

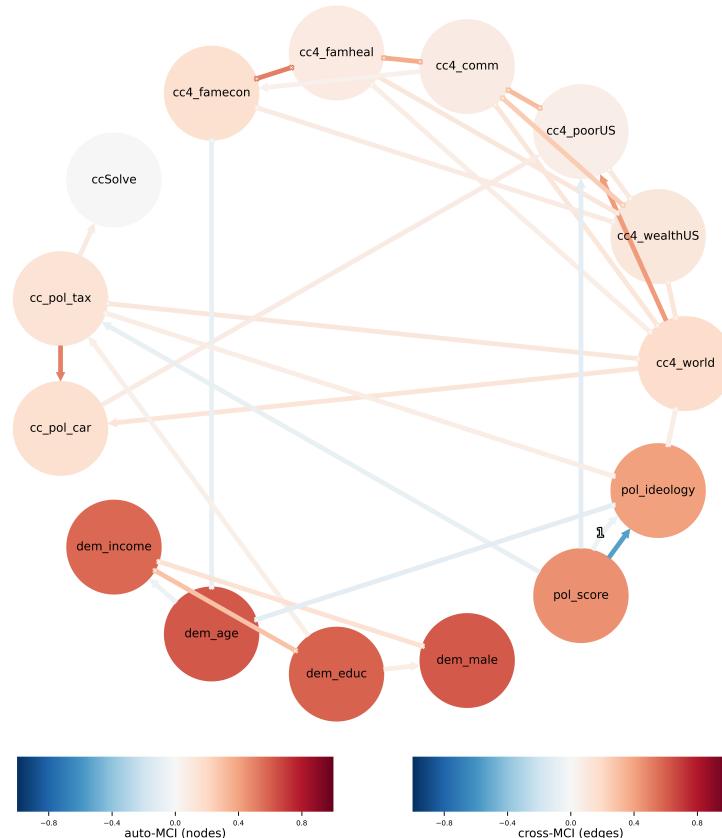
# ELECTIONS AND CLIMATE ATTITUDES: HOW DO PEOPLE'S VIEWS ON CLIMATE CHANGE AND RELATED POLICIES CHANGE DURING AN ELECTION?

SUBMITTED IN PARTIAL FULFILLMENT FOR THE DEGREE OF MASTER OF SCIENCE

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SUBMITTED ON 27.06.2025



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## 1 ABSTRACT

2 This thesis examines the impact of elections on climate change  
3 attitudes and policy support. Using a data set of 2,583 survey re-  
4 sponses collected over 3 waves, we apply two complementary tem-  
5 poral methods: a PVAR model (panel vector autoregression) and the  
6 PCMCI+ (Peter and Clark Momentary Conditional Independence).  
7 PVAR models the linear dynamic structure of climate-related at-  
8 titudes and PCMCI+ enables the data-driven discovery of causal  
9 links over time. By comparing their results, we assess how climate  
10 perceptions, willingness to pay for climate solutions, and support  
11 for specific climate policies evolve around the 2020 US elections.  
12 Our findings show that climate views remain mostly stable, but  
13 some changes in perceived harm and policy support occur around  
14 elections. Political beliefs also shape the amount of money people  
15 are willing to pay for climate action. The study contributes to un-  
16 derstanding how politics shape public opinion on climate issues,  
17 offering insights for policymakers and researchers.

## 18 CCS CONCEPTS

- 19 • Mathematics of computing → Time series analysis.

## 20 KEYWORDS

21 climate change, elections, causal data science, PCMCI+, PVAR

## 22 ACM Reference Format:

23 . 2025. : . In . ACM, New York, NY, USA, 17 pages. <https://doi.org/10.1145/nmnnnnnm.nmnnnnnm>

## 25 GITHUB REPOSITORY

26 The code used for the analysis in this thesis is available at: <https://github.com/paraskevasleivadaros/climate-opinions-and-elections>

## 28 1 INTRODUCTION

29 This paper explores the relationship between political events, poli-  
30 cies, and society's attitudes toward climate change. Climate change  
31 is one of the most important global challenges at the moment. For  
32 this reason, understanding how elections and policies shape public  
33 opinion is crucial. This knowledge is important for policy makers  
34 and researchers who need to get the public involved in tackling  
35 climate change.

36 *How do people's views on Climate Change and on related policies  
37 change during an election?*

38 The research question can be answered by examining people's  
39 opinions towards climate change and related policies during the  
40 2020 US elections. The following sub-questions will guide our anal-  
41 ysis:

- 42 **RQ1.** Does support for climate policies (like carbon taxes or emis-  
43 sions standards) change during elections? And is this support  
44 influenced by personal or community-level perceptions of  
45 climate harm?
- 46 **RQ2.** Does willingness to pay for climate solutions vary during  
47 elections and what factors influence it?
- 48 **RQ3.** Does political ideology moderate the relationship between  
49 perceptions of harm and willingness to pay?

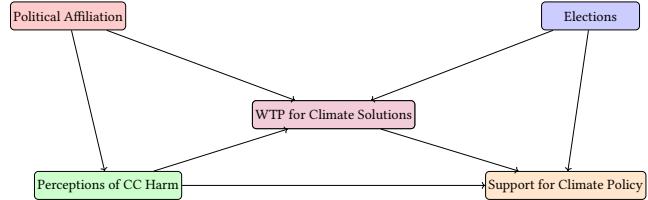


Figure 1: Conceptual Model: Key Relationships Based on Research Questions

## 50 2 RELATED WORK

51 This section reviews previous research on the relationship between  
52 elections, climate perceptions, and policy support.

53 Hahnel et al., 2020 [3] found that when political leaders frame cli-  
54 mate change as a divisive issue, public opinion becomes polarized on  
55 perceptions of climate harm. Similarly, Fisher (2022) [7] found that  
56 different ideologies influence how different parties assess climate  
57 risks, with left-leaning voters more likely to express concern for  
58 vulnerable populations (e.g., poor communities) than right-leaning  
59 voters. Given these findings, our study examines whether perceived  
60 harm to poor or wealthy communities changes during elections.

61 Fisher also found that ideological polarization influences whether  
62 people translate perceptions of climate risk into policy preferences.  
63 Studies on voter behavior suggest that Democrats are more likely to  
64 convert climate concern into higher WTP for solutions compared to  
65 Republicans. Based on this, our study investigates whether political  
66 affiliation moderates the effect of perceived harm on WTP during  
67 elections.

68 Schulze et al. (2021) [22] found that willingness to pay (WTP) for  
69 climate policies declines in pre-election periods, as voters become  
70 more sensitive to financial costs. Research suggests that conserva-  
71 tives are generally less supportive of costly interventions, but may  
72 express higher WTP when policies are framed as benefiting local  
73 communities or economic stability. Ogami (2024) [17] found that  
74 voters tend to prioritize low-cost climate solutions closer to elec-  
75 tions due to economic concerns influenced by campaign rhetoric.  
76 Based on these findings, our study examines whether elections  
77 shape WTP for climate solutions.

78 The Cires study on the opinions on climate change during  
79 elections [2] found that Democrats consistently express greater  
80 support for climate policies, such as carbon taxes, while Republicans  
81 remain more resistant. Similarly, Ogami explains that politicians  
82 often avoid promoting polarizing policies, such as carbon taxes, in  
83 the lead-up to elections to minimize losing voters. The Cires study  
84 also found that people experiencing direct climate impacts, such  
85 as extreme weather events, tend to support pro-climate candidates  
86 and policy measures. Based on this, our study examines whether  
87 support for specific policies changes during elections and whether  
88 these shifts are influenced by political affiliation or perceptions of  
89 family health and economic well-being.

### 90 3 METHODOLOGY

#### 91 3.1 Resources

92 Previous research has shown that elections influence climate attitudes and policy support, but the direction and magnitude of these  
93 effects are unclear. This study addresses this gap by applying two  
94 temporal methods: PVAR and the PCMCI+ algorithm. Although  
95 PVAR captures dynamic interdependencies among variables over  
96 time under parametric assumptions, PCMCI+ offers a data-driven  
97 approach to uncover causal relationships from time series. Using  
98 the Tigramite Python package [20], we will try to identify the causal  
99 impact of elections on climate perceptions, WTP, and support for  
100 climate policies.

