees Celsius), total precipitation, and average temperature of the year, and various temperature and precipitation bins indicating the number of days with temperature and precipitation within a fixed range for each grid cell.

To aggregate grid cell-by-year-level data to census block-group and congressional district level, we first match each census block's centroid to the four closest grid cells. The census block's estimated days with extreme temperature, precipitation, and other weather variables are the weighted average of the corresponding variables for the linked grid cells, inversely weighted by the grid cell's distance to the census block centroid. We then aggregate block-level data to the block-group level by taking a population weighted average of block-level variables.

Candidate Positions on the Environment: We use the campaign environmental ideal points calculated in Longuet-Marx (2024). These policy positions are calculated by combining text data from candidate official websites obtained from the Library of Congress with candidate survey information from Project Vote Smart, a non-partisan organization that collects and distributes information on candidates running for public office in the United States and whose data has long been used in the Political Science and Political Economy literature (Ansolabehere, Snyder Jr and Stewart III, 2001).[5] Candidate ideal points are estimated using a Bayesian item response model on the environment-specific questions posed to candidates in the Vote Smart survey. The campaign webpage text is then used to predict ideal points for the set of candidates in both samples, and then ideal points are predicted out-of-sample, ensur-

[5]See the Political Courage Test (formerly the National Political Awareness Test, NPAT) https://www.votesmart.org/.

ing an environmental ideal point for each candidate. Appendix Figure A.13 show that for winners, roll-call votes made in Congress on environmental bills are significantly correlated with the campaign ideal points used in our analysis. Reassuringly, the correlation of the campaign environmental ideal points is much stronger with roll-call ideal points on environmental bills specifically than on roll-call votes in general (Appendix Figure A.14), as measured by the first dimension of DW-Nominate (Poole and Rosenthal, 2011) or unbiased ideal point measures proposed by Canen, Kendall and Trebbi (2021).

Green and Brown Jobs: We construct a measure of employment in"green" jobs for residents of a block-group by combining multiple data sources. We adopt a definition of green jobs based on the Bureau of Labor Statistics (BLS) Green Goods and Services (GGS) survey, conducted in 2011. We classify as green those NAICS 4-digit industries that fall under category 1 ("Energy from renewable resources") and 2 ("Energy efficiency"). The BLS GGS also provides a share of employment, within each of those industries, that is deemed to be devoted to green activities. Ideally, we would observe each block-group b's residents employment in NAICS 6-digit industry i. Lacking such detailed industry employment information, we approximate $GreenEmp_{bt}$ as detailed in Appendix section B.2 using data on: i) block-group employment at NAICS 2-digit level from the Decennial Census and the Census LEHD Origin-Destination Employment Statistics (LODES) Residence Area Characteristics (RAC) dataset; ii) commuting flows from block-groups to counties at a super-sector level from the LODES Origin-Destination (OD) dataset; iii) county employment by NAICS 6-digit from the County Business Patterns (CBP) and the BLS Quarterly Census of Employment and Wages (QCEW). The logic behind this approximation is that, while we know b's residents' NAICS 2-digit sector of employment, we do not know which specific NAICS 6-digit industry employs them. Therefore we attribute the industry based on commuting to jobs in potentially different counties and those counties' shares of green employment within each NAICS 2-digit industry. In this process we employ a constrained imputation method analogous to Autor et al. (2024), detailed in the Online Appendix.[6]

The construction of the number of "brown" jobs in block-group b is analogous to that of green jobs. We classify as brown jobs those easily recognizable as related to oil and gas extraction, coal mining and their support activities (OGC). The list of eight 6-digit NAICS industries can be found in Appendix Section B.2, but they are all within

[6]We especially thank David Dorn for suggestions and sharing details about the code.

NAICS 2-digit industry 21 "Mining, Quarrying, and Oil and Gas Extraction".

The geographic variation in our main variables is illustrated in the maps in Figure 1. There is clear evidence of spatial correlation in voting patterns, weather changes, and employment changes. By looking at panel variation within congressional district-year units, we are controlling for a variety of confounds that might contaminate a simple regression of voting on weather. In particular, the positions of candidates, which we will see are essential for projections, are potentially correlated with climate changes. Controlling for (congressional district $\times$ election year) fixed effects effectively sweeps out any variation coming from politician responses to climate or employment changes.

Projections of Future Climate: Data for the weather projections come from the NASA Earth Exchange (NEX) Global Daily Downscaled Projections (GDDP) dataset. The NEX-GDDP dataset contains daily average temperatures and precipitation projections from 2015 up to year 2100 at the resolution of 25km $\times$ 25km (0.25 $\times$ 0.25 degrees in latitude $\times$ longitude) grids coming from different climate models of the 6th generation of the Coupled Model Intercomparison Project (CMIP6). We use the projections of Community Earth System Model 2 (CESM2), developed and maintained by the NSF's National Center for Atmospheric Research (NCAR).

All NEX-GDDP models, including CESM-2, projected outcomes correspond to four different "Shared Socioeconomic Pathway" (SSP) scenarios, named SSP126, SSP245, SSP370, and SSP585. Each SSP predicts how a different set of socioeconomic and policy responses could influence climate outcomes. SSP585 reflects a worst case "business as usual" where carbon emissions continue to increase along with historical trends without policy mitigation. SSP370 is a "middle of the road" outcome with still no climate policies, but milder increases in emissions relative to SSP585. SSP245 corresponds to a scenario where policy successfully restricted global warming to be below 3C by year 2100, while SSP126 reflects an optimistic outcome where warming will be below 2C. Each model $\times$ scenario is a dataset at the day $\times$ latitude-longitude grid cell level, describing the temperature and precipitation at the grid cell for each day of the year from 2024 to 2050.

We build a congressional district $\times$ election year level dataset of weather variables (average temperature, total precipitation, days of extreme temperature & precipitation) by comparing the projected temperatures with historical means under each scenario.

Projected Jobs Data: For jobs projections, we use the BLS Occupational Outlook Handbook (BLS OOH), which projects job growth between 2023 and 2033 for various

NAICS code sectors at the 3 to 6 digit levels. We construct the annualized growth rate of each 6 digit 2012 NAICS sector using the 2012-2022 NAICS crosswalk.[7]

Starting with our data of "brown" and "green" jobs at the block-group × 6 digit NAICS sector level in 2021, we construct the growth rate of brown and green jobs for each block-group between 2023 and 2033 by taking a weighted average of the BLS OOH growth rate for each 6-digit NAICS sector, weighted by the current importance of each sector in that block-group. For example, the annualized growth rate of green employment in block-group b is:

$$GreenGrowth_{bt} = \frac{\sum_i^I GrowthRate_{it} \times GreenEmp_{bi,2021}}{\sum_i^I GreenEmp_{bi,2021}} \tag{1}$$

where i indexes a 6-digit NAICS sector and $\text{GreenEmp}_{bi,2021}$ is the number of green jobs for sector i in block-group b in year 2021.

We also predict the growth rate of block-group-level total employment with the same method by aggregating all sectors, which gives us the growth rate of the proportion of green and brown jobs in each block-group, which we then collapse to the congressional district level.

The time-series averages of our variables along with the projections are plotted in Appendix Figure A.16. The geographic distribution projected in 2050 is presented in the maps in Figure A.17.

3 Voter Demand Specification

In this section we begin by examining the reduced-form effects of climate variation on voting patterns and the robustness of the sensitivity of Democratic vote shares to temperature, precipitation and employment shocks. We then augment the demand specification to include (instrumented) employment changes in "green" and "brown" jobs from climate adaptation in order to probe its robustness to issues of endogeneity.

We follow the climate-economy literature and include fine geographic (in our case census block-groups) fixed effects, as well as coarser geography by time fixed effects. Our baseline specification is given by:

$$y_{bt} = \beta^t Temp_{bt} + \beta^p Precip_{bt} + \alpha X_{bt} + \mu_b + \Omega_{c(b),t} + \epsilon_{bt} \tag{2}$$

where y_{bt} is the share of votes cast for the Democratic candidate minus the share of

[7] https://www.bls.gov/cew/classifications/industry/qcew-naics-hierarchy-crosswalk.htm

votes cast for the Republican candidate in block-group b in election year t. Recall that a block-group is the stable geographic unit that we employ. $Temp_{bt}$ and $Precip_{bt}$ are measures of temperature and precipitation in block-group b and election year t as described in Section 2. Let μ_b indicate block-group fixed effects, which absorb time-invariant heterogeneity. We refer to $c(b)$ as the congressional district to which b belongs. $\Omega_{c(b),t}$ are congressional district $\times$ election year fixed effects, and absorb all the variation coming from candidates and campaigns, as well as other sources of time-varying heterogeneity at the broader geographic level of a congressional district. More precisely, as congressional district boundaries change due to redistricting after each Decennial Census, by congressional district c we intend the geographic unit defined by a congressional district per redistricting cycle. We will use the term congressional district for brevity whenever it is not confusing. In X_{bt} we include varying sets of controls, and we cluster our standard errors two ways, at the congressional district $c(b)$ by election t level and at the block-group level.

While the exogeneity of weather shocks allows identification of parameters β^t and β^p, we still have to contend with the possible correlation of weather shocks with unobserved characteristics of voters that affect their political orientation. For example, climate change could induce changes in the composition of voters, due to selective migration (for example, by education). This omitted variable bias is alleviated by the extensive set of block-group-level controls and by the introduction of block-group fixed effects, which net out any time-invariant unobservable determinant of voting behavior.

3.1 Climate Results

Figure 2 shows binned scatter plots from a set of specifications corresponding to equation (2), including only block-group fixed effects and congressional district $\times$ election year fixed effects, with coefficients from these specifications shown on the graphs. The data clearly show an upward sloping relationship between Democratic vote share and extreme temperature.

The coefficients implied are quantitatively meaningful. A one standard deviation increase in days above 2 standard deviations from the historical average (8.09 days) results in 1.6 percentage point higher Democratic vote share. To put this number in context, the effect of an additional 10 days of extreme temperature is comparable to a persuasion effect of 7.5 additional minutes from Fox news a week (Martin and Yurukoglu, 2017), or slightly smaller than a one standard deviation of partisan differences in advertising as estimated by Spenkuch and Toniatti (2018). The effects of precipitation are smaller and less precise, but nonetheless we are unable to rule out

politically significant effects of precipitation. A one standard deviation increase in precipitation (6.73) results in a smaller and less significant increase of 0.3 percentage points in Democratic vote share.

To examine whether our results are driven by the particular transformations of daily weather data chosen, in Figure 3 we show our results using variables constructed by counting the number of days in temperature and precipitation bins as alternative independent variables. We find that the vote share effects of temperature appear indeed concentrated at the extreme temperature events, with largest effects found for a variable measuring the count of days greater than 25 degree Celsius. Precipitation, on the other hand, has significant positive effects at more moderate values.

Consistent with the larger effects of weather extremes, in Appendix figure A.8 we show similar binscatters using *average* rather than extreme temperature and precipitation outcomes. The average values of each of the variables have the same sign as in our preferred specification, but are, unsurprisingly, attenuated and less precise.

Much of the climate literature has focused on experience of environmental extremes as driving negative effects (e.g. in agriculture as in Schlenker and Roberts (2009) and on mortality as in Carleton et al. (2022)). Motivated by the above results, we focus on extremes in this paper as well. We focus on the extreme temperature variable throughout, but always include extreme precipitation as an additional independent variable.

In Appendix Figure A.9 we show binned scatterplots of turnout against our preferred climate variables. Temperature extremes do influence turnout, and this could drive some of the observed effects on Democratic vote share, but the effects are not large enough to explain all of it. Extreme precipitation does not have any statistically significant effect on turnout.[8]

Sensitivity: We probe the robustness of our climate estimates in the voter demand equation to a variety of specifications. We first experiment with adding extensive controls in columns 1 and 2 of Table 1. Columns 3 and 4 include controls, but probe robustness to omitting the block-group fixed effects. Because block-groups are so geographically small, and some congressional districts are very geographically large, the weather variation eliminated by controlling for block-group fixed effects might be substantial, and might mask effects coming from differential adaptation (e.g. some low-altitude parts of a Congressional district always experience high temperatures, and are more Republican, but temperature extremes have little effect). However, the Table

[8]We note that in specifications where we control for (endogenous variable) turnout the Democratic vote share effects remain significant, suggesting that not all the effects are coming from turnout.

shows that the climate effects become an order of magnitude larger when these fixed effects are removed, suggesting that the block-group fixed effects are capturing a latent *positive* correlation between (within-district-year) climate and Democratic vote share.

In Table 2 we further probe robustness. Column 1 replaces the block-group fixed effects with a time-varying six degree polynomial of latitude and longitude (including interactions). The coefficients here are closer to those without block-group fixed-effects, and so suggest other geographically smooth characteristics are not the unobserved variables picked up by the block-group FE. Because there are many unobserved variables at the block-group level that could influence the net partisanship of voting, we opt to maintain the conservative specification, including block-group fixed effects, as our primary one.

Column 2 of Table 2 augments the baseline specification with media market (DMA) by election year fixed effects, to control for any effects of climate driven by differential media exposure. Effects are slightly larger than in our main specification, but qualitatively similar, suggesting that differential media coverage is not a substantial driver of our results. Columns 3-5 report standard errors adjusted for spatial autocorrelation, using the Conley (1999) standard error formula. We use radii of 25, 50, and 75 kms across these columns, and find that all of our climate variable estimates are unchanged in their precision.

Appendix Tables A.6 and A.7 further show robustness to alternative specifications of the climate variables. We show results with and without block-group fixed effects, and with and without controls, for average temperature and precipitation, and extreme *negative* temperature and precipitation deviations. All of these specifications are qualitatively similar to our baseline specification.

3.2 Incorporating Climate Adaptation: Green and Brown Jobs:

In this section we introduce measures of the labor market dynamics associated with climate policies and the green transition. We capture the consequences of transitioning from fossil fuels to renewable energy with the shares of green and brown jobs in a block-group b as described in section 2. The availability of green jobs is expected to increase support for climate change policies, like carbon prices and green subsidies, and result in a higher vote share for Democrats, who are more supportive of such policies than Republican candidates over our time period of analysis. The opposite is expected for brown jobs.

We augment equation (2) as follows:

$$y_{bt} = \underbrace{\beta^t Temp_{bt} + \beta^p Precip_{bt} + \eta^B ShBrEmp_{bt} + \eta^G ShGrEmp_{bt}}_{\equiv \mathbf{V_{bt}}} + \alpha X_{bt} + \mu_b + \Omega_{c(b),t} + \epsilon_{bt} \quad (3)$$

where $ShGrEmp_{bt} = GreenEmp_{bt}/Emp_{bt}$ is the ratio of green employment $GreenEmp_{bt}$ as described in Section 2 and total employment Emp_{bt} in block-group b (from LODES RAC). Equation (2) maintains symmetry between weather and jobs in order to maintain a consistent demand model. The share of brown jobs $ShBrEmp_{bt}$ is defined analogously for brown jobs. For ease of reference, we collect all of our independent variables in the block-group election year vector $\mathbf{V_{bt}}$.

The causal identification of the effect of green and brown jobs on vote shares presents a distinct set of challenges, compared to the effect of temperature and precipitation.

A first challenge is that the extent of within-block-group variation over time is lower for green and brown jobs than for temperature and precipitation. The within-block-group data generating process has lower variation in jobs than climate shocks, as, intuitively, employment profiles of block-groups tend to be fairly stable from one congressional cycle to the next. This is a limitation we cannot circumvent. However, thanks to the granularity of the block-group level voting data, which is key for our identification of the effect of demand drivers, it turns out that one can still gather substantial information from the more substantial job changes that occasionally occur. For this reason in Equation (3) we maintain symmetry in the way temperature, precipitation, green and brown jobs enter the equation, allowing us to directly compare the effects of our mitigation variables with the effects of the climate variables.

A second challenge is potential endogeneity of jobs. The discussion of omitted variable bias due to unobserved characteristics affecting the residential selection of individuals into certain block-groups applies to employment as well. Individuals that live in block-groups with greater brown employment may be less prone to vote for Democrats just because fossil fuel industries tend to be located in more conservative areas of the country. An additional identification also challenge comes from the reality that green and brown jobs do not randomly appear in different areas. It is not clear which sign this bias would introduce in the estimation of η^G and η^B. It could be the case, for example, that green subsidies are granted more generously to politically contested areas that feature lower support for Democrats, in order to attract enough votes to win. On the other hand, it could be that green subsidies are spoils awarded to reliably Democratic areas. In order to address such endogeneity bias, we adopt

an instrumental variable approach. To assess the robustness of Equation (3) we build shift-share instruments for green and brown jobs by combining nation-wide yearly green and brown employment (the 'shift') and initial (i.e. year 2000) block-group b shares of green and brown employment (the 'share') as detailed in Appendix Section B.3. We follow recent developments in the literature focused on this methodology by controlling for initial shares of green and brown employment as suggested by Borusyak, Hull and Jaravel (2022).

The third and fourth rows of Table 1 reports the additional estimated coefficients from specification (3). Column 1 and 2 include only congressional district $\times$ election year fixed effects, while columns 3 and 4 additionally include block-group fixed effects. Columns 2 and 4 present IV regression results.

Across all columns, a larger share of brown jobs is associated with a lower Democratic percentage vote margin, confirming the view that areas whose labor markets depend more on fossil fuel industry employment tend to vote against Democratic candidates. The magnitude is economically relevant: a one standard deviation in the share of brown employment (corresponding to 1.79 percentage point) results in a 0.3 percentage point reduction in the Democratic vote margin.

Regarding green employment shares, column 1 returns a negative effect of green jobs on Democratic vote margins, which turns positive both in column 2 and column 3. This is contrary to our hypothesis that a large share of green jobs would signal job opportunities linked to climate policies and increase support for Democrats. An analysis of the role of controls reveals a potential reason behind this negative coefficient. The equivalent of column 1 in a specification without controls features a much larger coefficient on green jobs. It turns out that the share of green jobs is positively correlated with control variables, like the share of married individuals and the share of rural population, and negatively correlated with the share of population with tertiary education. In short, the share of Green employment, when included without controls, stands in for a number of variables that positively correlate with Republican voting, hence producing a negative correlation with the Democratic vote share in column 1. This implies that, not only one should include controls, but that only block-group fixed effects can properly account for this cross-sectional correlation between green employment share and tendency to vote Republican. The IV approach in column 2 also does so, confirming our explanation, but sometimes runs into issues of weak instruments due to the large share of variation absorbed by the block-group fixed effects in the first stage.

Overall, the effect of green jobs on Democratic vote share margins is large: a one standard deviation increase in $ShGrEmp_{bt}$ (which equals 0.48 percentage points)

corresponds to an increase in the Democratic vote margin of over 15 percentage points. By and large, the IV approach confirms the robustness of the main results of the OLS demand regression in Equation (3).

We examine robustness to various sets of spatial controls, just as above, in Table 2. As with the climate coefficients, the spatial controls do not alter the basic pattern of results in Table 1.

Overall, our demand analysis illustrates several important takeaways. To the question of whether lack of policy response on climate may be the result of lack of demand on the part of voters, the answer appears to be no. Local temperature and precipitation shocks affecting small groups of voters do significantly shift their political choices. This may be the direct result of updating and learning as postulated in Hoffmann et al. (2022) or the result of psychological salience of climate change. Shocks to local employment conditions also matter, with jobs associated with the green transition predicting support for more climate friendly candidates. In terms of relative magnitude of the share of variance of voting explained, temperature and precipitation shocks appear to be somewhat quantitatively larger than employment shocks. In terms of their relative importance in driving voter demand for Democratic candidates, we find that a one standard-deviation increase in extreme local temperature and precipitation have an approximately 80% larger effect in the OLS specification than a one standard-deviation change in green and brown employment.

In Appendix Tables A.9, we present a complimentary analysis of demand using partisan energy regulator elections in Texas, using data from Boomhower (2024). We show that our results are qualitatively similar to our full sample when restricted to house elections in the Texas subsample. We then show that these Texas-specific coefficients are quantitatively very similar when the outcome is precinct (block-group) level voting for energy regulators. Since energy regulators have a singular focus on environmental issues, this analysis shows that our shocks are indeed driving demand for climate policy, not other issues on which Democrats and Republicans differ.

3.3 Heteogeneity

To conclude our demand analysis, we also examine the heterogeneity implied by models of political competition (Persson and Tabellini, 2002). The effects of demand shocks on Democratic vote shares should be larger when the difference in the candidate climate ideal points is larger, which we show formally in Appendix C.

Appendix Figure A.12a and Appendix Figure A.12b both show that the climate effects are larger where the (exogenous component of) the difference in candidate ideal

points is larger. In Appendix Table A.8 we further show that the effects of *all* of our demand shocks are larger when the Republican and Democratic candidates are farther apart in climate ideology, either measured averaging over all years, or measured using only contemporaneously measured ideology.