101 The primary resource for this study is a longitudinal data set  
102 consisting of 2,583 survey responses from 861 participants collected  
103 over 3 waves from June 2020 to August 2021. Table 1 provides an  
104 overview of the key variables included in the dataset and groups  
105 them according to their thematic role in the analysis.

Variable	Description
<b>Climate Change Perception (cc4_*)</b>	
cc4_world	Perceived harm of climate change on the world
cc4_wealthUS	Perceived harm on wealthy U.S. communities
cc4_poorUS	Perceived harm on poor U.S. communities
cc4_comm	Perceived harm on local communities
cc4_famheal	Perceived harm on family health
cc4_famecon	Perceived harm on family economy
<b>WTP (ccSolve*)</b>	
ccSolve100	Support for policies at \$100/month
ccSolve50	Support for policies at \$50/month
ccSolve10	Support for policies at \$10/month
ccSolve1	Support for policies at \$1/month
ccSolve0	Support for policies (no cost specified)
<b>Climate Policy Support (cc_pol_*)</b>	
cc_pol_tax	Support for a carbon tax
cc_pol_car	Support for stricter car emissions
<b>Political Affiliation and Ideology (pol_*)</b>	
pol_party	Political party identification (Rep, Dem, Ind)
pol_lean	Political party leaning (Lean Rep, Lean Dem)
pol_ideology	Political ideology (Conservative, Moderate, Liberal)
<b>Demographics (dem_*)</b>	
dem_income	Respondent's reported income level
dem_male	Respondent's gender
dem_age	Respondent's age
dem_educ	Respondent's education level

106 **Table 1: Description of Key Variables (raw data)**

107 Table 2 summarizes the response options and coding for key  
108 variables used in the analysis.

Variable	Coding	Response Scale
cc4_*	1 to 4	Not at all to A great deal
ccSolve*	1 to 5	Strongly disagree to Strongly approve
cc_pol_*	1 to 5	Strongly oppose to Strongly support
pol_party	1 to 3	Republican, Democrat, Independent
pol_lean	1 to 4	Leaning Rep., Leaning Dem., Neither
pol_ideology	1 to 5	Very conservative to Very liberal
dem_income	1 to 6	<\$25k to >\$200k
dem_educ	1 to 6	<High School to Advanced degree
dem_age	18 to 99	Age in years
dem_male	0, 1, 77	Female, Male, Self-described

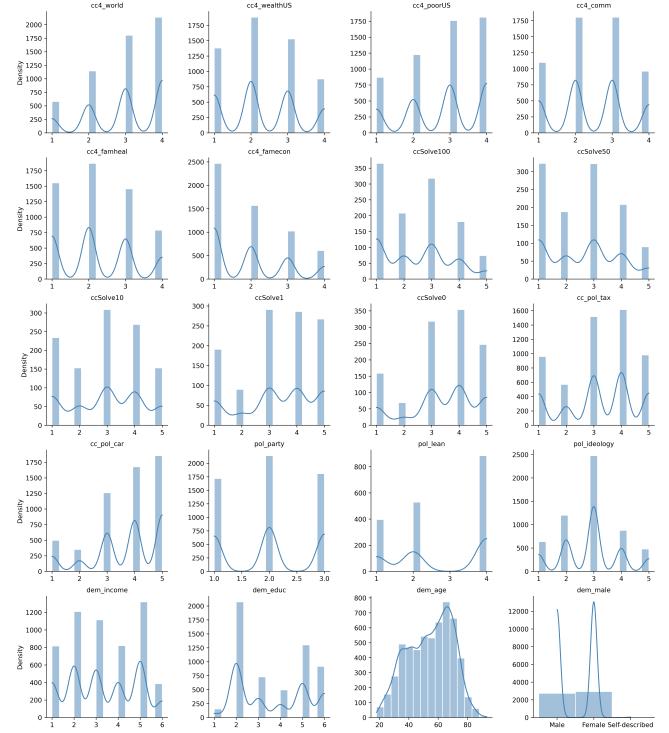
109 **Table 2: Variable coding and response scales (raw data)**

110 Table 3 provides summary statistics for all variables in the dataset  
111 prior to filtering. For each variable, the table reports the number and  
112 percentage of missing values, as well as key distribution metrics:  
113 mean, standard deviation, and the five-number summary (minimum,  
25th percentile, median, 75th percentile, and maximum).

Variable	NA%	Mean	SD	P0	P25	P50	P75	P100
cc4_world	0.00%	2.971	0.994	1	2	3	4	4
cc4_wealthUS	0.00%	2.336	1.010	1	2	2	3	4
cc4_poorUS	0.00%	2.797	1.053	1	2	3	4	4
cc4_comm	0.00%	2.464	0.988	1	2	2	3	4
cc4_famheal	0.00%	2.262	1.010	1	1	2	3	4
cc4_famecon	0.00%	1.959	1.021	1	1	2	3	4
ccSolve100	79.78%	2.469	1.261	1	1	2.5	3	5
ccSolve50	80.04%	2.606	1.287	1	1	3	4	5
ccSolve10	80.27%	2.959	1.327	1	2	3	4	5
ccSolve1	80.15%	3.309	1.367	1	3	3	4	5
ccSolve0	79.76%	3.402	1.275	1	3	4	4	5
cc_pol_tax	0.44%	3.193	1.314	1	2	3	4	5
cc_pol_car	0.44%	3.717	1.230	1	3	4	5	5
pol_party	0.00%	2.016	0.789	1	1	2	3	3
pol_lean	68.08%	2.758	1.265	1	2	2	4	4
pol_ideology	0.00%	2.887	1.068	1	2	3	3	5
dem_income	0.00%	3.314	1.543	1	2	3	5	6
dem_educ	0.00%	3.611	1.601	1	2	3	5	6
dem_age	0.00%	54.28	15.16	18	42	56	67	93
dem_male	0.00%	Female = 52.4%, Male = 47.4%, Self-described = 0.1%						

114 **Table 3: Data Summary (raw data)**

115 To complement the summary statistics above, Figure 2 visualizes  
the distribution of key variables (raw data).



116 **Figure 2: Distributions with Density Overlay (raw data)**

### 3.2 Approach

To analyze how climate attitudes change during elections, we apply two complementary time series methods: a PVAR model [11] and the PCMCI+ causal discovery algorithm [21].

PVAR models are well suited for analyzing systems of interdependent variables in panel data. Each variable is modeled as a function of its own lag and the lags of all other variables. This allows us to capture bidirectional feedback dynamics over time, making it ideal for understanding how climate concern, policy support, and political attitudes influence each other longitudinally [15].

PCMCI+ is a constraint-based causal discovery method designed for time-series data. It relies on conditional independence (CI) testing to infer the presence or absence of lagged causal relationships between variables. While PCMCI+ supports nonparametric CI tests such as GPDC or CMIknn, we use linear partial correlation (ParCorr) tests, given the short panel length ( $T = 3$ ) in our data. Nonparametric CI tests like GPDC or CMIknn typically require larger sample sizes to reliably estimate high-dimensional conditional distributions. With short panel data, these estimators become unstable or biased. In contrast, linear CI tests like partial correlation (ParCorr) assume a simpler structure (linear-Gaussian), which allows for more robust inference in small-sample sizes. [19]

Traditional approaches, such as pooled OLS or fixed-effects regressions, assume unidirectional influence and do not account for dynamic feedback loops. They may estimate average associations over time, but they cannot adequately model temporal causality or mutual interdependence among variables. In contrast, both PVAR and PCMCI+ allow for bidirectional, time-lagged relationships that better reflect the evolving nature of public opinion during elections.

This thesis contributes methodologically by combining a dynamic system-based model (PVAR) with a causal graph discovery framework (PCMCI+), a combination not previously applied in the context of climate policy attitudes shifts in election periods.

The PVAR model produces directed graphs that represent significant lagged effects between variables. PCMCI+ outputs a causal graph based on conditional independence tests. We compare these two graphs qualitatively to assess the robustness of the temporal relationships.