In principle, these and other sources of heterogeneity could be incorporated into the structural analysis and projections below. However, we focus on our simpler, linear model of demand in order to retain enough precision to make meaningful forecasts out to 2050.

4 Estimating Effects on Politician Supply

This section extends our empirical analysis beyond voter demand estimation. The reasons for focusing on political supply in the context of climate politics are twofold. First, by focusing on the demand-supply equilibrium, we are able to recover important parameters from the political economy perspective, such as the sensitivity of platforms to expected vote shares, as well as the sensitivity of vote shares to changes in the policy platforms of politicians. Second, a full system for demand and supply is necessary for forecasting future political equilibria.

The reduced-form estimates in the previous section are internally valid estimates of the effects of climate changes and climate-related employment changes on partisan vote shares, holding fixed candidates and campaign platforms in each U.S. House election. Given our interest in predicting the effect of climate change on equilibrium policy, however, we need to account for the sensitivity of policy platforms to expected vote shares. We also need to account for how shocks change the supply of environmental policies, as temperature, precipitation, and employment could directly affect candidate positioning on climate, independently of effects on voter demand. Estimating these effects means leaving the within (congressional district $\times$ election year) variation and moving to cross district$\times$year variation, as candidate platforms do not vary at block-group level within a congressional race, but rather across congressional races. Our demand estimates in Section 3 will still be important for identifying the supply of policies, and we will condition on the predictions implied by the estimates from the previous section to recover the direct effects of our shocks on supply, while accounting for the indirect effects via changing political demand.

In this section, we will work with an empirical model for integrating political demand and supply for our problem. As a simple microfoundation for our system of equations, we set up and solve a standard probabilistic voting model of political com-

petition over climate policy in Appendix C. The model illustrates why conditioning on district-year is important for recovering demand, and why controlling for demand parameters is important for recovering the direct effects on supply. We keep our structural framework deliberately streamlined (i.e. linear in all parameters). This is done in order to make identification of all parameters as transparent as possible to the reader. Furthermore, the model's parametric parsimony can pay off in terms of improving statistical precision in forecasting the effects of climate changes on future political equilibria, as we show in Section 5. Despite its simplicity, we show that our empirical framework can deliver non-obvious interactions of demand and supply changes in response to climate and employment shocks.

4.1 Supply Specification

As political competition occurs at the congressional district level c in election year t and policy platforms of Republicans, x^r_{ct}, and Democrats, x^d_{ct}, vary only across districts, we cannot rely solely on our block-group level b variation.

Denote by B_c the set of all block-groups in congressional district c. Maintaining the definition of y_{bt} as the block-group level winning margin of the Democrat at time t, denote $\bar{y}_{ct}$ the average winning margin of the Democratic candidate in district c. Further indicate with $\mathbf{V}_{bt}$ block-group exogenous determinants including weather shifters, employment, including green and brown jobs, and other exogenous covariates, such as the employment rate, and with $\bar{\mathbf{V}}_{ct}$ the vector of averages of these covariates in congressional district c at time t. Assume the policy position of the candidate is function of four different components. First is the set of exogenous determinants $\bar{\mathbf{V}}_{ct}$, capturing the changes in the candidate preferences directly linked to district conditions and candidate learning. Second, the position of the candidate is further driven by the expected support in the electorate, approximated by $\bar{y}_{ct}$. Third, we suppose that a component of the supply function for each candidate is a set of district and election year fixed effects, as well as an idiosyncratic error.

Fourth, we include a party-p specific supply shifter z^p_{ct} capturing party effects and non-local conditions influencing the candidate's platform choice. For the analysis in this paper we posit z^d_{ct} as the average of the environmental policy positions taken by Democrats in congressional districts immediately neighboring c within the state, and z^r_{ct} for Republicans. We assume that each party's supply shifter only affects that party's supply (conditional on district and election year fixed effects), and is orthogonal to other, unobserved determinants of policy supply and demand. Democrat supply of policy x^d_{ct} is only a function of z^d_{ct}, and similarly for the Republicans. These supply

shifters are not only useful for realism, adding a role for local party effects on candidate platforms (i.e. assuming that they are affected in part by considerations outside the specifics of the electoral race), but they also are crucial for identification. Without z^p_{ct}, our empirical model would lack the necessary exogenous variation to isolate the effects of changes in policy platforms and other endogenous variables on vote shares.

With these elements, we can write Democrat policy supply as:

$$x^d_{ct} = \lambda^d \bar{\mathbf{V}}_{ct} + \beta^d \bar{y}_{ct} + \pi^d z^d_{ct} + \omega^d_c + \zeta^d_t + \eta^d_{ct}, \tag{4}$$

and, similarly, the Republican policy supply function is given by:

$$x^r_{ct} = \lambda^r \bar{\mathbf{V}}_{ct} + \beta^r \bar{y}_{ct} + \pi^r z^r_{ct} + \omega^r_c + \zeta^r_t + \eta^r_{ct}. \tag{5}$$

To close the empirical model, let us recall our demand specification from Section 3:

$$y_{bt} = \delta \mathbf{V}_{bt} + \Omega_{ct} + \mu_b + \varepsilon_{bt}. \tag{6}$$

It is important to notice here that we can consistently estimate the coefficients δ using the approach of Section 3. To further capture cross-district variation in demand driven by candidate positions, we parameterize the district-by-year fixed effects Ω_{ct} as:

$$\Omega_{ct} = \gamma^d x^d_{ct} + \gamma^r x^r_{ct} + \mu_c + \kappa_t + \varepsilon_{ct}. \tag{7}$$

This specification allows the average democratic vote share in a district-year, net of block-group fixed effects and block-group covariates $\mathbf{V}_{bt}$, to be driven by Democratic and Republican campaign platform positions. Combining equations (6) and (7) and aggregating at the (c,t) level, we have the demand function:

$$\bar{y}_{ct} = \delta \bar{\mathbf{V}}_{ct} + \gamma^d x^d_{ct} + \gamma^r x^r_{ct} + \underbrace{(\mu_c + \bar{\mu_c})}_{\nu_c} + \kappa_t + \underbrace{(\varepsilon_{ct} + \bar{\varepsilon}_{ct})}_{\xi_{ct}} \tag{8}$$

where $\bar{\mu_c} = \dfrac{1}{\#B_c} \displaystyle\sum_{b \in B_c} \mu_b$, and $\bar{\varepsilon}_{ct} = \dfrac{1}{\#B_c} \displaystyle\sum_{b \in B_c} \varepsilon_{bt}$. Our empirical model therefore consists of the set of equations (4), (5), and (8), which jointly describe the congressional race political equilibrium.

4.2 Estimation

The system (4), (5), and (8) is identified and can be estimated following a two-step procedure. The first step involves a block-group level demand estimation which we have

already performed in Section 3. We employ equation (6) to estimate $\hat{\delta}$ and district-by-year fixed effects $\hat{\Omega}_{ct}$. The second step proceeds by performing the district-level estimation. Starting from equations (4), (5), and (7), we can substitute in the estimated district-by-year fixed effects $\hat{\Omega}_{ct}$ and employ a (weighted) two-step Generalized Method of Moments (GMM) to estimate all remaining parameters.

Specifically, we first apply the Frisch-Waugh-Lovell theorem to partial out the congressional district fixed effects and year fixed effects from $\bar{\mathbf{V}}_{ct}$, z^d_{ct}, z^r_{ct}, x^d_{ct}, x^r_{ct}, $\bar{y}_{ct}$, and $\hat{\Omega}_{ct}$, and obtain $\tilde{\bar{\mathbf{V}}}_{ct}$, $\tilde{z}^d_{ct}$, $\tilde{z}^r_{ct}$, $\tilde{x}^d_{ct}$, $\tilde{x}^r_{ct}$, $\tilde{\bar{y}}_{ct}$, and $\tilde{\Omega}_{ct}$. Denoting $\tilde{\eta}^d_{ct} = \tilde{x}^d_{ct} - \left(\lambda^d \tilde{\bar{\mathbf{V}}}_{ct} + \beta^d \tilde{\bar{y}}_{ct} + \pi^d \tilde{z}^d_{ct}\right)$, $\tilde{\eta}^r_{ct} = \tilde{x}^r_{ct} - \left(\lambda^r \tilde{\bar{\mathbf{V}}}_{ct} + \beta^r \tilde{\bar{y}}_{ct} + \pi^r \tilde{z}^r_{ct}\right)$, and $\tilde{\varepsilon}_{ct} = \tilde{\Omega}_{ct} - \gamma^d \tilde{x}^d_{ct} - \gamma^r \tilde{x}^r_{ct}$, our sample moment conditions are:

$$
\begin{aligned}
\tilde{\eta}^d_{ct} \cdot \left[\tilde{\bar{\mathbf{V}}}'_{ct}, \tilde{z}^d_{ct}, \tilde{z}^r_{ct}\right] &= \mathbf{0}, \\
\tilde{\eta}^r_{ct} \cdot \left[\tilde{\bar{\mathbf{V}}}'_{ct}, \tilde{z}^d_{ct}, \tilde{z}^r_{ct}\right] &= \mathbf{0}, \\
\tilde{\varepsilon}_{ct} \cdot \left[\tilde{z}^d_{ct}, \tilde{z}^r_{ct}\right] &= \mathbf{0}, \\
\mathrm{Cov}(\tilde{\eta}^d_{ct}, \tilde{\eta}^r_{ct}) &= 0, \\
\mathrm{Cov}(\tilde{\varepsilon}_{ct}, \tilde{\eta}^r_{ct}) &= 0, \\
\mathrm{Cov}(\tilde{\eta}^d_{ct}, \tilde{\varepsilon}_{ct}) &= 0,
\end{aligned}
$$

In order to correct for the fact that the demand district-by-year fixed effects, $\hat{\Omega}_{ct}$, which are outcomes in equation (7), are estimated and are therefore affected by sampling error, we weight each (c, t) observation by the inverse of the variance of the estimated $\hat{\Omega}_{ct}$ in the GMM objective function. We cluster the standard errors at the congressional district level. For the computation of the asymptotic variance covariance matrix of the GMM estimator, we use a degrees of freedom correction based on the number of equations in the system and cluster our standard errors at the congressional district level.

4.3 Results of the Equilibrium Model

Table 3 presents the estimates of our equilibrium model. The table is divided into three parts, corresponding to the system of equations (4), (5), and (8). The first part of the table reports estimates for the position of the environmental policy platform of the Democrats, based on equation (4). A one standard deviation increase in the number of days with temperatures exceeding two standard deviations results in Democrats

shifting their environmental policy position to the right by 0.0237 points, equivalent to a 3.6% increase from their average position. The effect of precipitation on Democratic positioning, however, is negligible.

Temperature making Democratic candidates more conservative may seem counter-intuitive. However, it is important to note that this effect is *net* of the effect on voter demand, and so can be interpreted as the additional effect of climate on position. Candidates are thus not pulled to the left on climate *as much* as would be predicted by demand alone. This could be because of a variety of within-party forces (e.g. primaries, campaign finance, candidate selection), or simply an unmodeled mechanism where climate shocks make climate policy more salient, and so candidates pivot to the center in order to compete more effectively on this dimension.

While imprecisely estimated, the effects of green and brown jobs on Democratic positioning are similar in magnitude, but intuitively opposite in direction. For instance, a one standard deviation increase in brown jobs moves Democrats 0.0427 points closer to the center, whereas a comparable increase in green jobs shifts their position 0.0410 points further to the left.

Democrats are also highly responsive to changes in expected voter demand. A one standard deviation increase in their expected vote share allows Democratic party candidates to shift 0.72 points further to the left in the policy space—equivalent to a two-standard-deviation shift. Furthermore, the coefficient on the supply shifter z^d_{ct} is statistically significant, indicating that Democrats, intuitively, adjust their positions based on the environmental policies of their local congressional delegation. This also indicates strength in the identifying variation of the Democratic supply equation. The estimated slope is 0.2, however, an effect well below a 1:1 pass-through of party policy onto candidates' positions. We interpret this magnitude as suggesting a non overwhelming party influence along the environmental platform dimension.

The second part of the table reports estimates for the Republicans' environmental policy positioning, based on equation (5). In contrast to Democrats, Republican candidates are generally less responsive to weather and job shocks. In the case of expected vote share, the effect is economically close to zero: a one standard deviation increase in Democratic vote share prompts Republican candidates to adopt slightly more conservative positions. Only the policy shifter z^r_{ct} and expected vote share coefficients are statistically significant. Similarly as for the Democrats, the estimated slope is around 0.2 and statistically different from 1, suggesting that party delegations are not overwhelmingly powerful in shaping platform choices in each specific congressional race.

The final part of the table provides estimates for the district-level demand equation

(equation (8)). By construction, the effects of weather and job shocks on voter demand are the same as those observed in Section 3. What the district-level demand equation reveals is that voters are significantly more responsive to shifts in Democratic positioning compared to Republican positioning. For example, holding the environmental position of the Republican candidate constant, a move of one standard deviation to the right (to the center) by a Democratic candidate increases their vote share by 9.2 percentage points. In contrast, a one standard deviation move to the right by Republican candidates decreases the Democratic vote share by only 0.59 percentage points.

In Appendix Table A.10, we re-estimate the model, incorporating controls for differences in employment, income, and the voting-age population at the congressional district level. The results confirm that our estimates remain robust even when accounting for these additional characteristics.

As an additional check on our supply estimation, we conduct a placebo exercise where we re-estimate the model but use only the *cultural* ideal points of the candidates, excluding the environmental dimension.[9] Appendix Table A.11 shows the resulting estimates. Naturally, the response of voter demand to our climate and job shocks remain unchanged, as these are estimated using within-district-year variation. However, we also see that none of these shocks affect candidate cultural ideal points. Further, the cultural ideal points do not affect overall voter demand, and these remain identified because the instruments (neighboring same-party cultural ideal points) are still relevant. This exercise shows that our environmental ideal points are not just reflecting overall ideological positions, but rather specific, climate-relevant ones.

Reduced-form Estimates. Given our structural estimates, we can also calculate the reduced-form coefficients, which provide insights into how the model's exogenous variables (e.g., weather shocks, employment, party supply shifters) influence equilibrium supply and demand responses. Specifically, define $\Xi = \frac{1}{1-\beta^d\gamma^d-\beta^r\gamma^r}$, $\Lambda_{ct} = \xi_{ct}+\gamma^d\eta^d_{ct}+\gamma^r\eta^r_{ct}$, $\alpha_{ct} = \nu_c+\kappa_t$, $\rho^d_{ct} = \omega^d_c+\zeta^d_t$, and $\rho^r_{ct} = \omega^r_c+\zeta^r_t$, then the reduced-form equations for the demand and supply system are:

[9] Longuet-Marx (2024) shows that Democrats treat environmental issues as cultural while Republicans treat them as economic.

$$
\begin{aligned}
\bar{y}_{ct} =& \Xi\left(\alpha_{ct} + \gamma^d \rho^d_{ct} + \gamma^r \rho^r_{ct}\right) + \Xi\left(\bar{\delta} + \underline{\gamma^d \lambda^d + \gamma^r \lambda^r}\right) \bar{\mathbf{V}}_{ct} \\
&+ \left(\Xi \gamma^d \pi^d\right) z^d_{ct} + \left(\Xi \gamma^r \pi^r\right) z^r_{ct} + \left(\Xi \Lambda_{ct}\right) \\
x^d_{ct} =& \left(\rho^d_{ct} + \beta^d \Xi\left(\alpha_{ct} + \gamma^d \rho^d_{ct} + \gamma^r \rho^r_{ct}\right)\right) + \left(\bar{\lambda^d} + \underline{\beta^d \Xi\left(\delta + \gamma^d \lambda^d + \gamma^r \lambda^r\right)}\right) \bar{\mathbf{V}}_{ct} \\
&+ \left(\beta^d \Xi \gamma^d \pi^d + \pi^d\right) z^d_{ct} + \beta^d \left(\Xi \gamma^r \pi^r\right) z^r_{ct} + \left(\beta^d \Xi \Lambda_{ct} + \eta^d_{ct}\right) \\
x^r_{ct} =& \left(\rho^r_{ct} + \beta^r \Xi\left(\alpha_{ct} + \gamma^d \rho^d_{ct} + \gamma^r \rho^r_{ct}\right)\right) + \left(\bar{\lambda^r} + \underline{\beta^r \Xi\left(\delta + \gamma^d \lambda^d + \gamma^r \lambda^r\right)}\right) \bar{\mathbf{V}}_{ct} \\
&+ \beta^r \left(\Xi \gamma^d \pi^d\right) z^d_{ct} + \left(\beta^r \Xi \gamma^r \pi^r + \pi^r\right) z^r_{ct} + \left(\beta^r \Xi \Lambda_{ct} + \eta^r_{ct}\right).
\end{aligned}
$$

These coefficients allow us to distinguish between direct effects and indirect effects. We added a bar ($\bar{\cdot}$) to the parameters that reflect the direct effects and underlined ($\underline{\cdot}$) the parameters that represent the indirect effects.

The results are presented in Table 4, which is divided into three panels, corresponding to the three estimation equations. The reduced-form coefficients related to weather and job shocks are shown across the rows. In columns (1)–(3), we report the effects of temperature shocks on Democratic vote share, decomposing the total effects into a direct component (δ_{temp}) and indirect effects arising from changes in policy positions ($\gamma^d \lambda^d + \gamma^r \lambda^r$). As observed in the previous table, temperature shocks are associated with an increase in the share of Democratic votes. Notably, Democrats respond to these shocks by shifting slightly to the right, and even small rightward shifts lead to higher vote shares. Consequently, the indirect effect is positive and comparable in magnitude to the direct effect.

Despite Democrats' tendency to shift rightward in response to temperature shocks, their actual movements in equilibrium are muted, with a total effect of only 0.001 (see column 6). This is because the increase in expected vote share simultaneously allows them to shift further to the left, as indicated by the β_d coefficient. Republican responses to temperature shocks are negligible, with small and statistically insignificant effects (see columns 7-9). Similarly, the effects of precipitation largely align with those of temperature shocks, though they are smaller in magnitude and statistically imprecise.

The last two rows of the table present the reduced-form effects of brown and green jobs. As observed in the demand-side estimation, a higher share of brown jobs is negatively associated with Democratic vote share. However, in equilibrium, these effects are muted as Democrats adopt more conservative environmental positions. The resulting shift is sufficiently large that the total effect becomes positive, although it is not

statistically significant (see column 6).

In contrast, the effects of green jobs are more pronounced. As seen in the demand-side estimation, a higher share of green jobs is positively associated with Democratic vote share. However, two supply-side factors offset this effect. First, as the share of green jobs increases, Democratic candidates shift their platforms further to the left. Second, as their vote share increases, they move even further leftward (column 6). The combined effects of these two forces result in a total effect that, although imprecisely measured, is negatively associated with Democratic vote share. A rationalization of this finding is plausible. It would appear as Democratic candidates, who may be uncertain about the exact elasticity of vote shares to green jobs, overestimate the the support they may garner from green transition employment, especially in terms of how extreme a policy position green jobs may afford them in the campaign.

5 Projecting Political Impacts of Climate Change

The results of the econometric model so far present a series of novel and economically relevant political elasticities, yet they do not make immediately explicit how climate shocks and employment changes may ultimately translate into different political equilibria in the future. For example, it is unclear based on Table 3 alone how big of a difference medium-term weather shocks to a solid Democratic state like California rather than weather shocks to a swing Republican leaning state like Arizona may matter electorally, and in terms of House majorities and roll-call voting. Indeed, shocks to California may lead to no major congressional composition change leaving Democratic seat shares unchanged. Temperature and precipitation shocks in Arizona may erode substantially Republican seat shares, shifting support to more climate friendly politicians.

Using the projected values of our independent variables discussed in Section 2, we obtain location-specific estimates for every election year from 2020 to 2050.

We use the model's reduced-form coefficients to project how the political equilibrium will evolve over time in response to climate and employment changes until the year 2050. To do so, we begin the projections in 2020, using each congressional district's observed baseline values for (i) the Democrat's vote share $\bar{y}_{ct}$, (ii) the Democrat's policy position x^d_{ct}, and (iii) the Republican's policy position x^r_{ct}. At two-year intervals (i.e., 2022, 2024, 2026, etc.), we construct the policy shifters z^d_{ct} and z^r_{ct} by taking the average of the lagged x^d and x^r from adjacent districts of district c. We then incorporate the predicted district-level weather shocks (temperature and precipitation extremes)—

obtained from multiple climate models—as well as predicted green and brown employment rates, and updated policy shifters into the reduced-form expressions to calculate the next-period values for $\bar{y}$, x^d, and x^r. In each projection step, we fix the district- and year-specific fixed effects (estimated from the structural estimation) to their 2020 values, thus assuming no redistricting and no further unobserved shocks beyond those captured by weather and employment. The updated outcomes, $\left(\bar{y}_{c,t+2}, x^d_{c,t+2}, x^r_{c,t+2}\right)$, then serve as initial conditions for the subsequent congressional cycle. Iterating this process through 2050 provides a forward simulation of each district's vote share and policy positions under evolving weather and employment structures, while holding the unobserved district and year-specific components at their baseline levels.