Table 4 maps each survey wave to the research questions it informs.

Wave	Research Questions Addressed
Wave 2	Provides baseline values for all lagged predictors
Wave 3	Captures dynamics during the election
Wave 4	Allows continued observation of attitudes after election

Table 4: Timeline structure and relevance of each wave

The implementation relied entirely on open-source Python packages. A complete list of the key tools and libraries used in the analysis is provided in Appendix C.

### 3.3 Steps

The process begins with preparing the panel dataset and estimating PVAR models to explore the temporal dynamics of climate attitudes followed by comparing them with a causal graph algorithm in the final step. An overview of these main stages is provided in Figure 3.

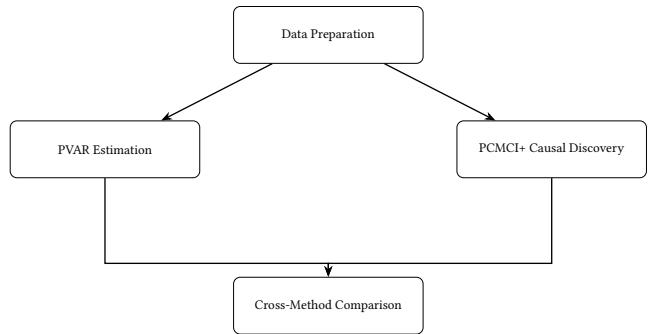


Figure 3: Overview of the main analytical steps in the study

3.3.1 *Data Preparation.* Several variables of harm perception were originally recorded on different Likert scales (some 1–4, others 1–6). These were linearly transformed to a common scale of 1 to 5 so that all predictors could be compared on the same scale.

The pol\_party and pol\_lean variables were merged into a single pol\_score variable to create a continuous scale of political alignment from left to right. This scale ranges from -2 (strong Democrat) to 2 (strong Republican). For those who identified as Independents (pol\_party = 3), their placement depended on their leaning: those leaning Democrat (pol\_lean = 2) received a score of -1, those leaning Republican (pol\_lean = 1) received a 1, and those who leaned neither way (pol\_lean = 4) were assigned a neutral score of 0.

Missing values in the two policy support variables (cc\_pol\_tax, cc\_pol\_car) were filled with the neutral midpoint (value 3). The dataset didn't specify why those values were missing, but it was only 25 out of 5,667 responses (0.44%). WTP variables (ccSolve100, ccSolve50, etc.) were combined into a single, scaled measure (ccSolve), rescaled to a 1–5 scale based on dollar weighting. Rows with no WTP response were excluded.

To enable comparisons between subgroups, three demographic variables were recoded into binary format, as shown in Table 5.

Variable	Binary Recoding Rule
dem_income	Low income (1–4) recoded as 0 High income (5–6) recoded as 1
dem_educ	Non-advanced degrees (1–5) recoded as 0 Advanced degree (6) recoded as 1
dem_male	Female (0) and self-described (77) recoded as 0 Male (1) recoded as 1

Table 5: Binary Recoding of Demographic Variables

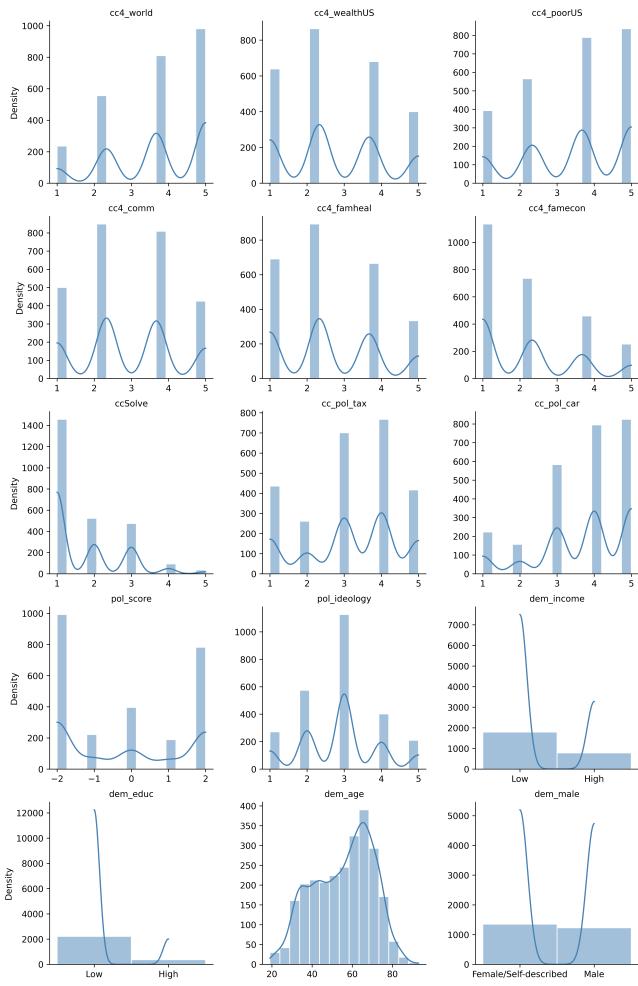
The data set was reshaped into a long format indexed by respondent ID and wave number (2, 3, and 4). Lagged versions of all time-varying variables were created for PVAR and causal modeling. Table 6 summarizes the descriptive statistics of the key variables in the data set after filtering.

To complement the summary statistics above, Figure 4 visualizes the distribution of key variables (after filtering).

Although the dataset includes 861 respondents in 3 waves, it does not represent the broader US population and the results should

Variable	NA%	Mean	SD	P0	P25	P50	P75	P100
cc4_world	0.00%	3.643	1.308	1	2.33	3.67	5.00	5
cc4_wealthUS	0.00%	2.767	1.350	1	2.33	2.33	3.67	5
cc4_poorUS	0.00%	3.401	1.407	1	2.33	3.67	5.00	5
cc4_comm	0.00%	2.932	1.310	1	2.33	2.33	3.67	5
cc4_famheal	0.00%	2.664	1.321	1	1.00	2.33	3.67	5
cc4_famecon	0.00%	2.245	1.337	1	1.00	2.33	3.67	5
ccSolve	0.00%	1.732	0.9707	1	1.00	1.00	2.00	5
cc_pol_tax	0.00%	3.182	1.299	1	2.00	3.00	4.00	5
cc_pol_car	0.00%	3.713	1.218	1	3.00	4.00	5.00	5
pol_score	0.00%	-0.1754	1.697	-2	-2.00	0.00	2.00	2
pol_ideology	0.00%	2.886	1.054	1	2.00	3.00	3.00	5
dem_income	0.00%	Low = 69.6%, High = 30.4%						206
dem_educ	0.00%	Low = 86.1%, High = 13.9%						207
dem_age	0.00%	55.47	14.80	19	43.00	58.00	67.00	93
dem_male	0.00%	Female/Self-described = 52.5%, Male = 47.5%						208

**Table 6: Data Summary (after filtering)**



**Figure 4: Distributions with Density Overlay (after filtering)**

**3.3.2 PVAR Estimation.** According to Abrigo and Love [1], a PVAR( $p$ ) model requires at least  $T \geq p + 2$  time periods per unit to identify and estimate the model reliably. For this reason we use PVAR(1) models because our dataset includes only three time points per respondent. For RQ1, we estimate one global PVAR(1) model for each policy support variable. Each support variable is then regressed on its own lag and all other predictors, allowing us to assess how support evolves over time and whether it is influenced by perceptions of harm. For RQ2, we focus on ccSolve as the dependent variable in a global PVAR(1) model, examining its evolution over time, the potential impact of elections on WTP, and identifying which predictors account for variation in WTP. For RQ3, our PVAR(1) model includes interaction terms between political ideology and each harm perception variable to determine whether the link between perceived climate harm and WTP differs between ideologies.

We treat demographics as exogenous variables, external to the system of endogenous relationships in the PVAR framework, meaning they are not influenced by other variables in the model but can help explain variation in them [14].

**3.3.3 PCMCI+ Causal Discovery.** : Apply PCMCI+ to estimate a time-lagged causal graph from the panel data.

**3.3.4 Cross-Method Comparison.** : Compare the structure and direction of PCMCI+ links with those found in the PVAR models.

### 3.4 Evaluation

To assess the reliability of our results, we performed bootstrap resampling to estimate confidence intervals and standard errors for the coefficients in our PVAR models. Specifically, we applied a case resampling procedure, where we sampled individuals (PIIDs) with replacement and re-estimated the models across 1,000 bootstrap iterations. For each iteration, we constructed a new dataset by selecting a set of PIIDs and concatenating their corresponding timeseries observations. We then refitted the PVAR models for each outcome of interest (e.g., support for carbon tax) and recorded the estimated coefficients. From the resulting distributions, we computed bootstrap based standard errors and 95% percentile confidence intervals. This resampling approach is commonly used in panel data settings [9] [5]. The full bootstrapping procedure is implemented in Python and documented in the project repository. Summary tables of the bootstrap distributions and coefficient intervals are provided in Appendix E.

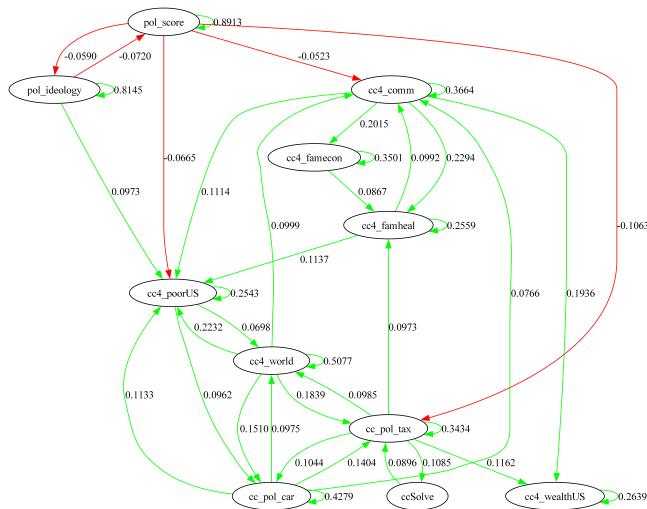
To assess the stability of causal links identified by PCMCI+, we implemented a bootstrap procedure across 100 resampled datasets. In each iteration, we resampled time points (with replacement) uniformly across all cross-sectional units to preserve the panel structure. For every bootstrap sample, we re-ran PCMCI+ using ParCorr as the CI test with  $\alpha = 0.01$  and a maximum lag of 1. We tracked the frequency with which each directed edge appeared as significant across the 100 runs. The most stable links were all autoregressive (e.g., cc4\_world  $\rightarrow$  cc4\_world), each appearing in 100% of the bootstrapped samples. Other non-autoregressive links, such as cc\_pol\_tax  $\rightarrow$  ccSolve, appeared less frequently (10%), indicating weaker or less stable relationships. The results are provided in Appendix E Table 32, and the code is available in the project repository.

195 be viewed as indicative of broader trends rather than as fully generalizable.  
196

## 4 RESULTS

### 4.1 PVAR Estimation

Before estimating the separate PVAR(1) models for each of our research questions, we first estimated a global PVAR model that includes all relevant variables simultaneously. This model serves as the foundation of our analysis, offering a comprehensive picture of the time-lagged relationships in the data. The global model captures the joint dynamics across climate beliefs, policy support, political orientation, and demographic factors, providing one of the main empirical results of this study. The individual models presented in later sections are subsets of this global model, extracted to focus on specific outcomes and facilitate interpretation. These targeted models are used primarily to generate simplified visualizations and to help the reader better understand the local structure of the relationships observed in the global PVAR graph. Figure 5 displays the PVAR lagged effects graph, capturing statistically significant ( $p < 0.01$ ) links from time  $t - 1$  to  $t$ . Each edge represents a standardized regression coefficient, with green and red indicating positive and negative effects, respectively.



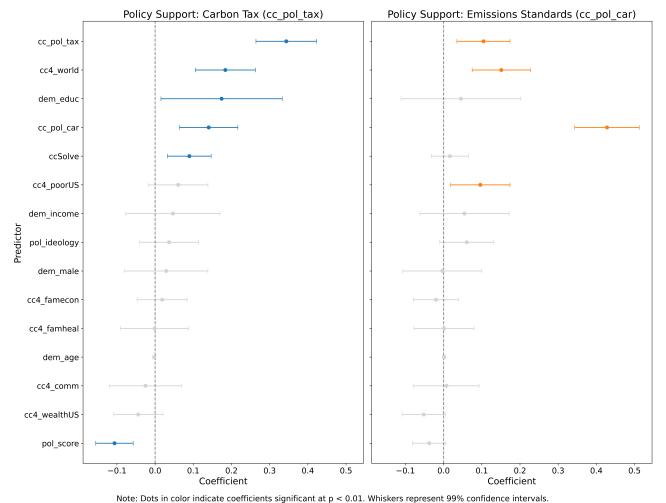
**Figure 5: PVAR Lagged Effects ( $p < 0.01$ ). Edge labels indicate standardized coefficients from lagged OLS models. Green = positive, Red = negative effects.**

Model performance statistics for each dependent variable are provided in Table 8 (Appendix 4). The model explains a substantial portion of the variance in political variables: both *pol\_score* and *pol\_ideology* show high  $R^2$  values of 0.889 and 0.826, respectively, indicating that the predictors explain political views very well. Climate concern indicators such as *cc4\_world* and *cc4\_poorUS* are also well explained ( $R^2 = 0.634$  and 0.553, respectively). Policy support variables, including *cc\_pol\_tax* and *cc\_pol\_car*, achieve moderately strong fits ( $R^2 \approx 0.50$ ). In contrast, the model performs poorly in explaining variation in willingness to pay (*ccSolve*), with a low  $R^2$  of 0.076. This suggests that factors beyond those included may influence payment preferences. Demographic variables were included as unlagged covariates, but did not emerge as statistically

significant predictors in the network and were excluded from the graph.

### 4.2 RQ1 – Drivers of Support for Climate Policy

The analysis focused on two outcome variables: support for carbon taxes (*cc\_pol\_tax*) and support for vehicle emissions standards (*cc\_pol\_car*). Each regression included lagged values for 15 predictors, and standard errors were clustered at the respondent level. Figure 6 displays the estimated coefficients using dot-whisker plots, highlighting statistically significant predictors at the  $p < 0.01$  level with 99% confidence intervals.



**Figure 6: Predictors of support for carbon taxes (*cc\_pol\_tax*) and emissions standards (*cc\_pol\_car*) (lag-1 variables).** The figure displays results from two reduced-form PVAR(1) regressions using dot-whisker plots. Each dot represents a regression coefficient estimate, and the horizontal lines denote 99% confidence intervals. Predictors are ordered by the size and direction of their effects, with statistically significant results ( $p < 0.01$ ) shown in color and non-significant ones in gray. A vertical line at zero indicates no effect.

Support for climate policies remains relatively stable over time. Prior support for either carbon taxes or emissions standards is a significant and positive predictor of subsequent support for the same policy, indicating that support for carbon taxes changes gradually at this time scale. There is also evidence of cross-policy spillover, with prior support for emissions standards (*cc\_pol\_car*) significantly predicting later support for carbon taxes and vice versa. These findings suggest that people's views on climate policies evolve gradually over time rather than shifting completely in response to other factors.

Individuals who perceive that climate change harms the world (*cc4\_world*) are more likely to support carbon taxation. This global perception of harm emerges as a robust positive driver of support, highlighting the role of broader environmental concern. Interestingly, personal perceptions of climate harm — such as concern for one's own community (*cc4\_comm*) or family health (*cc4\_famheal*)

— do not significantly influence support for carbon taxes at the stricter  $p < 0.01$  threshold. Education level (dem\_educ) is also positively associated with support ( $p = 0.0047$ ), suggesting that the more educated respondents are more receptive to market-based climate solutions. However, this relationship did not meet the stricter threshold ( $p < 0.01$ ) in the full joint model used to generate Figure 5.