To construct 95% confidence intervals, we perform a 5,000-round bootstrap. In each round, we draw the structural coefficients from a multivariate normal distribution with means equal to the estimated parameters and a covariance matrix given by the cluster-robust variance estimates from the two-step GMM. We also randomly sample residuals from the structural estimation and add them to the predicted $\bar{y}_{ct}$, x^d_{ct}, and x^r_{ct}. This procedure produces predictive intervals that account for both parameter uncertainty and unexplained variation in the original estimates.

In Panel A of Figure 4, we plot the contribution of temperature shocks to Democratic vote margins, averaged across congressional districts from 2022 to 2050, under two different temperature scenarios: the 585 Model and the 126 Model. The 585 Model assumes that carbon emissions continue to increase along historical trends without policy mitigation, while the 126 Model reflects the highest level of climate change mitigation, keeping global surface temperature changes below 2 degrees Celsius. For these reasons, the two scenarios can be interpreted as conceptual upper and lower bounds in this exercise. Figure 4 also decomposes the effects into temperature's direct impact on vote margins and the indirect effects generated by Democratic and Republican policy responses. The final plot in each panel presents the total effects.

Under the 585 Model, we project Democratic vote margins to increase by 4.2 percentage points by 2050. This increase arises equally from the direct effects of rising temperature shocks on vote share and the indirect effects of Democratic candidates shifting slightly to the right, a response that resonates strongly with voters. As expected, the effects are more muted under the 126 Model, where Democratic vote margins are projected to increase by only 1.6 percentage points.

In Panel B, we present the contribution of precipitation shocks to projected vote margins under the two climate scenarios. Unlike temperature shocks, the effects of precipitation are much smaller and statistically imprecise, as suggested by our reduced-form estimates. Both models indicate that the impact of precipitation on vote margins

will change very little over the projection period.

Panel C displays projections for the effects of employment shifts in green and brown jobs on Democratic vote margins, under the 585 Model. As observed in Table 4, an increasing share of green jobs in a district is associated with greater support for Democratic candidates. However, this support is unlikely to grow over time and may even decline slightly by 2050. Democrats respond to this increased support by adopting more liberal environmental platforms, leading to a total effect on vote share that remains negative throughout the period. This correction should not be overinterpreted, as the effect is not statistically significant.

The contribution of brown jobs to Democratic vote margins follows a similar, albeit opposite, trend. We project the total effects of brown jobs on vote margins to remain positive but small in magnitude and statistically imprecise throughout the projection period.

State Projections. The results presented in Figure 4 are averaged across all congressional districts and therefore mask significant heterogeneity in effects across states. To address this, Figure 5 presents the differences between 2050 and 2022 in the contributions of projected changes to exogenous variables on Democratic vote share, broken down by state.

In Panel A, we report the contribution of changes in climate shocks to Democratic vote share. The largest temperature shocks are projected to occur in the Southwest region of the United States, where extreme temperatures are expected to increase the most over the projection period (see Panel A of Appendix Figure A.17). For instance, under the 585 Model, the number of days with temperatures exceeding two standard deviations is projected to increase by an average of 68 days in Oklahoma, Colorado, Texas, and Arizona. As a result, we project that this rise in temperature shocks will increase Democratic vote share by approximately 7 percentage points in these states by 2050. In contrast, the smallest effects of temperature are projected in Oregon and Washington. In these states, we project less than a 1 percentage point increase.

Panel B presents the results for precipitation. Although there is substantial variation across states, with effects even changing sign in some cases, the magnitudes remain small and imprecise. For example, in California, which exhibits the largest effect in absolute value, we predict that changes in precipitation shocks will reduce projected Democratic vote share by less than 0.4 percentage points.

Panels C and D illustrate the differences in the contributions of green and brown jobs to the projected Democratic vote share. The results for green jobs are similar to those observed for precipitation. Despite notable heterogeneity across states, the

effect sizes are small and statistically insignificant. The largest projected effect occurs in New Mexico, which is expected to see the greatest increase in the share of green jobs over the next 30 years. Here, we estimate that the change in green jobs will result in a 0.4 percentage point decline in Democratic vote share.

For brown jobs, we predict a significant decline in Democratic vote share in West Virginia. Recall that while the direct effect of brown jobs on Democratic vote share is negative, the total effect – accounting for supply-side responses – is slightly positive. As the share of brown jobs in West Virginia declines over the projection period, so does their contribution to Democratic vote share.

Compositional Changes to the House of Representatives Given our projected effects on vote share, one might wonder whether these changes are sufficient to alter the composition of the House of Representatives and potentially its ideological orientation. In Figure 6, we present four plots. The upper-left quadrant shows the projected share of Democrats elected to the House of Representatives, while the upper-right quadrant depicts both the average and median projected campaign positions on environmental policies of all elected House members. The bottom panels focus on party-specific trends, with the bottom-left plot showing the average and median projected campaign positions among elected Democrats, and the bottom-right plot showing the same for elected Republicans.

Taken together, these plots reveal an intriguing set of findings. By 2050, the median member of the House, and to a lesser extent the average member, is projected to adopt a much more liberal stance on environmental policies compared to 2020. This shift occurs despite the fact that the average and median campaign positions of both elected Democrats and Republicans are becoming more conservative over time. These seemingly contradictory patterns are explained by the increasing share of House seats held by Democrats, who, while becoming more conservative themselves, remain significantly more liberal on environmental policies compared to their Republican counterparts. Although these results reflect campaign positions on environmental policies, as demonstrated in Section 4, these ideal points strongly correlate with elected members' actual policy positions based on roll-call voting.

6 Conclusions

This paper focuses on the politics of climate in the United States from an empirical perspective. Our main contribution is to econometrically decouple electoral demand drivers for pro-environment politicians from supply drivers of candidate policy platform

choices. Within the set of demand forces, we are able to separate effects due to extreme temperature and precipitation events from economic drivers, such as the loss of brown jobs and the gain of green jobs in certain geographic areas, which speak more to issues of adjustment and adaptation. High temperature shocks and high precipitation shocks increase support for Democrats, and similarly the arrival of green jobs. Brown job gains increase support for Republicans. Both sets of demand shifters have similar economic and statistical significance. On the supply side, Democrats appear more responsive to voter demand for climate policy. In turn, voters are sensitive to the environmental policy choices of candidates competing in their congressional races.

We use the parameter estimates from our demand and supply model to project the effects of climate and employment compositional trends 25 years into the future. Under our climate change scenarios, the analysis shows a consistent electoral shift towards more pro-environmental candidates (Democrats), even as both Democrats and Republicans endogenously become mildly less pro-environment.

Methodologically, along with Longuet-Marx (2024), we have constructed one of the first complete structural supply-and-demand equilibrium models of electoral political competition. Our identification leverages the unique granularity of the data, isolating within-district variation to estimate demand, and controlling for demand in recovering supply of policies, measured by ideal points of campaigns. We believe that these ingredients will be important for future, possibly richer, quantitative models of electoral competition in political economy.

Climate change appears set to be a major social cost for the foreseeable future. Adaptation to and mitigation of climate change is going to involve policy decisions that aggregate diverse interests and perspectives. Whether democratic institutions and electoral competition can deliver these policies remains an open question, one our paper tentatively answers in the affirmative. Our model is deliberately simple, however, and future work could incorporate many more margins of climate change and adaptation (e.g. disasters and migration, as in Desmet and Rossi-Hansberg (2024)) as well as many more margins of political influence (e.g. campaign finance and special interest politics). Finally, a large literature has modeled and measured the unavoidable international cooperation and conflicts over climate policy necessary for adequate mitigation and adaptation (for a recent quantitative macroeconomic example see Bourany (2024)). Rigorously incorporating domestic political economy into these models remains an area for future research.

References

Aklin, Michaël and Johannes Urpelainen. 2013. "Political Competition, Path Dependence, and the Strategy of Sustainable Energy Transitions." *American Journal of Political Science* 57(3):643–658.

Anderson, Soren, Ioana Marinescu and Boris Shor. 2023. "Can Pigou at the polls stop us melting the poles?" *Journal of the Association of Environmental and Resource Economists* 10(4):903–945.

Ansolabehere, Stephen, James M Snyder Jr and Charles Stewart III. 2001. "Candidate positioning in US House elections." *American Journal of Political Science* pp. 136–159.

Autor, David, Anne Beck, David Dorn and Gordon Hanson. 2024. "Help for the Heartland? The Employment and Electoral Effects of the Trump Tariffs in the United States.".
URL: *http://www.nber.org/papers/w32082.pdf*

Bergquist, Parrish and Christopher Warshaw. 2019. "Does global warming increase public concern about climate change?" *The Journal of Politics* 81(2):686–691.

Berry, Steve, Christian Cox and Phil Haile. 2024. "What Drives Voting: Estimates from a Multilevel Data." *mimeo Yale* .

Binder, Sarah A. 2004. *Stalemate: Causes and consequences of legislative gridlock*. Rowman & Littlefield.

Bombardini, Matilde, Bingjing Li and Francesco Trebbi. 2023. "Did US Politicians Expect the China Shock?" *American Economic Review* 113(1):174–209.

Bonica, Adam. 2013. "Ideology and interests in the political marketplace." *American Journal of Political Science* 57(2):294–311.

Boomhower, Judson. 2024. "When Do Environmental Externalities Have Electoral Consequences? Evidence from Fracking." *Journal of the Association of Environmental and Resource Economists* 11(4):999–1029.

Borusyak, Kirill, Peter Hull and Xavier Jaravel. 2022. "Quasi-experimental shift-share research designs." *The Review of Economic Studies* 89(1):181–213.

Bourany, Thomas. 2024. "Optimal Energy Policy and the Inequality of Climate Change.".

Burke, Marshall, Mustafa Zahid, Mariana CM Martins, Christopher W Callahan, Richard Lee, Tumenkhusel Avirmed, Sam Heft-Neal, Mathew Kiang, Solomon M Hsiang and David Lobell. 2024. Are We Adapting to Climate Change? Technical report National Bureau of Economic Research.

Burke, Marshall, Mustafa Zahid, Noah Diffenbaugh and Solomon M Hsiang. 2023. Quantifying climate change loss and damage consistent with a social cost of greenhouse gases. Technical report National Bureau of Economic Research.

Béland, Louis-Philippe and Vincent Boucher. 2015. "Polluting Politics." *Economics Letters* 137:176–181.

Calvo, Richard, Vincent Pons and Jesse M Shapiro. 2024. Pitfalls of demographic forecasts of us elections. Technical report National Bureau of Economic Research.

Canen, Nathan, Chad Kendall and Francesco Trebbi. 2020. "Unbundling polarization." *Econometrica* 88(3):1197–1233.

Canen, Nathan J, Chad Kendall and Francesco Trebbi. 2021. Political Parties as Drivers of US Polarization: 1927-2018. Technical report National Bureau of Economic Research.

Carleton, Tamma, Amir Jina, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, Robert E Kopp, Kelly E McCusker, Ishan Nath et al. 2022. "Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits." *The Quarterly Journal of Economics* 137(4):2037–2105.

Choi, Darwin, Zhenyu Gao and Wenxi Jiang. 2020. "Attention to global warming." *The Review of Financial Studies* 33(3):1112–1145.

Choi, Jiwon, Ilyana Kuziemko, Ebonya L Washington and Gavin Wright. 2021. Local economic and political effects of trade deals: Evidence from NAFTA. Technical report National Bureau of Economic Research.

Clinton, Joshua, Simon Jackman and Douglas Rivers. 2004. "The statistical analysis of roll call data." *American Political Science Review* 98(2):355–370.

Conley, Timothy G. 1999. "GMM estimation with cross sectional dependence." *Journal of econometrics* 92(1):1–45.

Cox, Christian. 2024. "The Equilibrium Effects of Campaign Finance Deregulation on US Elections." *mimeo University of Arizona* .

Dechezleprêtre, Antoine, Adrien Fabre, Tobias Kruse, Bluebery Planterose, Ana Sanchez Chico and Stefanie Stantcheva. 2022. Fighting climate change: International attitudes toward climate policies. Technical report National Bureau of Economic Research.

Dell, Melissa, Benjamin F Jones and Benjamin A Olken. 2012. "Temperature shocks and economic growth: Evidence from the last half century." *American Economic Journal: Macroeconomics* 4(3):66–95.

Deryugina, Tatyana. 2013. "How do people update? The effects of local weather fluctuations on beliefs about global warming." *Climatic change* 118:397–416.

Desmet, Klaus and Esteban Rossi-Hansberg. 2024. "Climate change economics over time and space." *Annual Review of Economics* 16.

Doyle, Timothy, Doug McEachern and Sherilyn MacGregor. 2015. *Environment and politics*. Routledge.

Druckman, James N and Mary C McGrath. 2019. "The evidence for motivated reasoning in climate change preference formation." *Nature Climate Change* 9(2):111–119.

Eckert, Fabian, Teresa Fort, Peter Schott and Natalie Yang. 2021. "Imputing Missing Values in the US Census Bureau's County Business Patterns.".
URL: *http://www.nber.org/papers/w26632.pdf*

Egan, Patrick J and Megan Mullin. 2012. "Turning personal experience into political attitudes: The effect of local weather on Americans' perceptions about global warming." *The Journal of Politics* 74(3):796–809.

Egan, Patrick J and Megan Mullin. 2017. "Climate change: US public opinion." *Annual Review of Political Science* 20:209–227.

Fredriksson, Per G, Le Wang and Khawaja A Mamun. 2011. "Are politicians office or policy motivated? The case of US governors' environmental policies." *Journal of Environmental Economics and Management* 62(2):241–253.

Gagliarducci, Stefano, M Daniele Paserman and Eleonora Patacchini. 2019. Hurricanes, climate change policies and electoral accountability. Technical report National Bureau of Economic Research.

Geels, Frank W, Frans Berkhout and Detlef P Van Vuuren. 2016. "Bridging analytical approaches for low-carbon transitions." *Nature climate change* 6(6):576–583.

Hahn, Robert W, Nathaniel Hendren, Robert D Metcalfe and Ben Sprung-Keyser. 2024. A welfare analysis of policies impacting climate change. Technical report National Bureau of Economic Research.

Hazlett, Chad and Matto Mildenberger. 2020. "Wildfire exposure increases pro-environment voting within democratic but not republican areas." *American Political Science Review* 114(4):1359–1365.

Hilbig, Hanno and Sascha Riaz. 2024. "Natural disasters and green party support." *The Journal of Politics* 86(1):241–256.

Hoffmann, Roman, Raya Muttarak, Jonas Peisker and Piero Stanig. 2022. "Climate change experiences raise environmental concerns and promote Green voting." *Nature Climate Change* 12(2):148–155.

Iaryczower, Matias, Sergio Montero and Galileu Kim. 2022. Representation failure. Technical report National Bureau of Economic Research.

Jud, Stefano and Quynh Nguyen. 2024. "Disasters and Divisions: How Partisanship Shapes Policymaker Responses to Climate Change." *Available at SSRN 4870935* .

Kahn, Matthew E and John G Matsusaka. 1997. "Demand for environmental goods: Evidence from voting patterns on California initiatives." *The Journal of Law and Economics* 40(1):137–174.

Kaplan, Ethan, Jörg L Spenkuch and Haishan Yuan. 2019. Natural disasters, moral hazard, and special interests in Congress. In *Moral Hazard, and Special Interests in Congress (September 2019)*.

Lazar, Nomi Claire and Jeremy Wallace. 2025. "Resisting the Authoritarian Temptation." *Journal of Democracy* 36(1):135–150.

List, John A. and Daniel M. Sturm. 2006. "How Elections Matter: Theory and Evidence from Environmental Policy." *The Quarterly Journal of Economics* 121(4):1249–1281.

Longuet-Marx, Nicolas. 2024. "Party Lines or Voter Prefereces? Explaining Political Realignment.".

Manson, Steven, Jonathan Schroeder, David Van Riper, Katherine Knowles, Tracy Kugler, Finn Roberts and Steven Ruggles. 2024. "IPUMS National Historical Geographic Information System: Version 19.0.".
URL: *https://www.nhgis.org/*

Martin, Gregory J and Ali Yurukoglu. 2017. "Bias in cable news: Persuasion and polarization." *American Economic Review* 107(9):2565–2599.

Moore, Frances C, Katherine Lacasse, Katharine J Mach, Yoon Ah Shin, Louis J Gross and Brian Beckage. 2022. "Determinants of emissions pathways in the coupled climate–social system." *Nature* 603(7899):103–111.

Pahontu, Raluca L. 2020. "The democrat disaster: Hurricane exposure, risk aversion and insurance demand." *Risk Aversion and Insurance Demand (January 2020)* .

Persson, Torsten and Guido Tabellini. 2002. *Political economics: explaining economic policy*. MIT press.

Poole, Keith T and Howard L Rosenthal. 2011. *Ideology and congress*. Vol. 1 Transaction Publishers.

Poole, Keith T and Howard Rosenthal. 1984. "The polarization of American politics." *The journal of politics* 46(4):1061–1079.

Poole, Keith T and Howard Rosenthal. 1985. "A spatial model for legislative roll call analysis." *American Journal of Political Science* pp. 357–384.

Rowan, Sam. 2023. "Extreme weather and climate policy." *Environmental Politics* 32(4):684–707.

Schlenker, Wolfram and Michael J Roberts. 2009. "Nonlinear temperature effects indicate severe damages to US crop yields under climate change." *Proceedings of the National Academy of sciences* 106(37):15594–15598.

Spenkuch, Jörg L and David Toniatti. 2018. "Political advertising and election results." *The Quarterly Journal of Economics* 133(4):1981–2036.

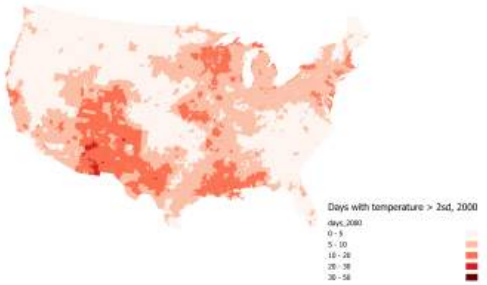
Stokes, Leah C. 2016. "Electoral backlash against climate policy: A natural experiment on retrospective voting and local resistance to public policy." *American Journal of Political Science* 60(4):958–974.

Voorheis, John, Nolan McCarty and Boris Shor. 2015. "Unequal incomes, ideology and gridlock: How rising inequality increases political polarization." *Ideology and Gridlock: How Rising Inequality Increases Political Polarization (August 21, 2015)* .

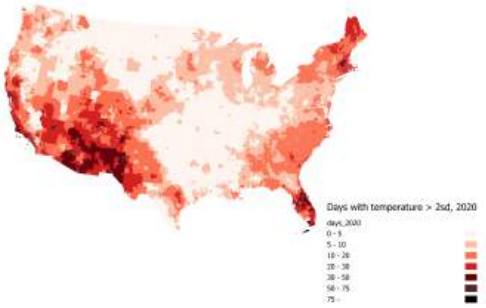
Wiliam, Dylan and Marnie Thompson. 2017. Integrating assessment with learning: What will it take to make it work? In *The future of assessment*. Routledge pp. 53–82.

Zaval, Lisa, Elizabeth A Keenan, Eric J Johnson and Elke U Weber. 2014. "How warm days increase belief in global warming." *Nature Climate Change* 4(2):143–147.

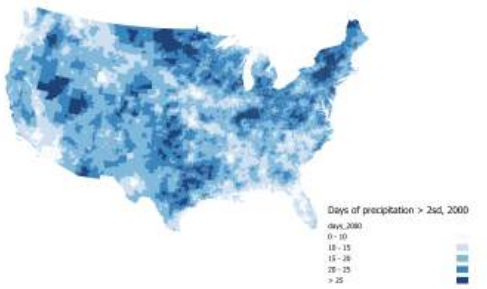
Figure 1: Maps showing main independent variables in 2000 and 2020



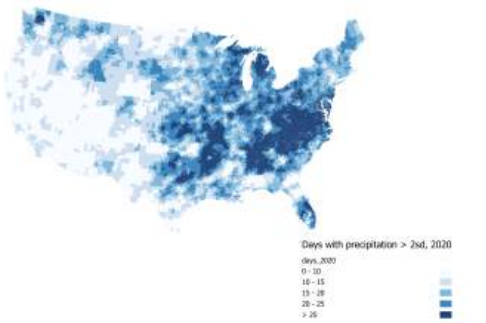
(a) Extreme temperature measure 2000



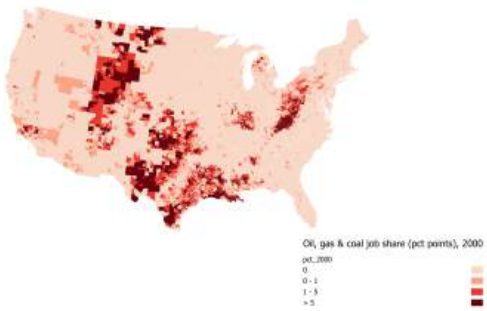
(b) Extreme temperature measure 2020



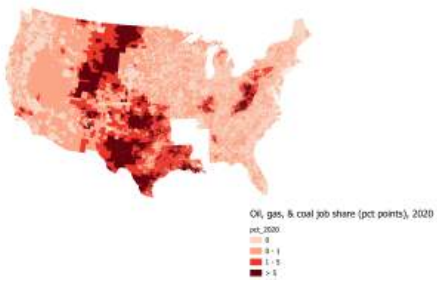
(c) Extreme Precipitation 2000



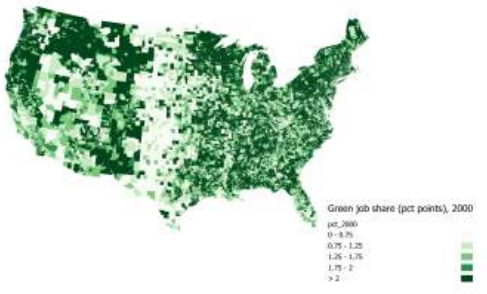
(d) Extreme Precipitation 2020



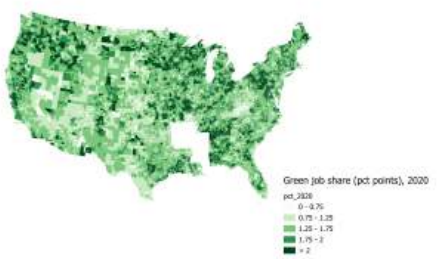
(e) Brown jobs 2000



(f) Brown jobs 2020

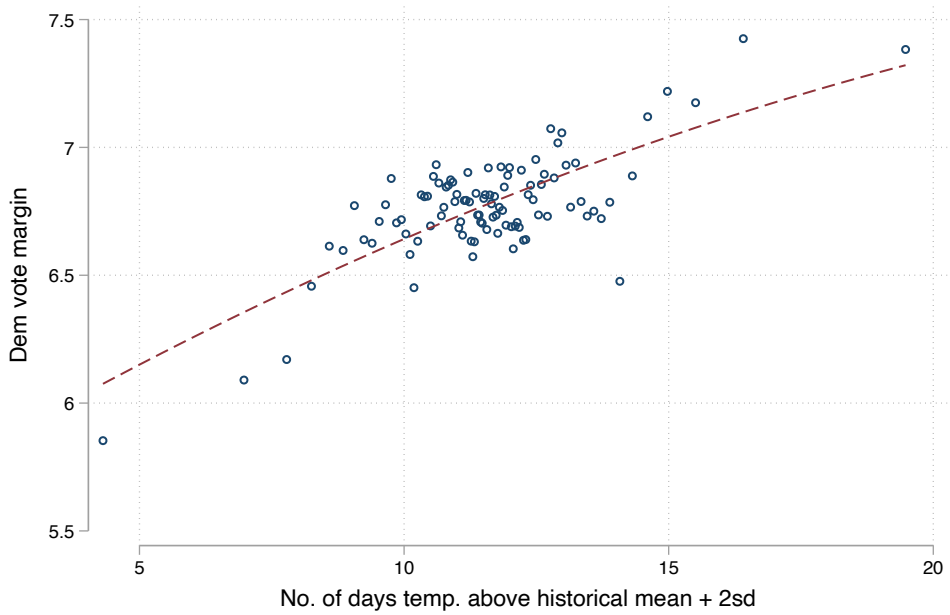


(g) Green jobs 2000

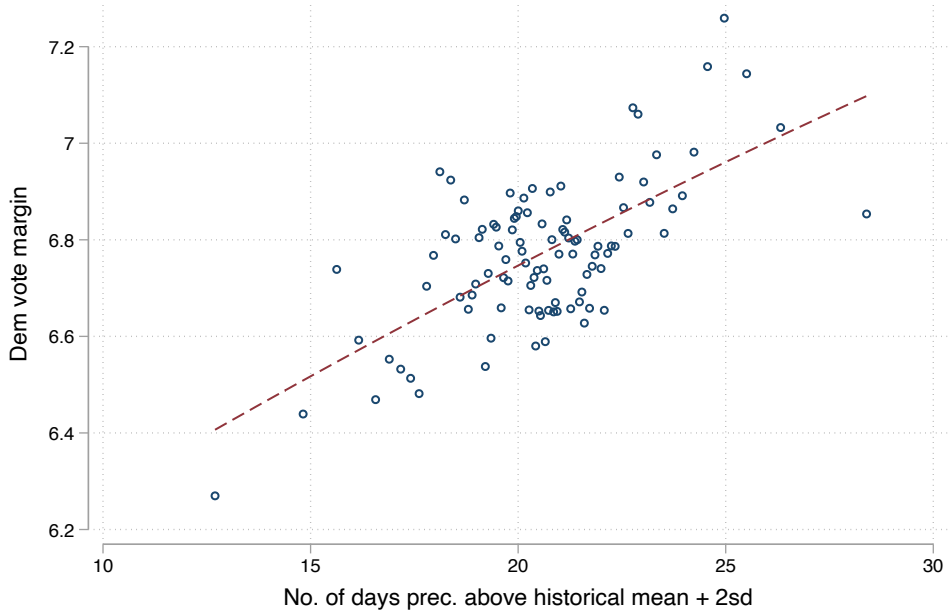


(h) Green jobs 2020

Figure 2: The Relationship Between Extreme Temperature and Precipitation and Democratic Vote Margin



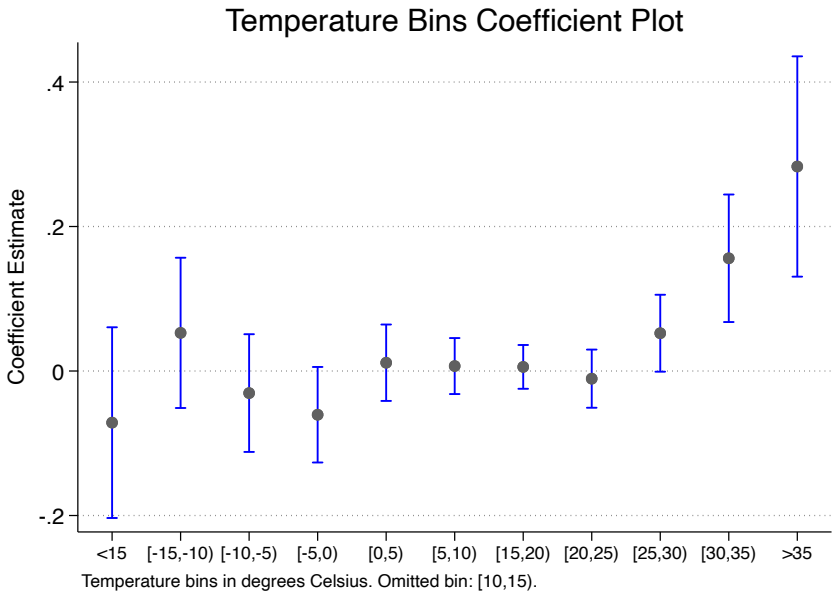
(a) Extreme Temperature (2+SD Above Historical Average)



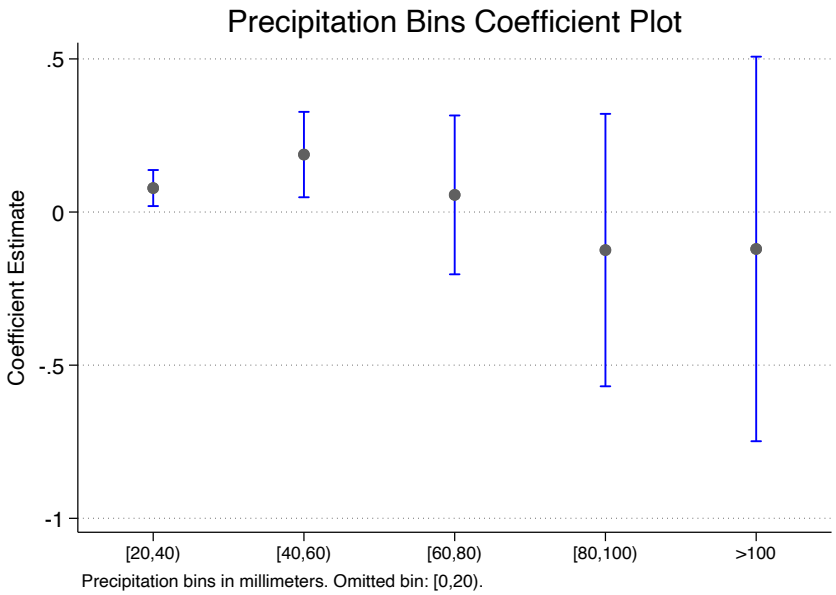
(b) Extreme Precipitation (2+SD Above Historical Average)

Notes: Each panel is a binscatter showing precinct-year-level Democratic vote margin as a function of extreme temperature or precipitation, controlling for block-group and Congressional-district-by-year fixed effects. The x-axis is extreme temperature or precipitation, defined as number of days in the year above the historical mean plus two standard deviations. The y-axis is the Democratic vote margin in the Congressional election. The red dotted lines are quadratic fits. The sample is Congressional elections from 2000 to 2020.

Figure 3: The Relationship Between Temperature and Precipitation Bins and Democratic Vote Margin



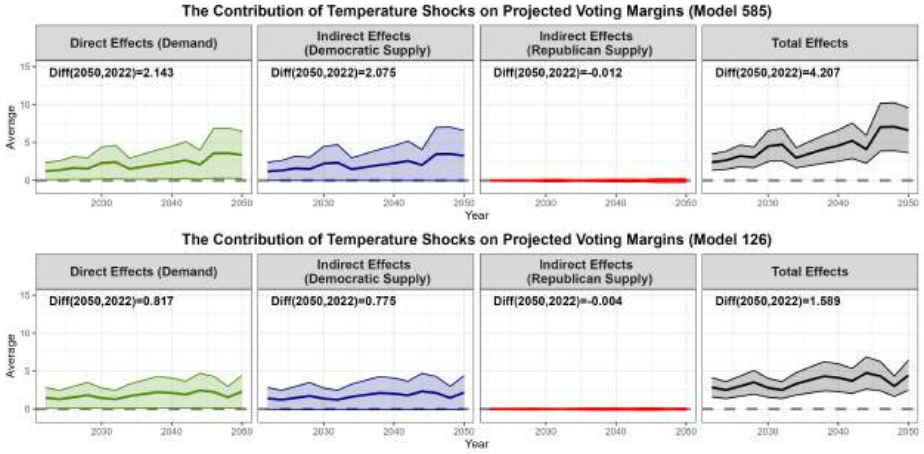
(a) Temperature



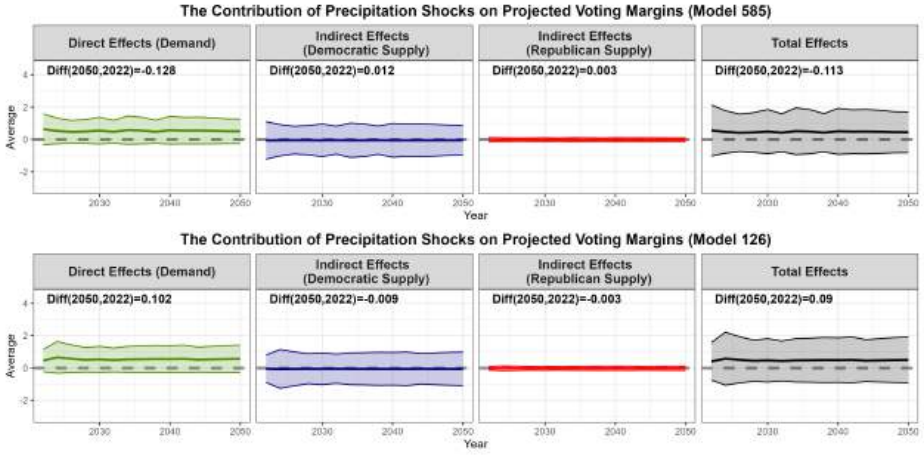
(b) Precipitation

Notes: Each panel shows estimates of the coefficients on bins of temperature or precipitation from a single regression at the precinct-year level where the dependent variable is Democratic vote margin. The regression also includes block-group and Congressional-district-by-year fixed effects, the shares of green and brown jobs, and a set of controls. The sample is Congressional elections from 2000 to 2020. The graphs plot coefficients with 95% confidence intervals calculated using standard errors clustered by block group and Congressional-district-by-year.

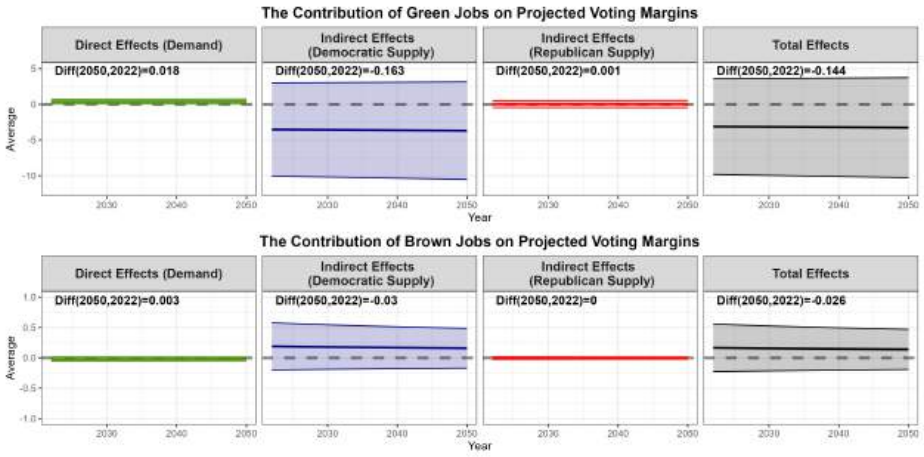
Figure 4: Contribution of weather shocks and employment shifts to projected Democratic vote margins



(a) Temperature Shock

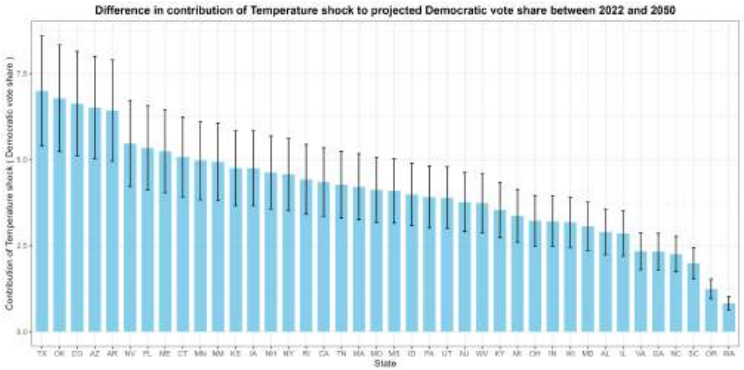


(b) Precipitation Shock

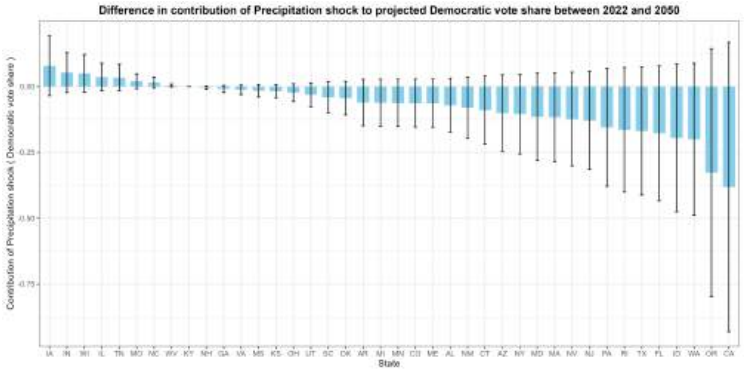


(c) Employment Shifts

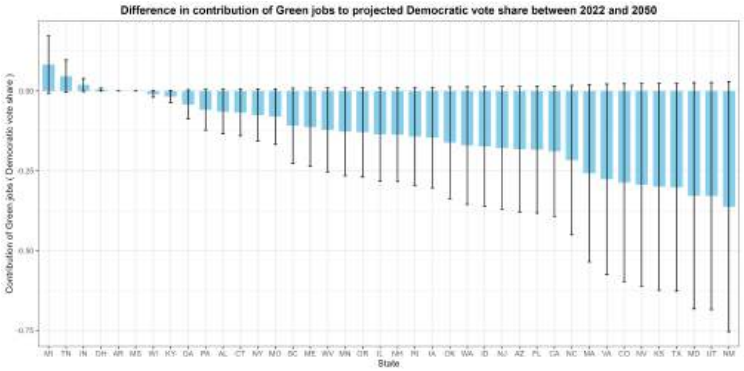
Figure 5: Projected Democratic Vote Margins By State



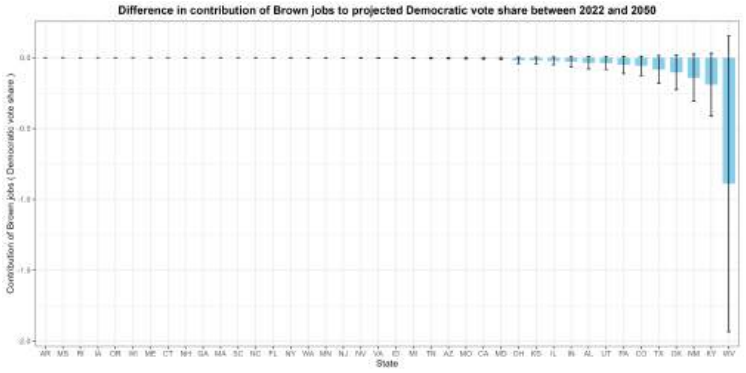
(a) Temperature Shock Difference



(b) Percipitation Shock Difference



(c) Green Jobs Difference



(d) Brown Jobs Difference

Notes.