Furthermore, the willingness to financially contribute to climate solutions (ccSolve) significantly predicts support for carbon taxes. In contrast, the political orientation (pol\_score) exhibits a negative significant relationship, with more conservative individuals being less supportive of carbon taxes.

The emission standards model reveals a somewhat different set of predictors. Again, global harm perception (cc4\_world) remains a significant and positive predictor of support. In addition, concern about the impact of climate change on the poor in the United States (cc4\_poorUS) is positively associated with support. This suggests that concerns about fairness, especially how climate change affects poorer people in the country, influence support for climate rules. As with the carbon tax model, both autoregressive and cross-policy predictors are significant. Past support for emissions standards (cc\_pol\_car) and carbon taxes (cc\_pol\_tax) each positively influence current support for emissions standards. Demographic characteristics do not reach statistical significance in this model. Unlike carbon taxes, emission standards appear less ideologically polarized, as political orientation does not emerge as a significant predictor.

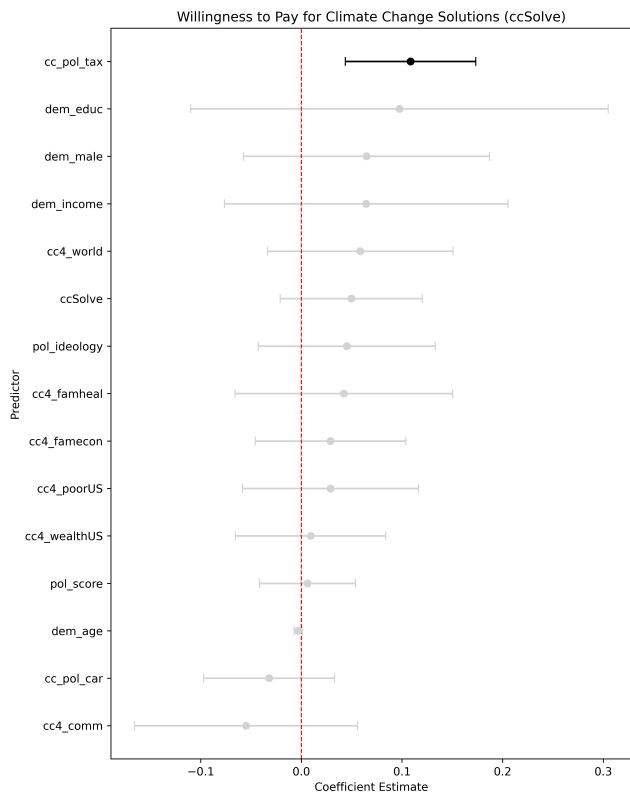
Demographic variables such as dem\_educ\_lag, dem\_income\_lag, and dem\_male\_lag show the highest standard errors in both the carbon tax and emissions standards models. These predictors contribute disproportionately to the general uncertainty of the model, as evidenced by their wide confidence intervals in the dot-whisker plots in Figure 6 and elevated standard errors in Appendix D Figure 12. Several factors may explain the imprecision associated with demographic predictors. First, characteristics such as gender and education are largely time-invariant, offering limited within-subject variation across survey waves. Second, some of the high standard errors for demographic variables such as gender, income, and education may be due to small subgroup sizes in the data. For example, there are only 42 observations from female or self-described respondents with low income and high education, 43 from male respondents with the same traits, and 46 from female or self-described respondents with high income and high education. These small groups reduce the ability of the model to estimate precise effects, likely contributing to the wide confidence intervals observed in Figures 6 and 12. Table 9 in Appendix D shows the number of observations for each subgroup. It should be noted that variance inflation factors (VIFs) for these variables are low (Table 10 in Appendix D) [13], indicating that multicollinearity is not the primary source of uncertainty. Together, these considerations suggest that demographic predictors should be interpreted with caution in this analysis.

Together, these results suggest that support for climate policy during elections is primarily shaped by global environmental concern, policy consistency, and - especially in the case of emissions standards - concern for social fairness. In contrast, perceptions of local or familial harm do not play a statistically significant role in shaping support, contrary to some expectations in the literature.

The difference in how political views affect support for the two policies suggests that carbon taxes are more politically divisive than policies like emissions standards.

### 4.3 RQ2 – Drivers of WTP for Climate Solutions

The PVAR(1) model for ccSolve (willingness to pay for climate action) reveals that attitudes remain highly stable throughout the election period. Among all lagged predictors, only one variable - prior support for a carbon tax (cc\_pol\_tax) — emerges as a statistically significant predictor at the  $p < 0.01$  level. This finding indicates that individuals who previously expressed support for carbon pricing are more likely to report a willingness to pay for broader climate solutions in subsequent waves. Figure 7 displays the estimated coefficients using dot-whisker plots, highlighting statistically significant predictors at the  $p < 0.01$  level with 99% confidence intervals.



**Figure 7: Predictors of willingness to pay for climate change solutions (ccSolve).** Dot-whisker plots show coefficient estimates with 99% confidence intervals. Only prior support for carbon tax (cc\_pol\_tax) is statistically significant ( $p < 0.01$ ), shown in black.

An inspection of the standard errors reveals that dem\_educ\_lag, dem\_income\_lag, and dem\_male\_lag exhibit the largest standard errors among all predictors (see Figure 13 in Appendix D). These three demographic variables contribute the most to the overall

uncertainty of the model, making their estimated effects less precise. This is visually reflected in the long whiskers observed in the dot-whisker plot (Figure 7), particularly for `dem_educ_lag`, which had the widest confidence interval despite being conceptually important. Several factors are likely to contribute to this uncertainty. First, there may be limited variation or small sample sizes within certain demographic subgroups. Second, demographic characteristics such as education and gender tend to remain constant between survey waves, reducing within-subject variability. In particular, the variance inflation factors (VIFs) for these predictors are low (see Table 11 in Appendix D), indicating that multicollinearity is not a primary concern in this model.

#### 397 4.4 RQ3 – Moderating Role of Political Ideology

398 To explore this question, we extended the PVAR(1) model to include  
399 interaction terms between perceived climate harms and the politi-  
400 cal ideology of the respondents. The aim was to test whether the  
401 effect of harm perceptions on the willingness to financially support  
402 climate solutions varies across the ideological spectrum.

403 Figure 11 in Appendix D presents the results of the full interac-  
404 tion model. The only variable that is statistically significant at the  
405  $p < 0.01$  level is prior support for a carbon tax (`cc_pol_tax`). This  
406 confirms a consistent pattern seen in previous models: individu-  
407 als who already support specific climate policies are more likely  
408 to express a willingness to pay for climate solutions in general.  
409 None of the interaction terms between harm perceptions and politi-  
410 cal ideology – such as `cc4_world × pol_ideology`, `cc4_poorUS`  
411 × `pol_ideology`, or `cc4_famheal × pol_ideology` – achieve  
412 statistical significance.

413 The full interaction model exhibits substantial multicollinear-  
414 ity, especially between harm perception variables and their inter-  
415 action terms. Standard errors for main harm predictors such as  
416 `cc4_famheal`, `cc4_comm`, and `cc4_world` exceed 0.10, with vari-  
417 ance inflation factors (VIFs) for interaction terms ranging from 40  
418 to 80 – well above acceptable thresholds (see Table 12 in Appen-  
419 dix D). This collinearity inflates standard errors, reduces statistical  
420 power, and makes it difficult to isolate individual effects (see Fig-  
421 ure 14 in Appendix D).

422 To address multicollinearity, we constructed a `harm_index` to  
423 summarize all six harm perception variables into a single factor,  
424 which was then interacted with political ideology. The simplified  
425 specification resulted in improved model stability. All variance in-  
426 flation factors (VIFs) for the harm index model remained below the  
427 conventional threshold of 10, except one (see Table 13 in Appen-  
428 dix D), and standard errors for key predictors and interaction terms  
429 were substantially reduced (see Figure 15 in Appendix D).