Figure 6: Projected Composition of the House of Representative

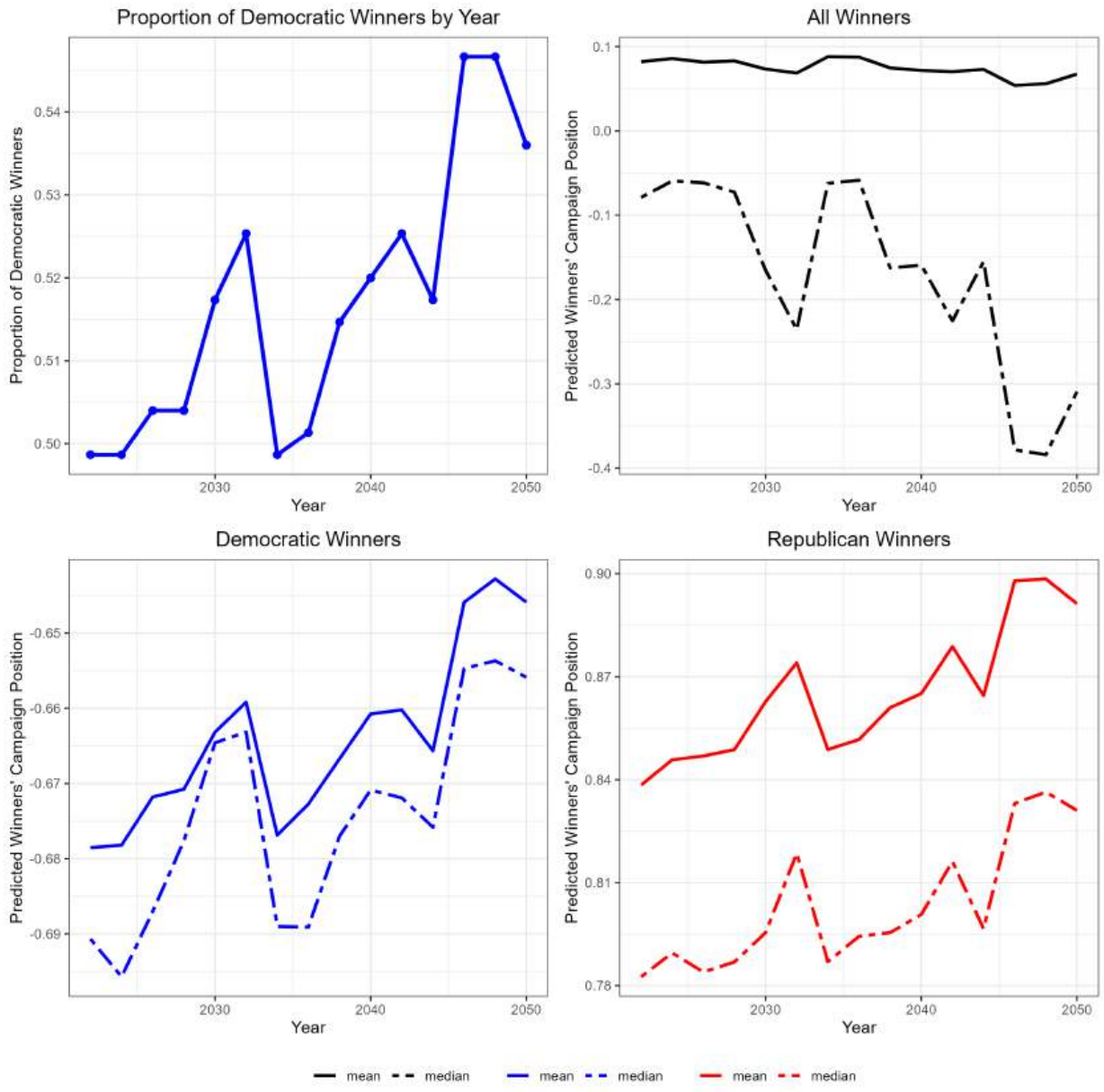


Table 1: Within-District Estimates of Voter Demand

Dep. var.: Dem-Rep vote share	TWFE	TWFE + IV	FE	FE + IV
	(1)	(2)	(3)	(4)
No. of days temp. above historical mean + 2sd	0.0804***	0.0849***	0.463***	0.433***
	(0.0225)	(0.0258)	(0.0471)	(0.0481)
No. of days prec. above historical mean + 2sd	0.0376*	0.0388	0.114***	0.138***
	(0.0210)	(0.0239)	(0.0423)	(0.0443)
Share Jobs in OGC	-0.171**	-1.324*	-0.984***	-2.346*
	(0.0710)	(0.695)	(0.103)	(1.273)
Share Jobs in Renewables or Energy Efficiency	0.450***	31.54***	-5.283***	9.485***
	(0.122)	(4.220)	(0.316)	(1.939)
District x Year FE	X	X	X	X
Block group FE	X	X		
Controls	Long	Long	Long	Long
F-stat		25.412		6.259
Total Effect of 1SD Climate Shocks	0.904***	0.959***	4.509***	4.483***
	(0.221)	(0.257)	(0.458)	(0.474)
Total Effect of 1SD Jobs Shocks	0.523***	16.299***	4.321***	8.402***
	(0.136)	(2.420)	(0.246)	(2.395)
Observations	1,320,575	1,253,659	1,329,167	1,255,372

In parentheses standard errors are clustered by District × Year and Block group

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: Each column shows the effects of climate and job shocks on voter demand from separate regressions. The unit of observation is a block-group-year, and the sample period is 2000 to 2020. The dependent variable is the vote share of the Democratic candidate minus that of the Republican candidate in percentage points. Share jobs in OGC and share jobs in renewables or energy efficiency are in percentage points. The regressions in columns (2) and (4) instrument for share jobs in OGC and share jobs in renewables or energy efficiency with their respective shift-share instruments as described in section 3.2. Rows displaying total effects of one standard deviation climate or jobs shocks are sums of the absolute values of effects of a one standard deviation increase in the two climate shocks or the two jobs shocks. Standard errors are clustered by block-group and district-year and are shown in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 2: Robustness of Within-District Demand Estimates

Dep. var.: Dem-Rep vote share	FE	Three-Way FE	TWFE: Conley SE		
	(1)	(2)	(3)	(4)	(5)
No. of days temp. above historical mean + 2sd	0.420***	0.0670***	0.0842***	0.0842***	0.0842***
	(0.0477)	(0.0236)	(0.0217)	(0.0249)	(0.0288)
No. of days prec. above historical mean + 2sd	0.164***	0.0432**	0.0384**	0.0384**	0.0384**
	(0.0420)	(0.0208)	(0.0187)	(0.0192)	(0.0195)
Share Jobs in OGC	-1.009***	-0.116*	-0.172***	-0.172**	-0.172
	(0.0965)	(0.0638)	(0.0664)	(0.0840)	(0.111)
Share Jobs in Renewables or Energy Efficiency	-5.189***	0.548***	0.433***	0.433***	0.433**
	(0.315)	(0.122)	(0.143)	(0.165)	(0.185)
District x Year FE	X	X	X	X	X
Block group FE		X	X	X	X
DMA x Year FE		X			
Polynomial in Lat. and Lon.	X				
Controls	Long	Long	Long	Long	Long
Conley SE Cutoff			25km	50km	100km
Observations	1,315,217	1,314,577	1,323,802	1,323,802	1,323,802

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: Each column shows the effects of climate and job shocks on voter demand from separate regressions. The unit of observation is a block-group-year, and the sample period is 2000 to 2020. The dependent variable is the vote share of the Democratic candidate minus that of the Republican candidate in percentage points. Share jobs in OGC and share jobs in renewables or energy efficiency are in percentage points. The polynomial in latitude and longitude is of degree six. The regression in column (2) includes, in addition to district-year and block-group fixed effects, fixed effects at designated-market-area-year level. The regressions in columns (3) to (5) have standard errors that account for spatial correlation (Conley (1999)). In all other regressions, standard errors are clustered by block-group and district-year. They are shown in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 3: Structural Parameter Estimates

Parameter	Estimate	Std Error	Z-value	P-value	Marginal Effects
			Democrat's Supply		
λ^d_{temp}	0.0030	0.0014	2.1994	0.0278	0.0237
λ^d_{prec}	-0.0001	0.0014	-0.0374	0.9702	-0.0003
λ^d_G	-0.1410	0.1512	-0.9325	0.3511	-0.0410
λ^d_B	0.0391	0.0361	1.0823	0.2791	0.0427
β^d	-0.0225	0.0130	-1.7320	0.0833	-0.7164
π^d	0.2034	0.0984	2.0672	0.0387	0.0396
			Republican's Supply		
λ^r_{temp}	0.0004	0.0016	0.2689	0.7880	0.0034
λ^r_{prec}	0.0005	0.0022	0.2481	0.8041	0.0035
λ^r_G	-0.0402	0.1513	-0.2659	0.7903	-0.0117
λ^r_B	0.0075	0.0260	0.2867	0.7744	0.0081
β^r	0.0038	0.0014	2.6918	0.0071	0.1206
π^r	0.2319	0.0615	3.7716	0.0002	0.0614
			District-level Demand		
δ_{temp}	0.0818	0.0247	3.3178	0.0009	0.6416
δ_{prec}	0.0388	0.0232	1.6682	0.0954	0.2465
δ_G	0.3983	0.1292	3.0815	0.0021	0.1158
δ_B	-0.1675	0.0751	-2.2313	0.0257	-0.1828
γ^d	29.3409	15.0254	1.9528	0.0508	9.1621
γ^r	-1.3714	1.0381	-1.3211	0.1865	-0.5866

Note: This table presents parameter estimates from the structural equations of Democrats' policy supply $\left(x^d_{ct}\right)$, Republicans' policy supply $\left(x^r_{ct}\right)$, and district-level Democratic vote share $\left(\bar{y}_{ct}\right)$. Standard errors (in parentheses) are clustered by congressional district; z-values and p-values reflect two-sided tests. The final column ("Marginal Effects") indicates the change in the outcome—Democrats' platform in the first panel, Republicans' platform in the second panel, and Democrats' vote share (on a 0–100 scale) in the third panel—arising from a one-standard-deviation increase in the corresponding regressor. Estimation uses a two-step GMM approach with instruments $\bar{\mathbf{V}}_{ct}, z^d_{ct}, z^r_{ct}$, and weighting by the inverse variance of the estimated district-by-year fixed effects in the first step.

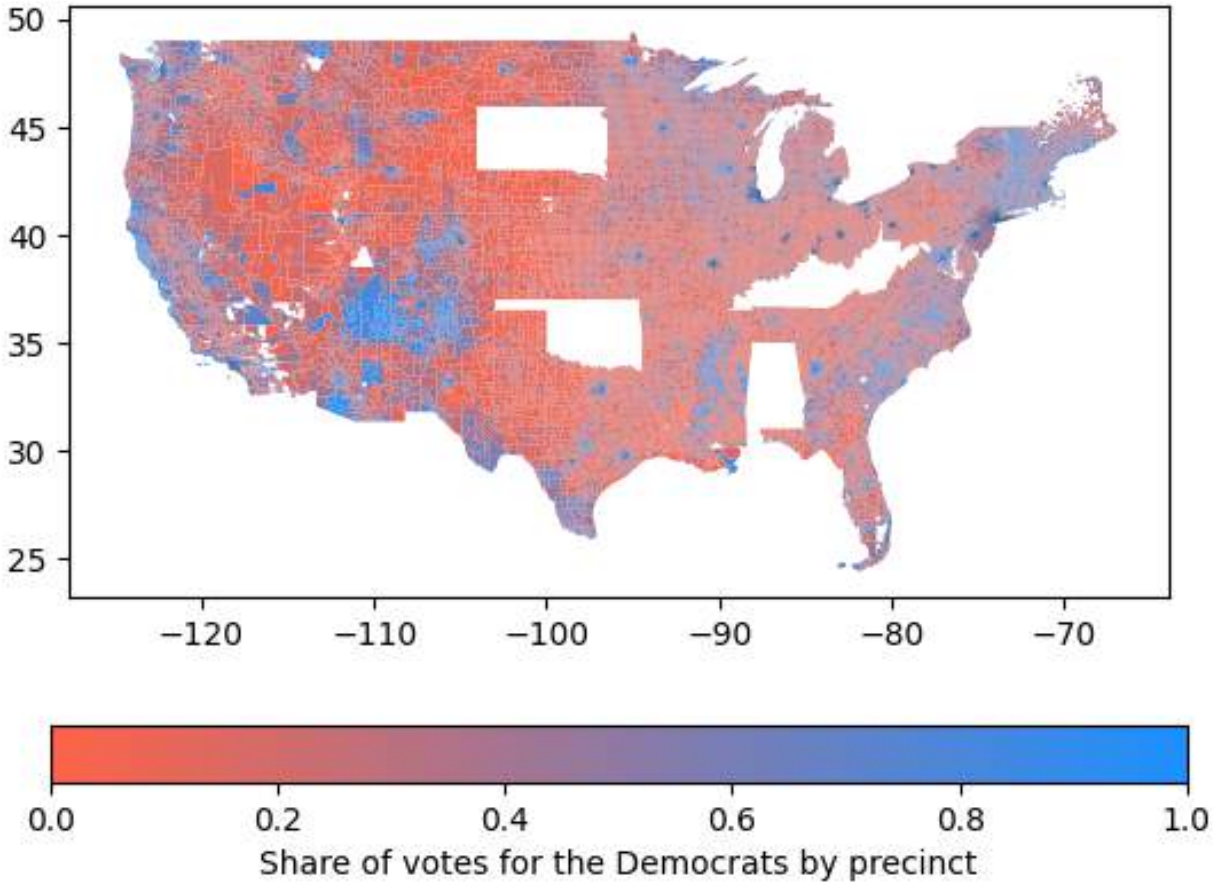
Table 4: Reduced-form District-Year Level Estimates

	Democrat's Vote Share			**Democrat's Position**			**Republican's Position**		
	Direct (1)	Indirect (2)	Total (3)	Direct (4)	Indirect (5)	Total (6)	Direct (7)	Indirect (8)	Total (9)
Temperature	0.049**	0.053**	0.102***	-0.002*	0.003**	0.001	0.000**	0.000	0.001
	(0.023)	(0.025)	(0.023)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)	(0.002)
Precipitation	0.023	-0.001	0.022	-0.000	-0.000	-0.001	0.000	0.001	0.001
	(0.017)	(0.021)	(0.029)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)	(0.002)
Brown Jobs	-0.101*	0.682	0.582	-0.013	0.039	0.026	0.002	0.007	0.010
	(0.060)	(0.584)	(0.588)	(0.016)	(0.036)	(0.026)	(0.002)	(0.026)	(0.026)
Green Jobs	0.239**	-2.450	-2.211	0.050	-0.141	-0.091	-0.008	-0.040	-0.049
	(0.119)	(2.318)	(2.385)	(0.089)	(0.153)	(0.084)	(0.008)	(0.152)	(0.153)

Note: This table reports the direct, indirect, and total reduced-form coefficients of temperature, precipitation, green jobs, and brown jobs on three outcomes: Democratic vote share, the Democrat's policy position, and the Republican's policy position. When the outcome is the Democratic vote share $(\bar{y}_{ct})$, the "direct effect" corresponds to the $\Xi\,\delta$ term, and the "indirect effect" corresponds to $\Xi(\gamma^d\lambda^d + \gamma^r\lambda^r)$. For the Democrat's policy position (x^d_{ct}), the direct effect is λ^d, while the indirect effect is $\beta^d\Xi(\delta + \gamma^d\lambda^d + \gamma^r\lambda^r)$. An analogous decomposition applies to the Republican's policy position (x^r_{ct}). Standard errors (in parentheses) are constructed using the structural parameter estimates and are clustered at the congressional-district level. A single asterisk $(*)$ indicates significance at the 10% level; two asterisks $(**)$ at the 5% level; and three asterisks $(***)$ at the 1% level.

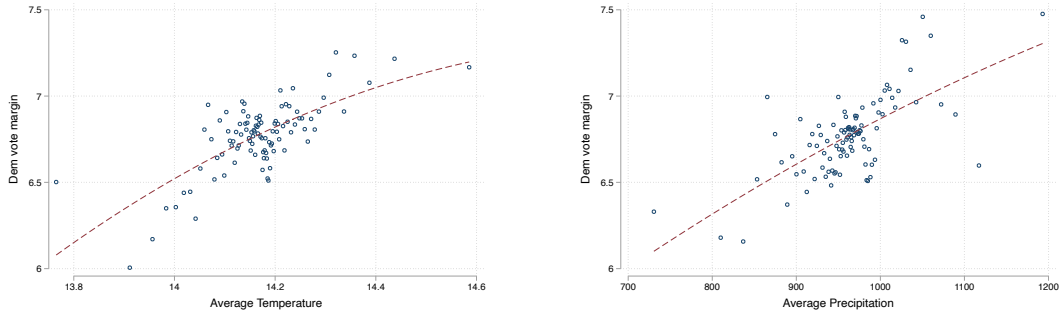
A Online Appendix for "Climate Politics in the United States", by M. Bombardini, F. Finan, N. Longuet-Marx, S. Naidu, F. Trebbi

Figure A.7: Map of precinct-level voting patterns in 2016 (from Longuet-Marx (2024)).



Notes.

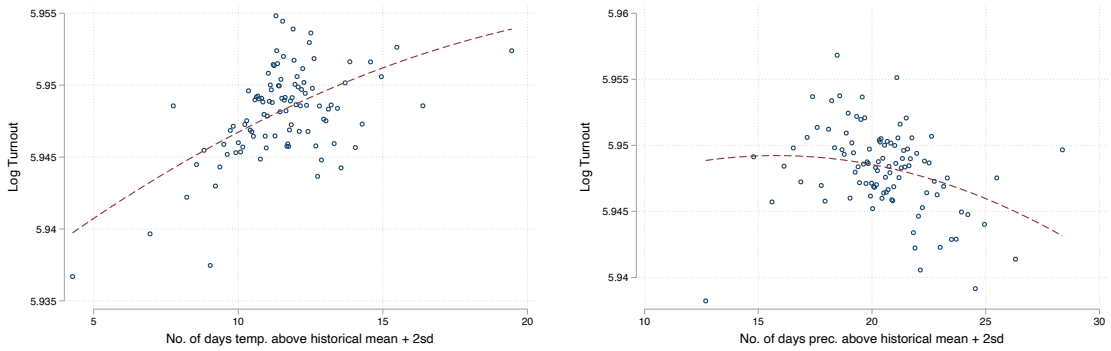
Figure A.8: The Relationship Between Average Temperature and Precipitation and Democratic Vote Margin



(a) Average Temperature (b) Average Precipitation

Notes: Each panel is a binscatter showing precinct-year-level Democratic vote margin as a function of average temperature or precipitation, controlling for block-group and Congressional-district-by-year fixed effects. The x-axis is average temperature or precipitation. The y-axis is the Democratic vote margin in the Congressional election. The red dotted lines are quadratic fits. The sample is Congressional elections from 2000 to 2020.

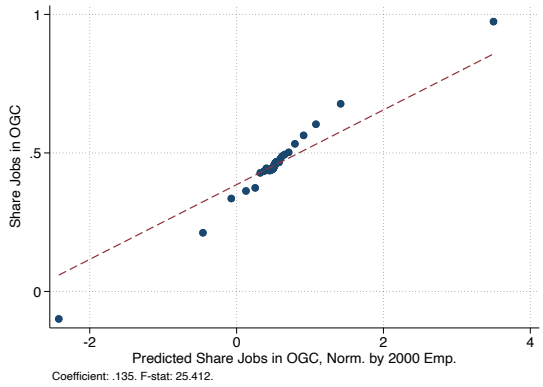
Figure A.9: The Relationship Between Extreme Temperature and Precipitation and Voter Turnout



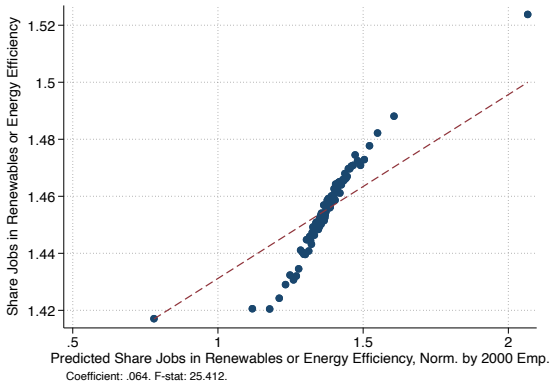
(a) Extreme Temperaturee (2+SD Above Historical Average) (b) Extreme Precipitation (2+SD Above Historical Average)

Notes: Each panel is a binscatter showing precinct-year-level voter turnout as a function of extreme temperature or precipitation, controlling for block-group and Congressional-district-by-year fixed effects. The x-axis is extreme temperature or precipitation, defined as number of days in the year above the historical mean plus two standard deviations. The y-axis is the log of voter turnout in the Congressional election. The red dotted lines are quadratic fits. The sample is Congressional elections from 2000 to 2020.

Figure A.10: The First-Stage Relationship Between Shift-Share Instruments and Brown and Green Jobs



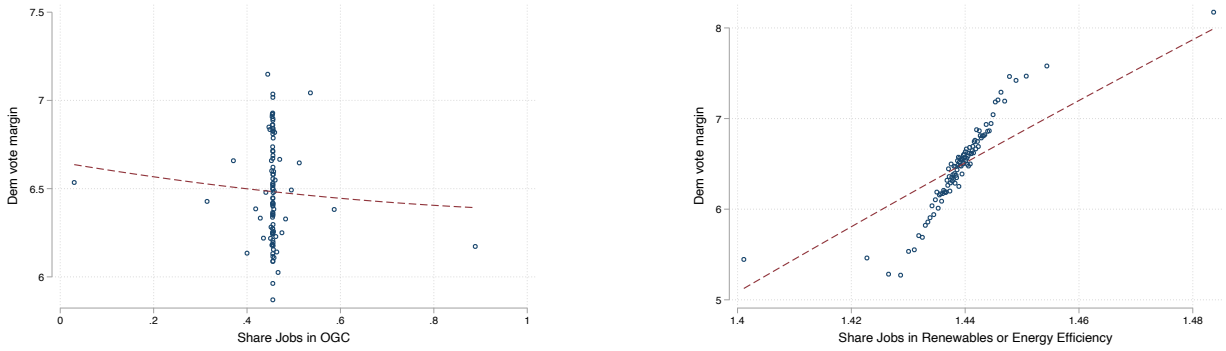
(a) First Stage for Brown Jobs



(b) First Stage for Green Jobs

Notes: Each panel is a binscatter showing the first-stage relationship between the shift-share instruments and brown or green jobs at the precinct-year level. Each binscatter controls for block-group and Congressional-district-by-year fixed effects, extreme temperature and precipitation as measured by number of days in the year above the historical mean plus two standard deviations, and a set of controls. The x-axis is the shift-share instrument, which is the predicted share of jobs in oil, gas, and coal–or the predicted share of jobs in renewables or energy efficiency–normalized by total employment in 2000. The y-axis is the share of jobs in oil, gas, and coal; or the share of jobs in renewables or energy efficiency. The red dotted lines are linear fits. The sample is Congressional elections from 2000 to 2020.

Figure A.11: The Relationship Between Brown and Green Jobs and Democratic Vote Margin

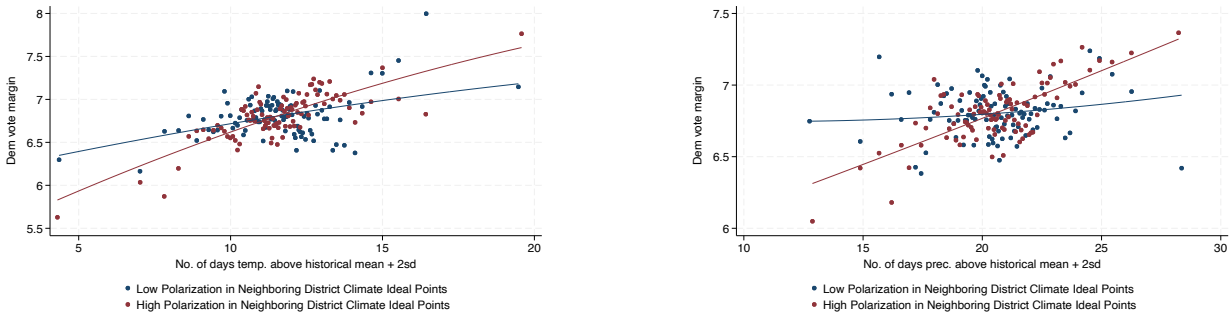


(a) Brown Jobs

(b) Green Jobs

Notes: Each panel is a binscatter showing precinct-year-level Democratic vote margin as a function of brown or green jobs. Each binscatter controls for block-group and Congressional-district-by-year fixed effects and the residuals from a first-stage regression of brown or green jobs on its shift-share instrument. The x-axis is share of jobs in oil, gas, and coal; or share of jobs in renewables or energy efficiency. The y-axis is the Democratic vote margin in the Congressional election. The red dotted lines are quadratic fits. The sample is Congressional elections from 2000 to 2020.

Figure A.12: Heterogeneity of Climate Variable Effect by Partisan Difference in Supply-Shifter.



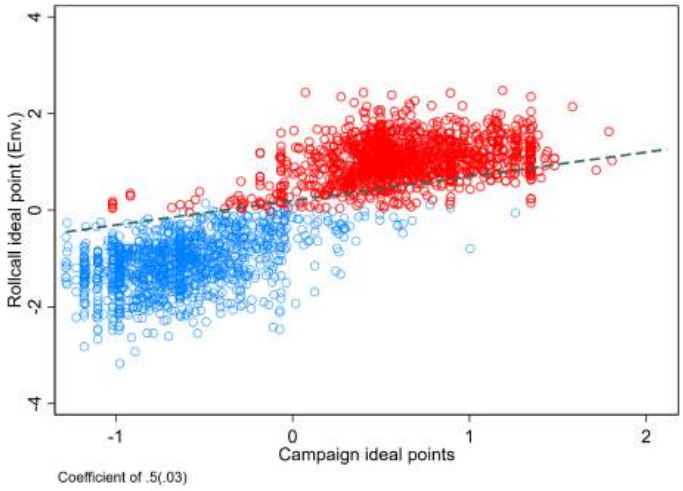
(a) Temperature

(b) Precipitation

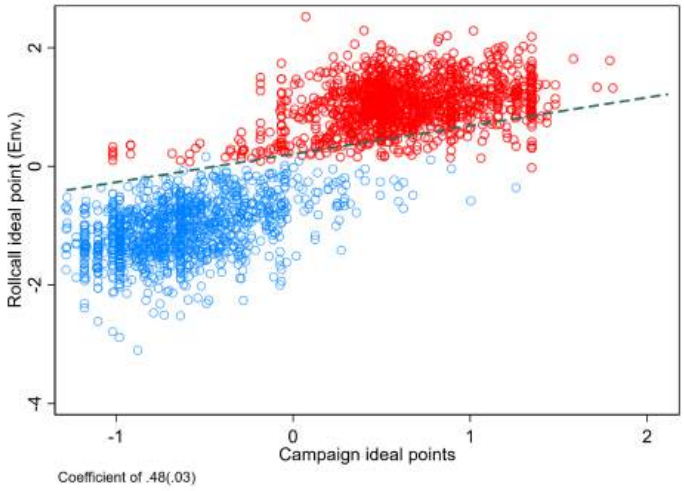
Notes: Each panel is a binscatter showing precinct-year-level Democratic vote margin as a function of brown or green jobs. Each binscatter controls for block-group and Congressional-district-by-year fixed effects and the residuals from a first-stage regression of brown or green jobs on its shift-share instrument. The x-axis is share of jobs in oil, gas, and coal; or share of jobs in renewables or energy efficiency. The y-axis is the Democratic vote margin in the Congressional election. The red dotted lines are quadratic fits. The sample is Congressional elections from 2000 to 2020.

Figure A.13: Correlation between candidate campaign ideal point on the environment and environmental rollcall ideal points.

(a) Narrow Environment Definition

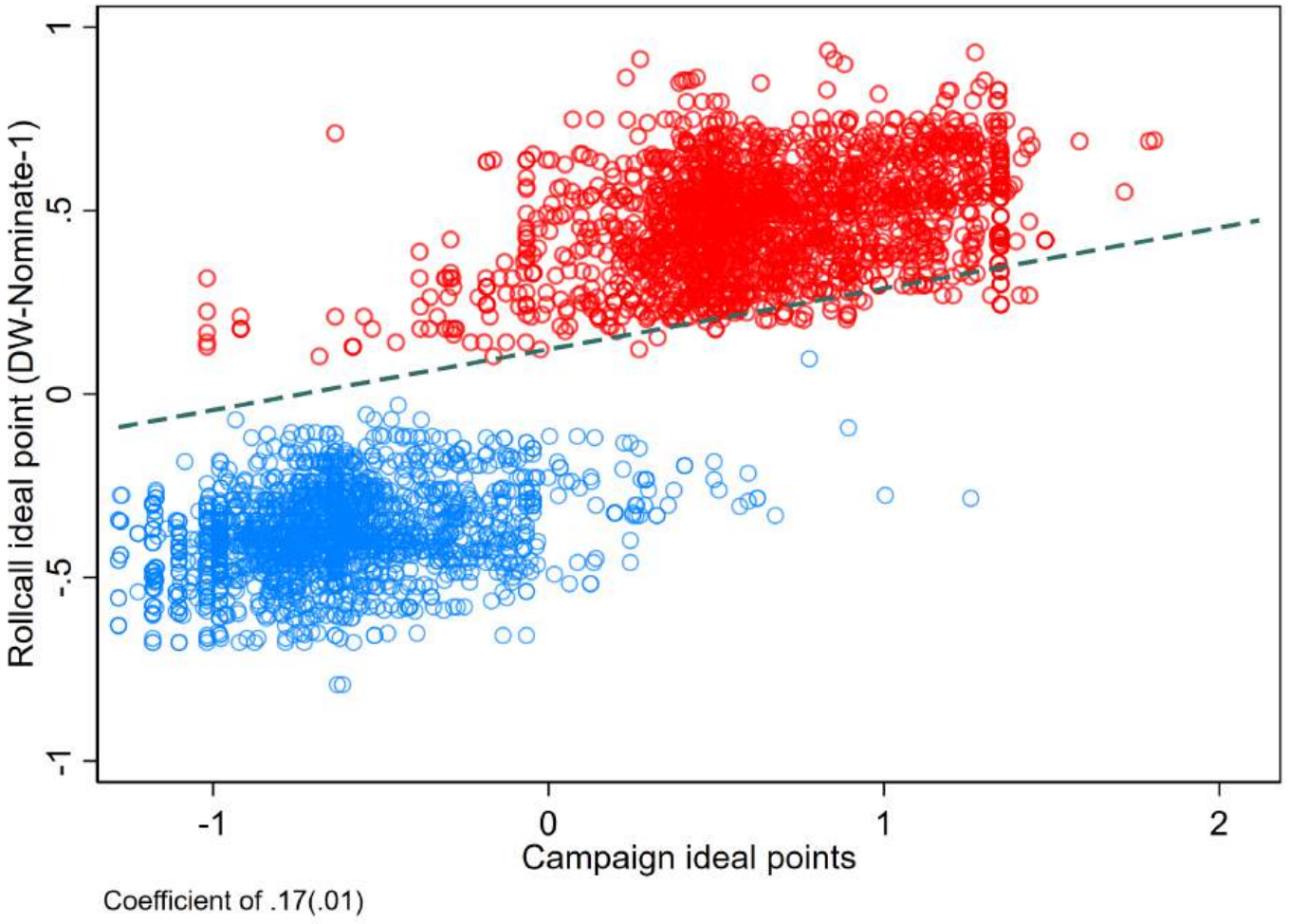


(b) Broad Environment Definition



Notes: The "narrow" definition uses CAP codes 700 (environment) and 800 (energy). The "broad" definition adds 400 (agriculture), 1000 (transportation), disaster relief (1523), and hazardous waste in military (1614) along with technology categories (1704,1706, and 1708 (commercial use of space, telecommunications, and weather forecasting), foreign resource exploitation (1902) as well as most of 2100 (Public lands, omitting indigenous affairs and dependencies and territories).

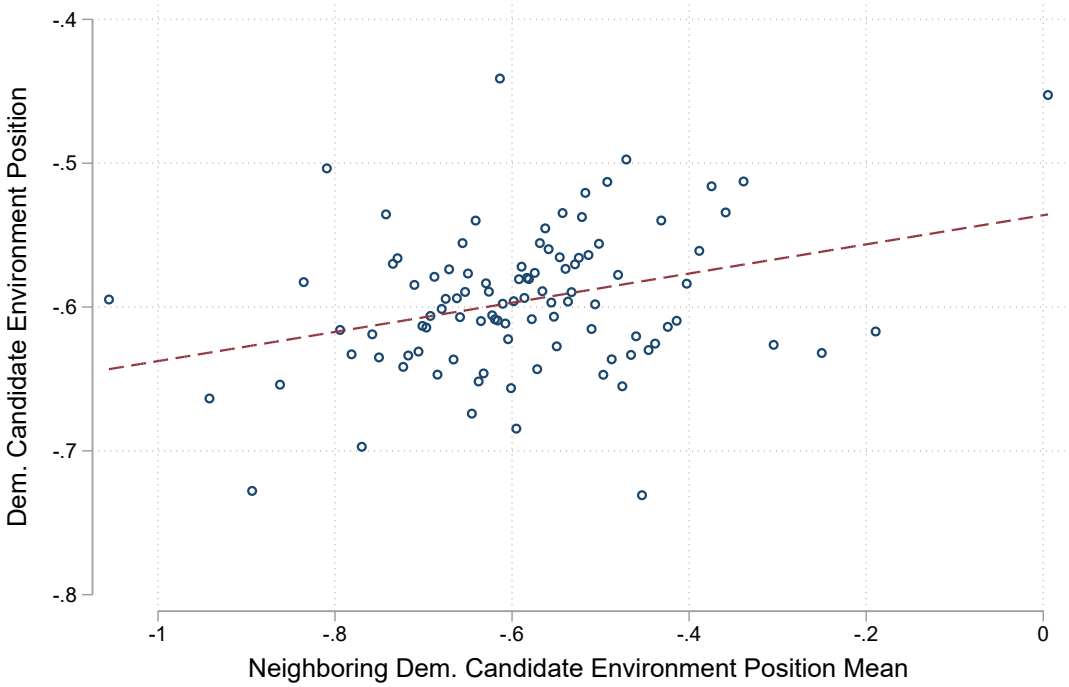
Figure A.14: Correlation between candidate campaign ideal point on the environment and overall roll-call voting ideology measured by DW-NOMINATE



Notes: This figure shows the scatter plot of congressional ideal points based on roll-call votes (as calculated by DW-NOMINATE, (Poole and Rosenthal, 1984) and the climate ideal points of winning candidates.)

Figure A.15: Correlation between candidate campaign ideal point on the environment and average ideal point of neighboring candidates of same party.

(a) Democratic Representatives



(b) Republican Representatives

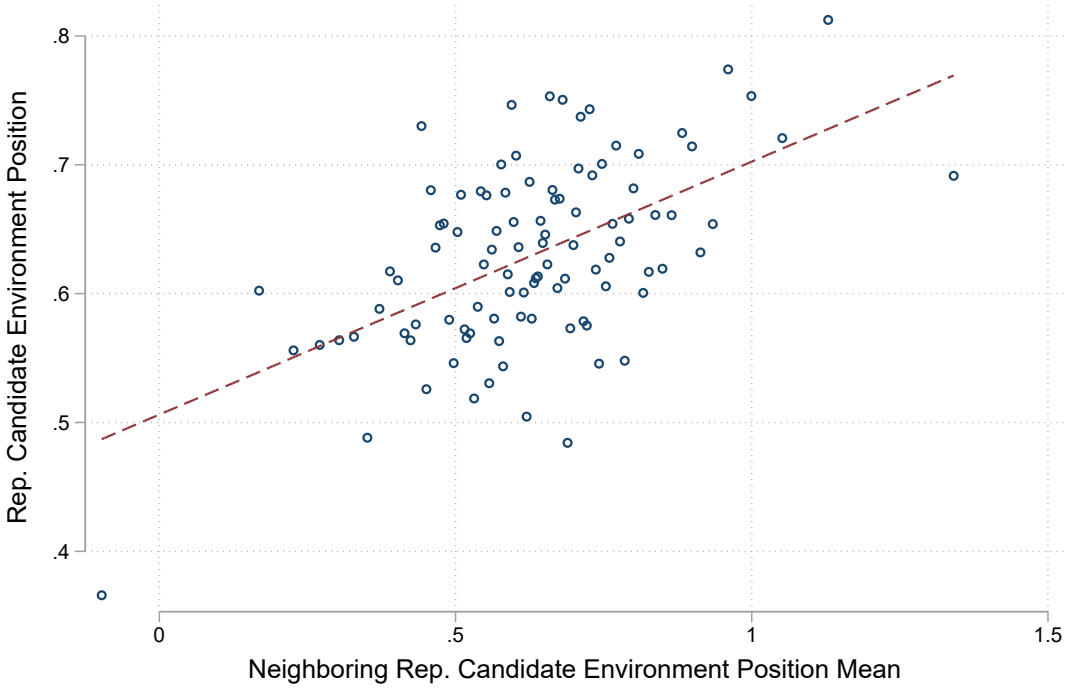
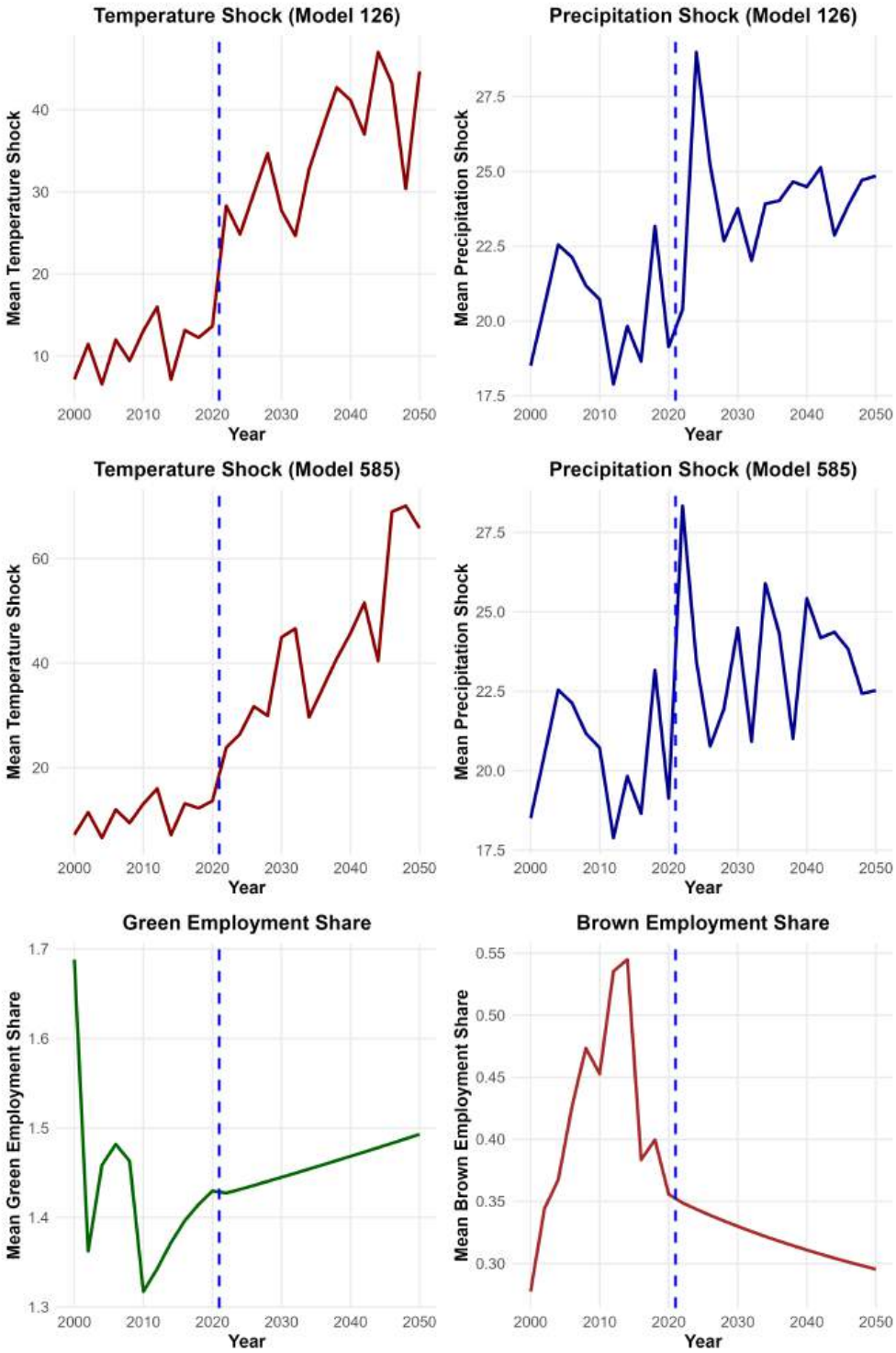
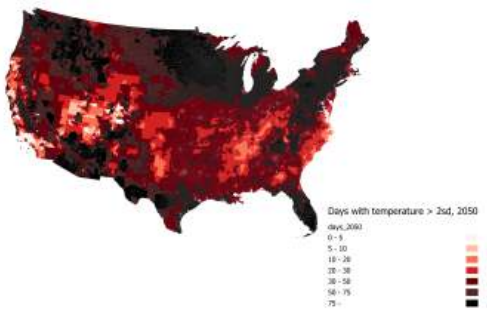


Figure A.16: Time series of sample averages and projections of main independent variables.

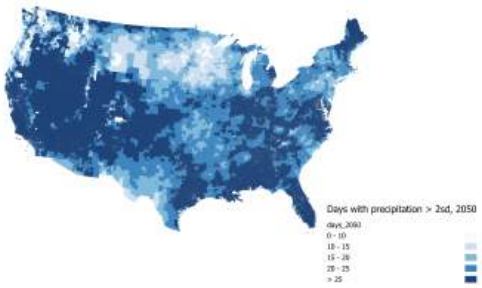


Notes: Sample Average and Projections of Independent Variables using 126 and 585 Model. The vertical dashed line indicates 2020, the last year of our sample.

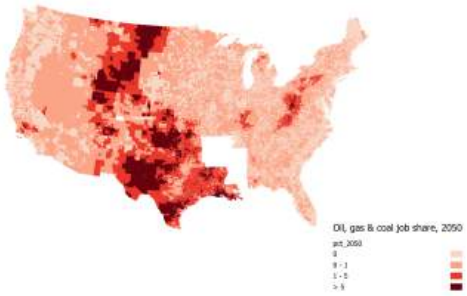
Figure A.17: Maps showing projections of main independent variables in 2050



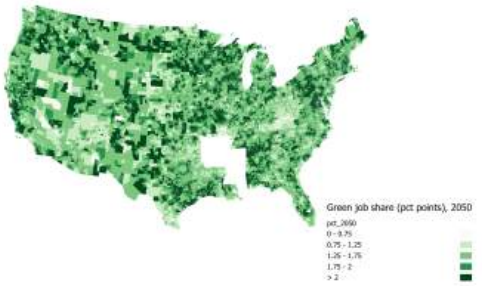
(a) Extreme temperature measure 2050



(b) Extreme Precipitation 2050



(c) Brown jobs 2050



(d) Green jobs 2050

Table A.5: States and Years Present in Sample

State	Years in Sample
Alabama	2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Arizona	2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Arkansas	2000, 2004, 2006, 2010, 2012, 2014, 2016, 2018
California	2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Colorado	2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Connecticut	2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Delaware	2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Florida	2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Georgia	2012, 2014, 2016, 2018, 2020
Idaho	2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Illinois	2012, 2014, 2016, 2018, 2020
Indiana	2012, 2016, 2018, 2020
Iowa	2000, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Kansas	2000, 2002, 2004, 2006, 2008, 2010, 2012, 2016, 2018, 2020
Kentucky	2010, 2012, 2014, 2016, 2018, 2020
Maine	2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Maryland	2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Massachusetts	2012, 2014, 2016, 2018, 2020
Michigan	2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Minnesota	2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Mississippi	2004, 2006, 2008, 2010, 2012, 2018
Missouri	2000, 2002, 2004, 2006, 2008, 2010, 2014, 2016, 2018, 2020
Montana	2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Nevada	2004, 2006, 2008, 2010, 2018, 2020
New Hampshire	2000, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
New Jersey	2000, 2002, 2004, 2008, 2012, 2014, 2016, 2018, 2020
New Mexico	2000, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
New York	2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
North Carolina	2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
North Dakota	2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Ohio	2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Oklahoma	2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Oregon	2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2018, 2020
Pennsylvania	2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Rhode Island	2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
South Carolina	2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
South Dakota	2008, 2016, 2018
Tennessee	2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Texas	2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Utah	2014, 2016, 2018, 2020
Vermont	2006, 2010, 2012, 2014, 2018, 2020
Virginia	2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Washington	2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
West Virginia	2008, 2010, 2012, 2014, 2016, 2018, 2020
Wisconsin	2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020
Wyoming	2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020

Notes: States and the years each is present in the sample.