430 Figure 8 presents the results of the simplified moderation model  
431 using the `harm_index`.

432 The results of both the full interaction and simplified harm in-  
433 dex models suggest that political ideology does not significantly  
434 moderate the relationship between climate harm perceptions and  
435 willingness to pay. However, simplifying the model structure sub-  
436 stantially improved the statistical clarity. The harm index approach  
437 yielded lower multicollinearity, narrower confidence intervals while  
438 preserving the conclusion that prior climate policy support remains

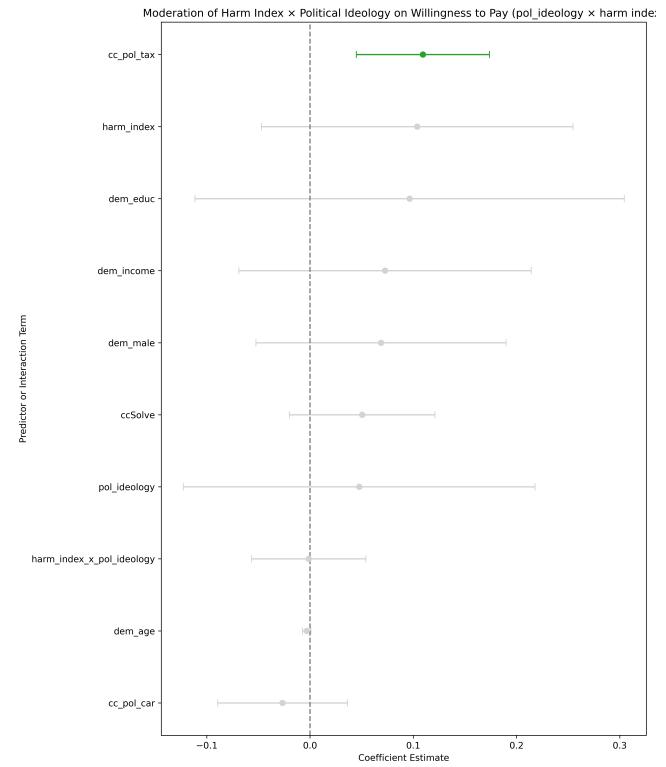


Figure 8: Moderation model using a composite harm index. Interaction with political ideology is not significant, but more precisely estimated.

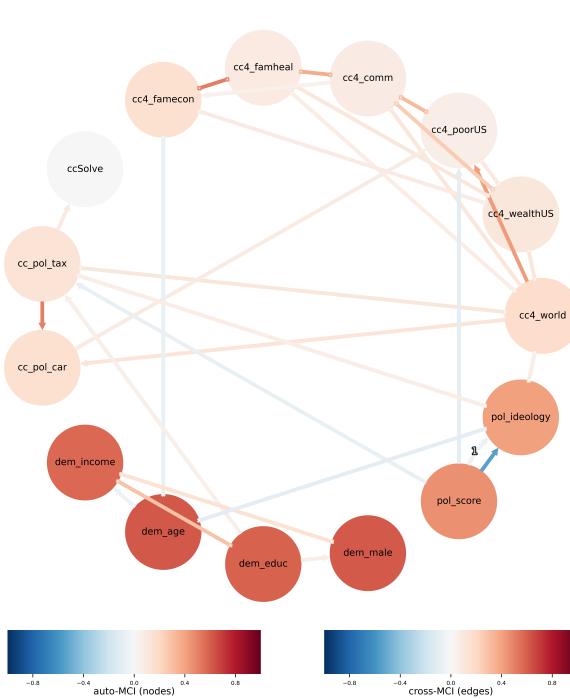
439 the strongest and most consistent predictor of financial engagement  
440 with climate solutions.

#### 441 4.5 PCMCI+ Causal Discovery

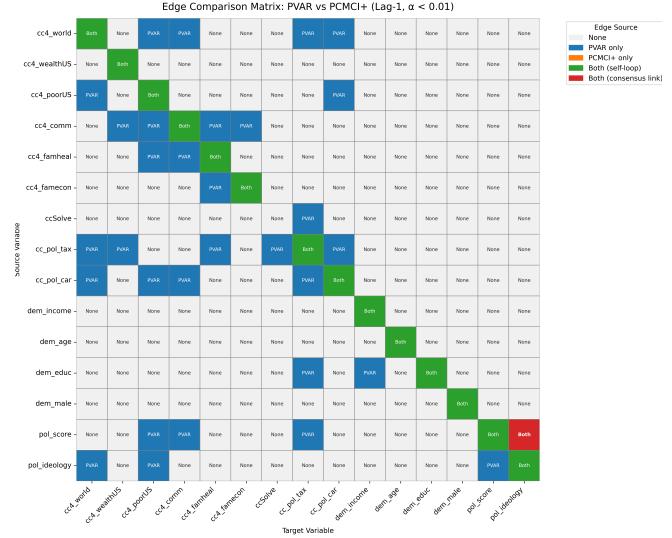
442 Figure 9 shows the graph generated by PCMCI+, which uses par-  
443 tial correlation as the CI test to isolate direct causal links. Edge  
444 colors represent momentary conditional information (MCI), with  
445 red indicating positive effects and blue indicating negative effects.  
446 The color intensity reflects the strength of the dependency. This  
447 PCMCI+ graph shows that most variables are strongly influenced  
448 by their own past values. We can tell this from the dark red colors  
449 of the nodes, which represent strong self-dependence (auto-MCI).  
450 There are only a few meaningful connections between different  
451 variables. One example is that `pol_score` has a small but statis-  
452 tically significant effect on `pol_ideology`, suggesting that when  
453 someone's political score changes, their reported ideology tends to  
454 shift slightly in the opposite direction at the next time point.

#### 455 4.6 PVAR and PCMCI+ Comparison

456 To understand the temporal and causal structure of climate attitudes,  
457 we compare PVAR and PCMCI+. Both rely on longitudinal panel  
458 data, but differ in their underlying assumptions and inference logic.  
459 To directly compare results, Figure 10 presents a matrix of lag-1  
460 edges detected by each method at  $\alpha = 0.01$ . PVAR identifies 46



**Figure 9: PCMCI+ causal graph. Nodes are colored by auto-MCI (self-dependence), and edges reflect causal strength.**



**Figure 10: Edge Comparison Matrix: Directed lag-1 edges detected by PVAR and PCMCI+. Only statistically significant links at  $\alpha < 0.01$  are displayed.**

Contrary to the expectations of the CIRES study (2024), perceptions of personal and local harm (community, family) are not significant predictors of policy support or WTP. This finding challenges the assumptions that direct exposure or proximity to harm is a primary driver of climate action support.

Political ideology does not significantly moderate how climate harm perceptions translate into WTP, contradicting parts of the literature (Fisher (2022)). Even after improving model stability through a harm index, no moderation effect emerged, thus indicating that ideological commitments shape climate action indirectly rather than interactively.

High standard errors for demographic variables (especially gender, income, and education) reflect time-invariant traits and small subgroup sizes. These predictors should be interpreted with caution. There is no evidence of multicollinearity for demographics (low VIFs), so imprecision probably is a result of data sparsity, not model redundancy.

PVAR detects broader temporal correlations. PCMCI+ produces a sparser and more conservative network that isolates direct causal links. One key difference is that PCMCI+ does not include variables that show little or no variation over time, whereas PVAR can still assign predictive value to them. This contributes to the lower number of edges in PCMCI+. Fewer shared edges overall reflect the differing inference logic of the two methods: predictive modeling in PVAR versus conditional independence testing in PCMCI+. The shared edge (`pol_score` → `pol_ideology`) found by both PVAR and PCMCI+ suggests that people's political identity, such as whether they lean Democrat or Republican, strongly influences how they describe themselves ideologically. The fact that this link appears in both models makes it more reliable and highlights the central role political identity plays in shaping climate attitudes and policy preferences.

links, while PCMCI+ finds just 15. In this analysis, PCMCI+ uses partial correlation (ParCorr) as its CI test, which captures only linear associations, potentially missing non-linear effects. Similarly, we estimated the Panel Vector Autoregression (PVAR) using Ordinary Least Squares (OLS), which also assumes linearity. Therefore, while both methods help uncover temporal dependencies, they are limited in their ability to detect complex, nonlinear relationships that may exist in the data.

The edge from `pol_score` to `pol_ideology` is detected by both methods.