Table A.6: Robustness of Demand Estimates to Varying Measures of Climate

	(1)	(2)	(3)	(4)
Average Temperature	1.529***		1.613***	
	(0.451)		(0.459)	
No. of days temp. above historical mean + 2sd		0.0806***		0.0828***
		(0.0225)		(0.0227)
No. of days temp. below historical mean - 2sd		0.0578		0.0563
		(0.0361)		(0.0366)
Average Precipitation	0.00270***		0.00270***	
	(0.000920)		(0.000934)	
No. of days prec. above historical mean + 2sd		0.0339		0.0349
		(0.0212)		(0.0215)
District x Year FE	X	X	X	X
Block group FE	X	X	X	X
Controls	Long	Long	None	None
Total Effect of 1SD Climate Shocks	7.963***	1.195***	8.335***	1.212***
	(2.085)	(0.288)	(2.119)	(0.292)
Observations	1,320,575	1,320,575	1,320,575	1,320,575

In parentheses standard errors are clustered by District × Year and Block group

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: Each column shows the effects of climate shocks on voter demand from separate regressions. The unit of observation is a block-group-year, and the sample period is 2000 to 2020. The dependent variable is the vote share of the Democratic candidate minus that of the Republican candidate in percentage points. Total effect of one standard deviation climate shocks is sum of the effects of a one standard deviation increase in all climate shocks. Standard errors are clustered by block-group and district-year and are shown in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.7: Robustness of Demand Estimates to Varying Measures of Climate

	(1)	(2)	(3)	(4)
Average Temperature	0.990***		3.098***	
	(0.179)		(0.262)	
No. of days temp. above historical mean + 2sd		0.431***		0.693***
		(0.0474)		(0.0618)
No. of days temp. below historical mean - 2sd		-0.504***		-0.955***
		(0.0763)		(0.0995)
Average Precipitation	0.00599***		0.00286**	
	(0.00111)		(0.00132)	
No. of days prec. above historical mean + 2sd		0.181***		0.287***
		(0.0425)		(0.0544)
District x Year FE	X	X	X	X
Block group FE				
Controls	Long	Long	None	None
Total Effect of 1SD Climate Shocks	6.902***	7.438***	15.052***	12.722***
	(0.945)	(0.626)	(1.341)	(0.820)
Observations	1,329,167	1,329,167	1,329,167	1,329,167

In parentheses standard errors are clustered by District × Year and Block group

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: Each column shows the effects of climate shocks on voter demand from separate regressions. The unit of observation is a block-group-year, and the sample period is 2000 to 2020. The dependent variable is the vote share of the Democratic candidate minus that of the Republican candidate in percentage points. Total effect of one standard deviation climate shocks is sum of the effects of a one standard deviation increase in all climate shocks. Standard errors are clustered by block-group and district-year and are shown in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.8: Heterogeneity of Within-District Demand Estimates by Partisan Difference in Supply-Shifters

	(1)	(2)	(3)	(4)	(5)	(6)
No. of days temp. above historical mean + 2sd	0.0704**	0.0716**	0.0860**	0.0665**	0.0677**	0.0789**
	(0.0277)	(0.0279)	(0.0334)	(0.0266)	(0.0269)	(0.0319)
No. of days prec. above historical mean + 2sd	0.0353	0.0353	0.0262	0.0350	0.0353	0.0262
	(0.0285)	(0.0285)	(0.0324)	(0.0275)	(0.0275)	(0.0315)
Share Jobs in OGC		-0.105	0.0933		-0.112	0.0788
		(0.126)	(0.983)		(0.121)	(0.890)
Share Jobs in Renewables or Energy Efficiency		-0.373	34.02***		-0.298	33.79***
		(0.239)	(7.347)		(0.238)	(7.360)
Republican Minus Democratic Shifter × No. of days temp. above historical mean + 2sd	0.391***	0.366***	0.359***	0.386***	0.362***	0.358***
	(0.0934)	(0.0919)	(0.111)	(0.0945)	(0.0930)	(0.111)
Republican Minus Democratic Shifter × No. of days prec. above historical mean + 2sd	0.174*	0.144	0.0638	0.178*	0.150	0.0749
	(0.0964)	(0.0939)	(0.102)	(0.0934)	(0.0910)	(0.0989)
Republican Minus Democratic Shifter × Share Jobs in OGC		-0.858***	-1.319***		-0.819***	-1.202***
		(0.271)	(0.371)		(0.269)	(0.359)
Republican Minus Democratic Shifter × Share Jobs in Renewables or Energy Efficiency		-4.454***	-1.646		-4.301***	-1.052
		(0.602)	(2.315)		(0.595)	(2.269)
District x Year FE	X	X	X	X	X	X
Block group FE	X	X	X	X	X	X
Controls	None	None	None	Long	Long	Long
Spec.	TWFE	TWFE	IV	TWFE	TWFE	IV
Observations	1,351,498	1,351,498	1,304,409	1,212,851	1,212,851	1,171,024

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes:

Table A.9: U.S. House vs. Railroad Commissioners

Dep. var.: Dem-Rep vote share	USH		RR	
	(1)	(2)	(3)	(4)
days where avg temp ¿ 1959-2000 mean + 2SD	0.453***	0.0977	0.497***	0.176*
	(0.101)	(0.149)	(0.0974)	(0.102)
days where avg prec ¿ 1959-2000 mean + 2S	0.0215	0.117	0.119	0.148*
	(0.0866)	(0.127)	(0.0734)	(0.0829)
Share Jobs in OGC	-0.412***	-1.366***	-0.391***	-1.053***
	(0.126)	(0.375)	(0.102)	(0.192)
Share Jobs in Renewables or Energy Efficiency	-1.479**	1.469	-0.382	0.0357
	(0.607)	(1.938)	(0.452)	(0.984)
District x Year FE	X		X	
Year FE		X		X
Block group FE	X	X	X	X
Controls	Long	Long	Long	Long
Observations	93,324.000	93,324.000	120,686.000	120,686.000

In parentheses standard errors are clustered by District × Year and Block group

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: This table presents estimates of the Democratic-Republican vote share for U.S. House and Texas Railroad Commissioner elections (2002–2020, excluding 2012). The regressors include climate shocks (temperature and precipitation anomalies) and employment shares in oil, gas, and renewables. District × year FE is used where appropriate, given the localized nature of House elections. Observations are limited to competitive districts. Standard errors are clustered at the district × year and block group levels.

Table A.10: Structural Parameter Estimates with Control Variables

Name	Estimate	Std Error	Z-value	P-value	Effects
			Democrat's Supply		
λ^d_{temp}	0.0030	0.0014	2.1806	0.0292	0.0234
λ^d_{prec}	0.0002	0.0013	0.1333	0.8940	0.0011
λ^d_G	-0.1518	0.1563	-0.9712	0.3315	-0.0441
λ^d_B	0.0323	0.0370	0.8754	0.3813	0.0353
$\lambda^d_{log_emp}$	0.3243	0.2256	1.4375	0.1506	0.0802
$\lambda^d_{mean_ln_income_all}$	-0.0432	0.1363	-0.3165	0.7516	-0.0117
$\lambda^d_{log_voting_age_pop}$	-0.3914	0.3367	-1.1624	0.2451	-0.0638
β^d	-0.0223	0.0130	-1.7188	0.0856	-0.7088
π^d	0.1995	0.0975	2.0460	0.0408	0.0389
			Republican's Supply		
λ^r_{temp}	0.0003	0.0016	0.1689	0.8659	0.0022
λ^r_{prec}	0.0004	0.0022	0.1918	0.8479	0.0027
λ^r_G	-0.0280	0.1546	-0.1810	0.8563	-0.0081
λ^r_B	0.0050	0.0267	0.1862	0.8523	0.0054
$\lambda^r_{log_emp}$	0.0062	0.1738	0.0359	0.9714	0.0015
$\lambda^r_{mean_ln_income_all}$	-0.5332	0.2498	-2.1346	0.0328	-0.1440
$\lambda^r_{log_voting_age_pop}$	0.4071	0.4512	0.9024	0.3669	0.0664
β^r	0.0038	0.0014	2.6451	0.0082	0.1198
π^r	0.2340	0.0617	3.7945	0.0001	0.0619
			District-level Demand		
δ_{temp}	0.0812	0.0245	3.3095	0.0009	0.6364
δ_{prec}	0.0377	0.0231	1.6315	0.1029	0.2396
δ_G	0.4033	0.1288	3.1301	0.0018	0.1173
δ_B	-0.1559	0.0752	-2.0729	0.0383	-0.1701
δ_{log_emp}	-0.9010	0.1079	-8.3518	0.0000	-0.2227
$\delta_{mean_ln_income_all}$	4.9299	0.3905	12.6234	0.0000	1.3315
$\delta_{log_voting_age_pop}$	-3.3386	0.1700	-19.6445	0.0000	-0.5445
γ^d	29.0211	14.9957	1.9353	0.0530	9.0622
γ^r	-1.2678	1.0633	-1.1924	0.2331	-0.5423

Note: This table presents parameter estimates from the structural equations for Democrats' environmental policy supply, x^d_{ct}; Republicans' environmental policy supply, x^r_{ct}; and the district-level Democratic vote share, $\bar{y}_{ct}$. Standard errors (in parentheses) are clustered by congressional district. z-values and p-values correspond to two-sided tests. The final column ("Marginal Effects") reports the change in the outcome-Democrats' platform in the first panel, Republicans' platform in the second panel, and Democrats' vote share (on a 0-100 scale) in the third panel-resulting from a one-standard deviation increase in the corresponding regressor. Estimation follows a two-step GMM approach, using instruments $\overline{\mathbf{V}}_{ct}, z^d_{ct}, z^r_{ct}$ and weighting by the inverse variance of the estimated district-by-year fixed effects in the first step.

Table A.11: Placebo Structural Estimation Using Only Cultural Ideal Points

Name	Estimate	Std Error	Z-value	P-value	Effects
			Democrat's Supply		
λ^d_{temp}	0.0017	0.0011	1.5727	0.1158	0.0130
λ^d_{prec}	-0.0015	0.0016	-0.9304	0.3522	-0.0094
λ^d_G	0.0666	0.1150	0.5791	0.5626	0.0194
λ^d_B	0.0716	0.0527	1.3579	0.1745	0.0760
β^d	-0.0005	0.0086	-0.0524	0.9582	-0.0144
π^d	0.0836	0.0507	1.6485	0.0993	0.0259
			Republican's Supply		
λ^r_{temp}	-0.0003	0.0014	-0.1940	0.8462	-0.0021
λ^r_{prec}	0.0009	0.0018	0.5297	0.5963	0.0059
λ^r_G	0.0227	0.1489	0.1523	0.8789	0.0066
λ^r_B	0.0256	0.0319	0.8013	0.4230	0.0271
β^r	0.0054	0.0104	0.5233	0.6007	0.1727
π^r	0.1358	0.0561	2.4191	0.0156	0.0343
			District-level Demand		
δ_{temp}	0.0818	0.0247	3.3178	0.0009	0.6436
δ_{prec}	0.0388	0.0232	1.6682	0.0954	0.2439
δ_G	0.3983	0.1292	3.0815	0.0021	0.1159
δ_B	-0.1675	0.0751	-2.2313	0.0257	-0.1777
γ^d	2.5484	7.9654	0.3199	0.7490	1.1084
γ^r	-3.1160	9.2844	-0.3356	0.7372	-1.1918

Note: This table presents parameter estimates from the structural equations for Democrats' policy supply (cultural issues excluding environmental issues), x^d_{ct}; Republicans' policy supply (cultural issues excluding environmental issues), x^r_{ct}; and the district-level Democratic vote share, $\bar{y}_{ct}$. Standard errors (in parentheses) are clustered by congressional district. z-values and p-values correspond to two-sided tests. The final column ("Marginal Effects") reports the change in the outcome-Democrats' platform in the first panel, Republicans' platform in the second panel, and Democrats' vote share (on a 0-100 scale) in the third panel-resulting from a one-standard deviation increase in the corresponding regressor. Estimation follows a two-step GMM approach, using instruments $\overline{\mathbf{V}}_{ct}, z^d_{ct}, z^r_{ct}$ and weighting by the inverse variance of the estimated district-by-year fixed effects in the first step.

B Constructing Green and Brown Employment and Corresponding Instruments

Our analysis requires measuring green and brown employment at the block-group-year level for 2000 to 2020. Since our definition of green and brown employment is based on 6-digit NAICS (NAICS6) industries, in order to construct green and brown employment series, we need employment data at the block-group-NAICS6-year level. Unfortunately, no such data series exist, so we construct these series from a combination of various data sources.

B.1 Data Sources

Employment at County-NAICS6-Year Level We obtain employment data at the level of workplace county, NAICS6, and year from two sources. The first is the Census County Business Patterns (CBP) database, which contains annual employment data at the geographic-area-industry level in various detail, down to the county-NAICS6-year level. Because the data are suppressed for most county-NAICS6 series to protect confidentiality, we use an imputed dataset constructed by Eckert et al. (2021) which uses the non-suppressed CBP data at higher levels of aggregation along the geographic and industry dimensions to impute the data. We use their imputed CBP data for 2000 to 2003.

The second source is the BLS Quarterly Census of Employment and Wages (QCEW) database. Similarly to the CBP, the QCEW contains annual employment data at geographic-area-industry level in various detail, down to the county-NAICS6-year level, with the data suppressed for most county-NAICS6 series for confidentiality. We implement an imputation procedure developed in Autor et al. (2024), which, similarly to Eckert et al. (2021), uses the non-suppressed data at higher levels of aggregation to impute the data. We construct imputed QCEW data for 2004 to 2020.

We take several steps to harmonize the data across 2000 to 2020. First, we concord all revisions of NAICS6 codes to 2012 NAICS. This was done in Eckert et al. (2021) for the imputed CBP data by splitting employment equally for NAICS6 that split into multiple 2012 NAICS6. We do the same for our imputed QCEW data. We also concord all county FIPS codes to 2010 FIPS, similarly splitting employment equally for FIPS codes that split into multiple 2010 FIPS. Finally, to harmonize our data series, we calculate the ratio of county-level employment in our imputed QCEW data to the imputed CBP data in 2004. We multiply each county-NAICS6 series in the imputed CBP data for 2000 to 2003 by its county-level ratio.

Employment at Block-Group-NAICS2-Year Level Employment data at the level of residence block-group, NAICS2, and year are from two sources. The first is the 2000 Decennial Census from IPUMS (Manson et al. (2024)). The second is the Census LEHD Origin-Destination Employment Statistics (LODES) Residence Area Characteristics (RAC) dataset at the block-2-digit-NAICS-year level, which we use for 2002 to 2020.

To harmonize the data across 2000 to 2020, we concord all block-group and block FIPS codes to 2010 FIPS, using population weights to apportion the employment data, and collapse the data at block-group-NAICS2-year level. Since neither data source covers the year 2001, for block-group-NAICS2 series we observe in both 2000 and 2002, we interpolate linearly to obtain estimates for 2001.

Commuting Flow Data at Block-Group-County-Supersector-Year Level We use commuting flow data from the LODES Origin-Destination (OD) dataset, which measures employment at the level of residence block, workplace block, NAICS supersector (specifically, the three supersectors are "Goods Producing", "Trade, Transportation, and Utilities", and "All Other Services"), and year, and which is available for 2002 to 2020. We concord block FIPS codes to 2010 FIPS, using population weights to apportion the employment data, and collapse the data at the level of residence block-group, workplace county, NAICS supersector, and year.

Green Industries and Industry Share of Green Employment We use a classification of NAICS6 industries that potentially produce green goods and services, as well as estimates of the industry shares of employment in each of these industries that are within green establishments, from the BLS Green Goods and Services (GGS) survey. Specifically, the classification we use is the industries that produce energy from renewable sources or that produce products and services that improve energy efficiency (GGS categories "1. Energy from renewable sources" and "2. Energy efficiency"). The GGS was only conducted for 2010 and 2011; we use the 2011 survey which is missing data for slightly fewer industries. The survey sample was stratified mostly at the NAICS4 level, with some highly environmental industries stratified at the NAICS6 level; to avoid bias due to sample stratification, we use only the industry estimates at NAICS4 level.

B.2 Constructing Green and Brown Employment

We construct green employment at the block-group-year level as follows, where all employment variables additionally have year t subscripts, omitted for brevity:

$$GreenEmp_b = \sum_{i \in G} GreenEmp_{bi},$$

$$GreenEmp_{bi} = \sum_{c \in C(b)} Emp_{b,k(i)} \times \frac{Emp_{bc,l(i)}}{Emp_{b,l(i)}} \times \frac{\gamma_{j(i)} \times Emp_{ci}}{Emp_{c,k(i)}}.$$

$GreenEmp_b$ is green employment at the level of residence block-group b and year t; $GreenEmp_{bi}$ is green employment at the level of block-group b and NAICS6 industry i; G is the set of green industries and $\gamma_{j(i)}$ is the industry share of green employment for NAICS4 $j(i)$ corresponding to NAICS6 i as described above; and c is a county and $C(b)$ the set of counties where residents of block-group b work during the sample period. $Emp_{b,k(i)}$ is employment at the level of residence block-group b, NAICS2 $k(i)$ corresponding to NAICS6 i, which is from the 2000 Census and LODES RAC datasets as described above. $Emp_{bc,l(i)}$ is employment residing in block-group b, working in county c, in NAICS super-sector $l(i)$ corresponding to NAICS6 i, which is from the LODES OD dataset as described above; $Emp_{b,l(i)} = \sum_{c \in C(b)} Emp_{bc,l(i)}$. When data are not available for this variable, we assume all residents of the given block-group-super-sector-year work in the county they reside in. Emp_{ci} is employment at the level of workplace county and NAICS6 i, and is from the CBP and QCEW datasets as described above, and $Emp_{c,k(i)} = \sum_{i \in k(i)} Emp_{ci}$.

Note that our construction of green employment relies on the sufficient assumptions

$$\frac{Emp_{bc,l(i)}}{Emp_{b,l(i)}} = \frac{Emp_{bc,k(i)}}{Emp_{b,k(i)}}$$

$$\frac{\gamma_{j(i)} \times Emp_{ci}}{Emp_{c,k(i)}} = \frac{\gamma_{bcit} \times Emp_{bci}}{Emp_{bc,k(i)}}$$

which must be made due to data availability.

We analogously construct brown employment at the block-group-year level as follows, where all employment variables additionally have year t subscripts omitted for brevity:

$$BrownEmp_b = \sum_{i \in B} BrownEmp_{bi},$$

$$BrownEmp_{bi} = \sum_{c \in C(b)} Emp_{b,k(i)} * \frac{Emp_{bc,l(i)}}{Emp_{b,l(i)}} * \frac{\mathbf{1}(i \in B) * Emp_{ci}}{Emp_{c,k(i)}}.$$

$BrownEmp_b$ is brown employment at the level of residence block-group b and year t; $BrownEmp_{bi}$ is brown employment at the level of block-group b, NAICS6 industry i, and year t; and B is the set of brown industries, which we define as those involved in oil and gas extraction, coal mining, and their support activities. Specifically, the eight industries are "211111 Crude Petroleum and Natural Gas Extraction," "211112 Natural Gas Liquid Extraction," "212111 Bituminous Coal and Lignite Surface Mining," "212112 Bituminous Coal Underground Mining", "212113 Anthracite Mining," "213111 Drilling Oil and Gas Wells," "213112 Support Activities for Oil and Gas Operations," and "213113 Support Activities for Coal Mining." The rest of the variables and assumptions are as defined previously.

Finally, our analysis uses *shares* of green and brown employment at the block-group-year level, so we divide our constructed measures of green and brown employment by total employment, constructed from the 2000 Census and LODES RAC datasets described above.