## 5 DISCUSSION

Support for climate policies remains stable during elections, consistent with findings from the CIRES study [2] and Ogami (2024) [17], which suggest that attitudes are shaped by values, not elections. Global harm perception is a consistent predictor of support across policies, reinforcing theories that threats to the whole world motivate us to act (Hahnel et al. (2020) [3], Fisher (2022) [7]). Support for one policy (e.g., carbon tax) predicts support for another (e.g., emissions standards). Only prior support for carbon taxes predicts WTP, suggesting that voters' financial commitment to climate action is slow to change in elections (Schulze et al., (2021) [22]).

Carbon tax support is ideologically polarized, with conservatives less supportive, which is consistent with the CIRES and Fisher studies. In contrast, emissions standards are less polarized. Concern for the poor (`cc4_poorUS`) significantly predicts support for emissions standards, highlighting that fairness considerations (Fisher (2022)) influence regulatory policy support more than taxation.

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This study has several limitations. First, the data are not nationally representative, so findings should be interpreted with caution and not generalized beyond the sample. Second, the short time series (T=3) restricts the ability to detect complex causal relationships. Third, the analysis lacks a control group; future work could address this by building a synthetic control. Although the data set includes quota designed to align with actual voting patterns, the filtering applied in this analysis may have affected that balance. Future work should verify whether the filtered sample still reflects the broader voting population. Fourth, although binary demographic groupings (for income and education) were included in the models, no adjustments were made to ensure these groups were balanced or representative. This may help explain why demographic variables consistently failed to reach significance across models. Future research should revisit the construction of these groupings to correct any imbalances and improve reliability. Finally, future research should employ longer panel datasets and explore non-linear modeling techniques to capture more complex dynamics.

## 6 CONCLUSION

This study examined how public support for climate policies and willingness to pay (WTP) for climate solutions evolve during elections. Applying both Panel VAR and PCMCI+ models, we found that climate attitudes are remarkably stable over time. Prior support for climate policies, especially carbon taxes, strongly predicts both policy support and WTP, while global perceptions of climate harm (e.g., harm to the world) are more influential than localized or personal concerns.

While ideology shapes overall policy preferences, it does not appear to influence how people translate climate risks into financial support contrary to previous studies. These findings suggest that values, not elections, drive climate attitudes thus highlighting the importance of long-term engagement strategies over short-term campaign messaging.

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## Appendix A RISK ASSESSMENT

### A.1 Computational Challenges

**Risk:** Both the PCMCI+ algorithm and the bootstrapping procedure are computationally expensive. PCMCI+ can become particularly intensive with large panel datasets and multiple time lags, while bootstrapping, especially at the respondent level and across multiple outcomes, adds a substantial processing burden due to repeated model estimations.

**Mitigation:** Start with a reduced subset of the data to test and profile both the PCMCI+ and bootstrapping pipelines. Optimize code efficiency (e.g., vectorization, parallelization) and make use of high-performance computing environments such as cloud infrastructure or the Snellius Dutch National Supercomputer.

**Plan B:** If computational limitations remain a bottleneck, simplify the model structure (e.g., fewer lags, limited predictors) or reduce the number of bootstrap replications while maintaining statistical reliability.

### A.2 Ethical Considerations

**Risk:** Potential misuse of the findings for political purposes.

**Mitigation:** Clearly state the limitations of the study and provide guidelines for ethical use of the results in the thesis and repository.

**Plan B:** Include an "Ethical Use" section, outlining specific scenarios of appropriate and inappropriate use of the findings.

## Appendix B GENERATIVE AI

Throughout the research process, GenAI tools were used in a limited and clearly defined manner to support productivity, not to generate academic content. Specifically, OpenAI's ChatGPT and GitHub's Copilot were used to debug Python code and improve the visualization of causal graphs. In all cases, the modeling choices, and interpretation of results were made by the author. No text or analysis was generated or copied without critical review and full authorship responsibility. The use of GenAI adhered to the University's guidelines for ethical use of AI in research.

## Appendix C SOFTWARE TOOLS

Tool/Library	Purpose
graphviz [6]	Rendering directed acyclic graphs (DAGs)
matplotlib [12]	Static plotting
networkx [8]	Construction and layout of causal graphs
numpy [10]	Numerical operations and array handling
pandas [16]	Data manipulation and panel structuring
plotly [18]	Interactive network visualizations
seaborn [24]	Statistical graphics for EDA
skimpy [4]	Quick summaries and data diagnostics
statsmodels [23]	PVAR estimation
tigramite [21]	Time-lagged causal discovery (PCMCI+)

Table 7: Software Tools Used in the Analysis.

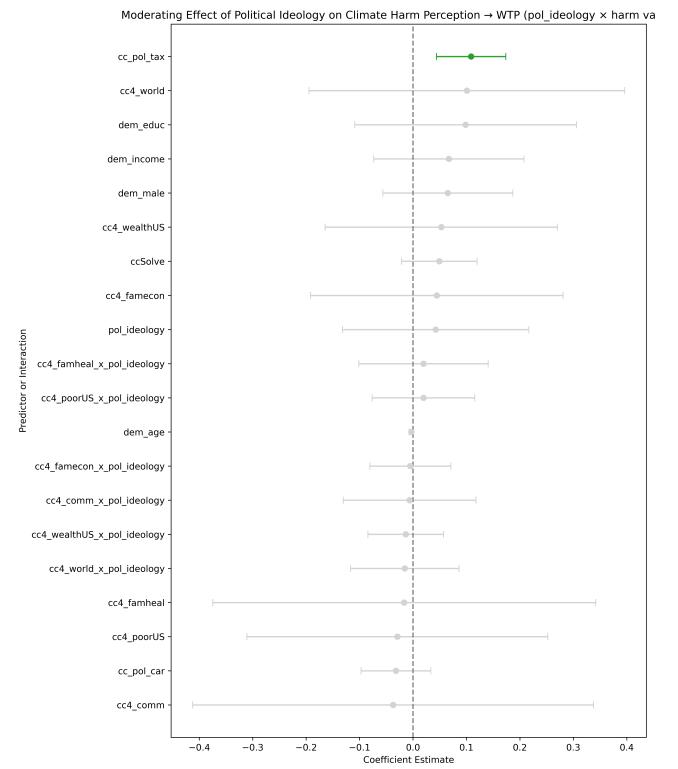


Figure 11: Moderation model with interaction terms between harm perceptions and political ideology. Only prior support for a carbon tax is significant ( $p < 0.01$ ).

	Dependent Variable	R-squared	Adj. R-squared	AIC	BIC
0	cc4_world	0.634	0.631	4087.31	4174.53
1	cc4_wealthUS	0.370	0.364	5105.95	5193.17
2	cc4_poorUS	0.553	0.549	4673.02	4760.24
3	cc4_comm	0.507	0.502	4616.12	4703.34
4	cc4_famheal	0.465	0.461	4793.37	4880.59
5	cc4_famecon	0.361	0.356	5128.48	5215.70
6	ccSolve	0.076	0.068	4726.43	4813.65
7	cc_pol_tax	0.501	0.497	4614.25	4701.47
8	cc_pol_car	0.507	0.503	4403.83	4491.05
9	pol_score	0.889	0.888	2945.85	3033.07
10	pol_ideology	0.826	0.824	2080.67	2167.89
11	dem_income	1.000	1.000	-113811.37	-113724.15
12	dem_age	1.000	1.000	-101516.90	-101429.68
13	dem_educ	1.000	1.000	-116356.65	-116269.43
14	dem_male	1.000	1.000	-115817.82	-115730.60

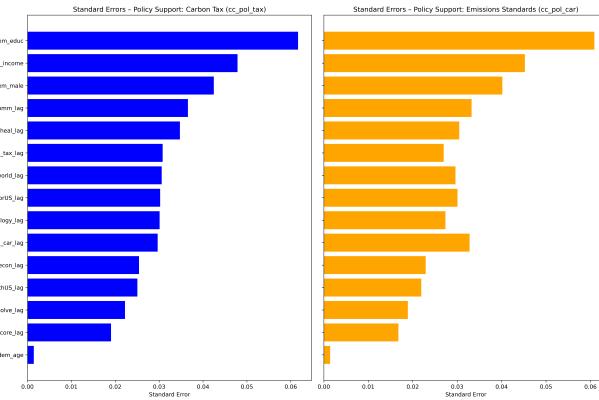
Table 8: Model fit statistics for each dependent variable

671 reported for RQ2. The bootstrap results for RQ3 are available in the  
672 project code repository.