B.3 Constructing Instruments

We construct a shift-share instrument for our share of green employment variable as follows:

$$\frac{\widehat{GreenEmp}_{bt}}{Emp_{b,2000}} = \sum_{i \in G} \frac{GreenEmp_{bi,2000}}{Emp_{b,2000}} * \frac{GreenEmp_{it}}{GreenEmp_{i,2000}}.$$

$\hat{GreenEmp}_{bt}$ is predicted green employment in block-group b and year t; we normalize by dividing by $Emp_{b,2000}$, employment in block-group b in the year 2000. i, G, $GreenEmp_{bi,2000}$, and $Emp_{b,2000}$ are defined and constructed the same way as previously described with the year being 2000. $GreenEmp_{it}$ is green employment in NAICS6 i and year t and is constructed by summing $GreenEmp_{bit}$ over block-groups b.

In our setting, the shares, or exposure weights, of our shift-share instrument are the $\frac{GreenEmp_{bi,2000}}{Emp_{b,2000}}$, and the sum of these shares is not generally equal to one across block-groups, a potential issue in shift-share IV regressions highlighted by Borusyak, Hull and Jaravel (2022). We implement the proposed solution in Borusyak, Hull and Jaravel (2022), which is to control for the sum of shares in our IV regressions. The sum of shares $\frac{GreenEmp_{bi,2000}}{Emp_{b,2000}}$ is simply the share of green employment in block-group b in 2000.

We construct a shift-share instrument for our share of brown employment variable analogously.

C Political Competition Over Environmental Policy

This appendix presents a simple microfoundation for the system of equations estimated in Section 4 of the paper. Our empirical model is considerably more general than the stylized model of political competition presented here, but the economic intuition, identification challenges, and sources of variation used to estimate the empirical model, are all captured by the simple model.

Suppose there are a continuum of voters with utility function over environmental policy x is given by $U_V(x) = -(x - \theta_M)^2$. We think of our demand-side shocks (e.g. climate and employment) as changing θ_M.

We suppose two ideological candidates, D and R, who cannot commit to policies θ, with $\theta_D < \theta_M < \theta_R$ (the bliss point of the Republican is to the right of the voters, who are to the right of the Democrats). The politician utility function is given by:$U_p = -\alpha (x_p - \theta_p)^2 + W_p$, with $p = \{D, R\}$ and W_p is the probability of winning, x_p is the politician's policy platform, θ_p is the candidate's ideal point, and α is the weight politicians place on their own ideal point vs the probability of winning. While we leave this unmodeled, the preference over θ could be the politician's preferences, or it could stem from party discipline as in Longuet-Marx (2024) and Canen, Kendall and Trebbi (2021). Our climate and jobs shocks can also affect θ_R and θ_D directly, either by changing candidate preferences or changing the various non-electoral constraints facing candidates (e.g. fundraising or primary competition). This is on top of the *indirect* effects the shocks will have on x^R and x^D via changing θ^M.

So the vote share for Democrat candidate is

$$\pi_D = F\left(-(x_D - \theta_M)^2 + (\theta_M - x_R)^2\right) \tag{9}$$

where F is a cdf on $\left[\frac{-1}{2\phi}, \frac{1}{2\phi}\right]$ and so the probability of winning for candidate D is:

$$W_D = \left(-(x_D - \theta_M)^2 + \psi(x_R - \theta_M)^2 + \frac{1}{2\psi}\right) \tag{10}$$

The Democratic candidate problem is:

$$\underset{x_D}{max} - \alpha \left(x_D - \theta_D\right)^2 + \psi \left(-(x_D - \theta_M)^2 + (x_R - \theta_M)^2 + \frac{1}{2\psi} \right) \tag{11}$$

The optimal choice of x_D is:

$$x_D = \frac{\alpha\theta_D + \psi\theta_M}{\psi + \alpha} \tag{12}$$

Similarly the Republican ideal point is given by:

$$x_R = \frac{\alpha\theta_R + \psi\theta_M}{\psi + \alpha} \tag{13}$$

- x_D is closer to voter preferred policy θ_M when ψ is larger: this is the gain in votes from a change in the policy (this is a sort of "elasticity" of votes to policy)
- x_D is further away from θ_M and closer to θ_D when α is large (candidates value their own ideal points more relative to the probability of winning).
- x_D does not depend on x_R directly, only via the vote-share. The uniform distribution assumption ensures that only θ_M and x_D enter the marginal voter demand for x_D so x_R does not appear, but even in a more general model conditioning on the vote share would be sufficient for controlling for the effect of x_R on x_D.

Note that the equilibrium vote share (including effects on choices of policies) is given by:

$$\pi_D = \frac{1}{2} + \psi(\frac{\alpha}{(\alpha + \psi)})^2(\theta_R^2 - \theta_D^2 - 2(\theta_R - \theta_D)\theta_M) \tag{14}$$

In particular, as voter preferences for left-wing climate policy increase, democrat vote share increases so long as $\theta_R - \theta_D > 0$, i.e. Democrats are more left wing than Republicans on climate. Note also that extreme ideological positions are punished by voters as $\frac{d\pi_D}{d\theta_R} = 2\psi(\frac{\alpha}{\alpha + \psi})^2(\theta_R - \theta_M) > 0$ and $\frac{d\pi_D}{d\theta_R} = -2\psi(\frac{\alpha}{\alpha + \psi})^2(\theta_D - \theta_M) < 0$.

If $\theta_R, \theta_D, \theta_M$ are all functions of (can all be influenced by) the climate and jobs variables $\mathbf{V}$ in our empirical analysis, this model shows why controlling for θ_R and θ_L is important for recovering the direct effect of shocks on voter preferences, given by $\frac{d\pi_D}{d\theta_M} \times \frac{d\theta_M)}{d\mathbf{V}}$, which is why the within-district-by-year variation is important for recovering the effect of demand.

Similarly, the supply equations show that controlling for θ_M (e.g. voter demand) is important for recovering the *direct* effect of climate on party ideal points $\frac{dx_p}{d\theta_p} \times \frac{d\theta_p}{d\mathbf{V}}$.

The demand model makes an auxiliary prediction, which is that demand shocks to

θ_M will be larger when $\theta_R - \theta_D$ is larger. While we don't observe θ_R and θ_D directly, our identification, through the lens of the model, assumes that the instruments we constructed for x_D and x_R, operate solely through θ_D and θ_R, once demand is controlled for, and we can use this variation to test for the predicted heterogeneity.

The model further clarifies that candidate ideal points (the θ_p) are *not* the observed environmental policy positions of the candidates (the x_p), which are endogenous functions of both voter demand and candidate partisan preferences (the ideal points). For this reason, we use our supply-side instruments to form exogenous shifters for the candidate ideology in Appendix Figures A.12a ,A.12b, and Table A.8.

D Proof of Identification

This appendix provides a proof of point identification for the structural parameters in the joint demand and supply model for climate policy platforms described in Section 4 of the main text.

D.1 Setup and key equations

Our political supply equations (see equations (4) and (5) in the main text) can be written as:

$$x^d_{ct} = \lambda^d \bar{\mathbf{V}}_{ct} \; + \; \beta^d \bar{y}_{ct} \; + \; \pi^d z^d_{ct} \; + \; \omega^d_c \; + \; \zeta^d_t \; + \; \eta^d_{ct}, \tag{15}$$

$$x^r_{ct} = \lambda^r \bar{\mathbf{V}}_{ct} \; + \; \beta^r \bar{y}_{ct} \; + \; \pi^r z^r_{ct} \; + \; \omega^r_c \; + \; \zeta^r_t \; + \; \eta^r_{ct}, \tag{16}$$

where

- x^d_{ct} and x^r_{ct} are the policy positions (e.g., climate platforms) of the Democratic and Republican candidates in congressional district c at election year t;
- $\bar{\mathbf{V}}_{ct}$ is the (population-weighted) average of exogenous district-level characteristics, such as weather shocks or green/brown employment share;
- $\bar{y}_{ct}$ is the (population-weighted) average of Democratic vote margins in district c (i.e. the expected support) at time t;
- z^d_{ct} and z^r_{ct} are exogenous party-specific shifters (e.g., local party trends) that affect only the Democrat's or the Republican's platform, respectively;
- ω^p_c and ζ^p_t are district and time fixed effects (indexed by party $p \in \{d, r\}$);
- η^p_{ct} are idiosyncratic errors.

On the demand side, aggregating equation (6) from the main text to the district level (as in (8)), we have:

$$\bar{y}_{ct} \;=\; \delta\,\bar{\mathbf{V}}_{ct} \;+\; \gamma^{d}\,x^{d}_{ct} \;+\; \gamma^{r}\,x^{r}_{ct} \;+\; \nu_{c} \;+\; \kappa_{t} \;+\; \xi_{ct}, \tag{17}$$

where δ captures the direct impact of exogenous covariates $\bar{\mathbf{V}}_{ct}$ on vote margins, γ^{d} and γ^{r} measure how the Democrat's and Republican's platforms shift the average Democratic vote margin, ν_{c} and κ_{t} are district and time fixed effects, and ξ_{ct} is an error term.

We are interested in identifying the structural parameters:

$$\big\{\,\beta^{d},\,\beta^{r},\,\gamma^{d},\,\gamma^{r},\,\pi^{d},\,\pi^{r},\,\lambda^{d},\,\lambda^{r},\,\delta\big\}.$$

Below, we show how these parameters can be uniquely recovered from appropriate *first-order* (linear) moment conditions, which underlie the GMM approach detailed in Section 4 of the main text.

D.2 Reduced-Form Relationships

Recall the structural equations for our demand and supply system at the district level:

$$\begin{aligned}
\bar{y}_{ct} &= \delta\,\bar{\mathbf{V}}_{ct} \;+\; \gamma^{d}\,x^{d}_{ct} \;+\; \gamma^{r}\,x^{r}_{ct} \;+\; \nu_{c} \;+\; \kappa_{t} \;+\; \xi_{ct},\\
x^{d}_{ct} &= \lambda^{d}\,\bar{\mathbf{V}}_{ct} \;+\; \beta^{d}\,\bar{y}_{ct} \;+\; \pi^{d}\,z^{d}_{ct} \;+\; \omega^{d}_{c} \;+\; \zeta^{d}_{t} \;+\; \eta^{d}_{ct},\\
x^{r}_{ct} &= \lambda^{r}\,\bar{\mathbf{V}}_{ct} \;+\; \beta^{r}\,\bar{y}_{ct} \;+\; \pi^{r}\,z^{r}_{ct} \;+\; \omega^{r}_{c} \;+\; \zeta^{r}_{t} \;+\; \eta^{r}_{ct}.
\end{aligned}$$

Here, $\bar{y}_{ct}$ is the average Democratic vote margin in district c, and x^{d}_{ct} and x^{r}_{ct} denote the platforms of the Democratic and Republican candidates, respectively. The variables $\bar{\mathbf{V}}_{ct}$ are exogenous district-level covariates, and z^{d}_{ct} and z^{r}_{ct} are party-specific policy shifters. We collect the district and time fixed effects into $\{\nu_{c},\kappa_{t},\omega^{d}_{c},\omega^{r}_{c},\zeta^{d}_{t},\zeta^{r}_{t}\}$ and the stochastic terms into $\{\xi_{ct},\eta^{d}_{ct},\eta^{r}_{ct}\}$.

Because x^{d}_{ct} and x^{r}_{ct} each depend on $\bar{y}_{ct}$ (which itself depends on x^{d}_{ct} and x^{r}_{ct}), we substitute the demand equation into the supply equations and collect terms. Denote

$$\Xi \;=\; \frac{1}{1 \;-\; \beta^{d}\,\gamma^{d} \;-\; \beta^{r}\,\gamma^{r}}, \quad \alpha_{ct} \;=\; \nu_{c}+\kappa_{t}, \quad \rho^{d}_{ct} \;=\; \omega^{d}_{c}+\zeta^{d}_{t}, \quad \rho^{r}_{ct} \;=\; \omega^{r}_{c}+\zeta^{r}_{t},$$

$$\Lambda_{ct} \;=\; \xi_{ct} \;+\; \gamma^{d}\,\eta^{d}_{ct} \;+\; \gamma^{r}\,\eta^{r}_{ct}.$$

Then we can write the reduced-form expressions as:

$$\begin{aligned}
\bar{y}_{ct} &= \Xi\Big(\alpha_{ct} \;+\; \gamma^d \rho^d_{ct} \;+\; \gamma^r \rho^r_{ct}\Big) \;+\; \Xi\Big(\,\delta \;+\; \gamma^d\,\lambda^d + \gamma^r\,\lambda^r\Big)\,\bar{\mathbf{V}}_{ct} \\
&\quad +\; \big(\Xi\,\gamma^d\,\pi^d\big)\,z^d_{ct} \;+\; \big(\Xi\,\gamma^r\,\pi^r\big)\,z^r_{ct} \;+\; \big(\Xi\,\Lambda_{ct}\big), \\
x^d_{ct} &= \Big[\rho^d_{ct} \;+\; \beta^d\,\Xi\big(\alpha_{ct} \;+\; \gamma^d \rho^d_{ct} \;+\; \gamma^r \rho^r_{ct}\big)\Big] \;+\; \Big[\lambda^d \;+\; \beta^d\,\Xi\big(\delta + \gamma^d\lambda^d + \gamma^r\lambda^r\big)\Big]\,\bar{\mathbf{V}}_{ct} \\
&\quad +\; \Big[\beta^d\,\Xi\,\gamma^d\,\pi^d \;+\; \pi^d\Big]\,z^d_{ct} \;+\; \beta^d\,\big(\Xi\,\gamma^r\,\pi^r\big)\,z^r_{ct} \;+\; \Big[\beta^d\,\Xi\,\Lambda_{ct} \;+\; \eta^d_{ct}\Big], \\
x^r_{ct} &= \Big[\rho^r_{ct} \;+\; \beta^r\,\Xi\big(\alpha_{ct} \;+\; \gamma^d \rho^d_{ct} \;+\; \gamma^r \rho^r_{ct}\big)\Big] \;+\; \Big[\lambda^r \;+\; \beta^r\,\Xi\big(\delta + \gamma^d\lambda^d + \gamma^r\lambda^r\big)\Big]\,\bar{\mathbf{V}}_{ct} \\
&\quad +\; \beta^r\,\big(\Xi\,\gamma^d\,\pi^d\big)\,z^d_{ct} \;+\; \Big[\beta^r\,\Xi\,\gamma^r\,\pi^r \;+\; \pi^r\Big]\,z^r_{ct} \;+\; \Big[\beta^r\,\Xi\,\Lambda_{ct} \;+\; \eta^r_{ct}\Big].
\end{aligned}$$

To see how the system parameters can be recovered from simple linear regressions, consider regressing each district-level outcome on the exogenous instruments $\bar{\mathbf{V}}_{ct}$, z^d_{ct}, and z^r_{ct}, partialling out district and year fixed effects. We define the following reduced-form slopes:

- From the regression of $\bar{y}_{ct}$ on ($\bar{\mathbf{V}}_{ct}$, z^d_{ct}, z^r_{ct}) with district and year fixed effects, let

  $$k_{y,\bar{\mathbf{V}}} \quad k_{y,z^d} \quad \text{and} \quad k_{y,z^r}$$

  denote the estimated coefficients on $\bar{\mathbf{V}}_{ct}$, z^d_{ct} and z^r_{ct}, respectively.

- From the regression of x^d_{ct} on ($\bar{\mathbf{V}}$, z^d_{ct}, z^r_{ct}) with district and year fixed effects, let

  $$k_{x^d,\bar{\mathbf{V}}} \quad k_{x^d,z^d} \quad \text{and} \quad k_{x^d,z^r}$$

  denote the estimated coefficients on $\bar{\mathbf{V}}_{ct}$, z^d_{ct} and z^r_{ct}, respectively.

- Similarly, from the regression of x^r_{ct} on ($\bar{\mathbf{V}}_{ct}$, z^d_{ct}, z^r_{ct}) with district and year fixed effects, let

  $$k_{x^r,\bar{\mathbf{V}}} \quad k_{x^r,z^d} \quad \text{and} \quad k_{x^r,z^r}$$

  denote the estimated coefficients on $\bar{\mathbf{V}}_{ct}$, z^d_{ct} and z^r_{ct}, respectively.

Reduced-Form Expressions. From the algebraic derivations here, we obtain:

$$
\begin{aligned}
k_{x^d,\bar{\mathbf{V}}} &= \lambda^d + \beta^d \Xi \left(\delta + \gamma^d \lambda^d + \gamma^r \lambda^r\right) \\
k_{x^d,z^d} &= \beta^d \Xi \gamma^d \pi^d + \pi^d = \Xi \left[\pi^d - \pi^d \beta^r \gamma^r\right], \\
k_{x^d,z^r} &= \Xi \left[\pi^r \beta^d \gamma^r\right], \\
k_{x^r,\bar{\mathbf{V}}} &= \lambda^r + \beta^r \Xi \left(\delta + \gamma^d \lambda^d + \gamma^r \lambda^r\right) \\
k_{x^r,z^d} &= \Xi \left[\pi^d \beta^r \gamma^d\right], \\
k_{x^r,z^r} &= \beta^r \Xi \gamma^r \pi^r + \pi^r = \Xi \left[\pi^r - \pi^r \beta^d \gamma^d\right], \\
k_{y,\bar{\mathbf{V}}} &= \Xi(\delta + \gamma^d \lambda^d + \gamma^r \lambda^r) \\
k_{y,z^d} &= \Xi \gamma^d \pi^d, \\
k_{y,z^r} &= \Xi \gamma^r \pi^r,
\end{aligned}
$$

where

$$
\Xi = \frac{1}{1 - \beta^d \gamma^d - \beta^r \gamma^r}.
$$

Hence, all reduced-form slopes $\{k_{x^d,\bar{\mathbf{V}}}, k_{x^d,z^d}, k_{x^d,z^r}, k_{x^r,\bar{\mathbf{V}}} k_{x^r,z^d}, k_{x^r,z^r}, k_{y,\bar{\mathbf{V}}}, k_{y,z^d}, k_{y,z^r}\}$ are functions of the structural parameters $\left\{\beta^d, \beta^r, \gamma^d, \gamma^r, \pi^d, \pi^r, \lambda^d, \lambda^r, \delta\right\}$.

D.3 Recovering the Structural Parameters

Solving these equations for the unknowns structural parameters yields a unique solution (provided that Ξ is well-defined). In particular:

$$
\begin{aligned}
\beta^d &= \frac{k_{x^d,z^r}}{k_{y,z^r}}, \qquad \beta^r = \frac{k_{x^r,z^d}}{k_{y,z^d}}, \\
\gamma^d &= -\frac{k_{x^r,z^d} k_{y,z^r} - k_{x^r,z^r} k_{y,z^d}}{k_{x^d,z^d} k_{x^r,z^r} - k_{x^d,z^r} k_{x^r,z^d}}, \quad \gamma^r = \frac{k_{x^d,z^d} k_{y,z^r} - k_{x^d,z^r} k_{y,z^d}}{k_{x^d,z^d} k_{x^r,z^r} - k_{x^d,z^r} k_{x^r,z^d}}, \\
\pi^d &= \frac{k_{x^d,z^d} k_{y,z^r} - k_{x^d,z^r} k_{y,z^d}}{k_{y,z^r}}, \qquad \pi^r = -\frac{k_{x^r,z^d} k_{y,z^r} - k_{x^r,z^r} k_{y,z^d}}{k_{y,z^d}}.
\end{aligned}
$$

Similarly, the expressions for λ^d and λ^r are:

$$\lambda^d = k_{x^d,\bar{\mathbf{V}}} - \frac{k_{y,\bar{\mathbf{V}}} k_{x^d,z^r}}{k_{y,z^r}}$$
$$\lambda^r = k_{x^r,\bar{\mathbf{V}}} - \frac{k_{y,\bar{\mathbf{V}}} k_{x^r,z^d}}{k_{y,z^d}}$$

and finally the expression of δ can be expressed as:

$$\delta = k_{y,\bar{\mathbf{V}}}(1 - \beta^d\gamma^d - \beta^r\gamma^r) - \gamma^d\lambda^d - \gamma^r\lambda^r$$

Hence, using the direct reduced-form coefficients

$$\{k_{x^d,\bar{\mathbf{V}}}, k_{x^d,z^d}, k_{x^d,z^r}, k_{x^r,\bar{\mathbf{V}}}, k_{x^r,z^d}, k_{x^r,z^r}, k_{y,\bar{\mathbf{V}}}, k_{y,z^d}, k_{y,z^r}\}$$

we can recover the entire set of structural demand and supply parameters

$$\left\{\beta^d, \beta^r, \gamma^d, \gamma^r, \pi^d, \pi^r, \lambda^d, \lambda^r, \delta\right\}.$$

In the estimation presented in the main text, we extend this point-identifiable model in two ways. First, given that we observe voting margins, climate shocks, and employment shifts at a more granular block level, we employ block-level regression to estimate the parameters δ in the first stage. This approach yields greater precision compared to relying solely on district-level variations. Second, we impose additional second-order moment conditions to restrict the dependence structure between the demand side and the idiosyncratic errors on both parties' supply sides. These two extensions enhance the precision of the estimation and render the system over-identified.