## Appendix D RESULTS

### Appendix E BOOTSTRAPPING

669 We do not include a separate table of bootstrap results for RQ3,  
670 as the estimated effects and their stability closely mirror those



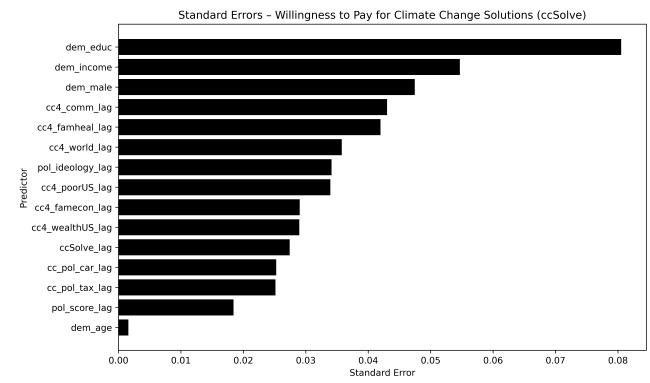
**Figure 12:** Standard errors for predictors in the carbon tax model (cc<sub>pol</sub>\_tax, left) and emissions standards model (cc<sub>pol</sub>\_car, right). In both cases, the demographic variables – education, income, and gender – exhibit the highest standard errors

**Table 9: Subgroup Sizes by Gender, Income, and Education**

Gender	Income	Education	Count
Female / Self-described	Low	High	42
Male	Low	High	43
Female / Self-described	High	High	46
Male	High	High	111
Female / Self-described	High	Low	153
Male	High	Low	213
Male	Low	Low	453
Female / Self-described	Low	Low	661

**Table 10: Variance Inflation Factors (VIF) - RQ1**

Variable	VIF	Interpretation
cc4_comm_lag	4.66	Some correlation (acceptable)
cc4_famheal_lag	4.22	Some correlation (acceptable)
cc4_poorUS_lag	3.94	Some correlation (acceptable)
cc4_world_lag	3.60	Some correlation (acceptable)
cc4_famecon_lag	2.44	Some correlation (acceptable)
cc4_wealthUS_lag	2.38	Some correlation (acceptable)
cc_pol_car_lag	2.17	Some correlation (acceptable)
cc_pol_tax_lag	2.16	Some correlation (acceptable)
pol_score_lag	1.99	Low correlation (no multicollinearity)
pol_ideology_lag	1.94	Low correlation (no multicollinearity)
dem_income_lag	1.16	Low correlation (no multicollinearity)
dem_educ_lag	1.14	Low correlation (no multicollinearity)
ccSolve_lag	1.07	Low correlation (no multicollinearity)
dem_age_lag	1.06	Low correlation (no multicollinearity)
dem_male_lag	1.06	Low correlation (no multicollinearity)



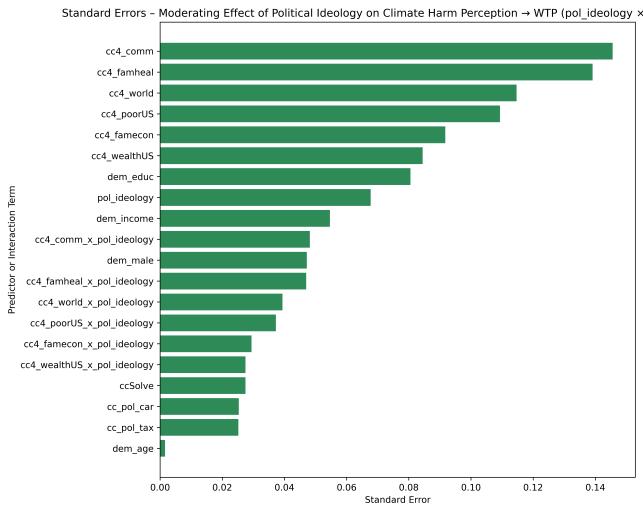
**Figure 13:** Standard errors of predictors in the ccSolve model. Variables with the highest uncertainty are shown at the top.

**Table 11: Variance Inflation Factors (VIF) - RQ2**

Variable	VIF	Interpretation
cc4_comm_lag	4.66	Some correlation (acceptable)
cc4_famheal_lag	4.22	Some correlation (acceptable)
cc4_poorUS_lag	3.94	Some correlation (acceptable)
cc4_world_lag	3.60	Some correlation (acceptable)
cc4_famecon_lag	2.44	Some correlation (acceptable)
cc4_wealthUS_lag	2.38	Some correlation (acceptable)
cc_pol_car_lag	2.17	Some correlation (acceptable)
cc_pol_tax_lag	2.16	Some correlation (acceptable)
pol_score_lag	1.99	Low correlation (no multicollinearity)
pol_ideology_lag	1.94	Low correlation (no multicollinearity)
dem_income_lag	1.15	Low correlation (no multicollinearity)
dem_educ_lag	1.13	Low correlation (no multicollinearity)
ccSolve_lag	1.07	Low correlation (no multicollinearity)
dem_age_lag	1.06	Low correlation (no multicollinearity)
dem_male_lag	1.06	Low correlation (no multicollinearity)

**Table 12: VIF - Full Interaction Model (RQ3)**

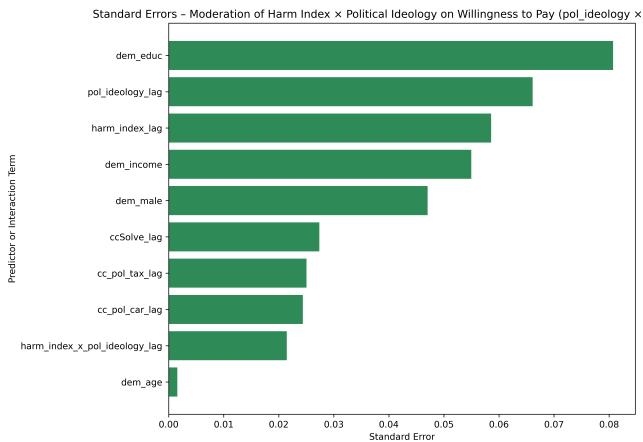
Variable	VIF	Interpretation
cc4_comm_x_pol_ideology	86.92	High multicollinearity (problematic)
cc4_world_x_pol_ideology	77.89	High multicollinearity (problematic)
cc4_famheal_x_pol_ideology	76.56	High multicollinearity (problematic)
cc4_poorUS_x_pol_ideology	71.04	High multicollinearity (problematic)
cc4_comm	46.93	High multicollinearity (problematic)
cc4_famheal	41.32	High multicollinearity (problematic)
cc4_wealthUS_x_pol_ideology	39.09	High multicollinearity (problematic)
cc4_famecon_x_pol_ideology	32.90	High multicollinearity (problematic)
cc4_poorUS	31.39	High multicollinearity (problematic)
cc4_world	28.55	High multicollinearity (problematic)
cc4_wealthUS	23.77	High multicollinearity (problematic)
cc4_famecon	22.58	High multicollinearity (problematic)
pol_ideology	10.80	High multicollinearity (problematic)
cc_pol_car	2.18	Some correlation (acceptable)
cc_pol_tax	2.16	Some correlation (acceptable)
dem_income	1.16	Low correlation (no multicollinearity)
dem_educ	1.15	Low correlation (no multicollinearity)
ccSolve	1.08	Low correlation (no multicollinearity)
dem_age	1.07	Low correlation (no multicollinearity)
dem_male	1.06	Low correlation (no multicollinearity)



**Figure 14: Standard errors for predictors in the full interaction model (RQ3). Harm perception variables and their interaction terms exhibit the largest uncertainty.**

**Table 13: VIF - Harm Index Moderation Model (RQ3)**

Variable	VIF	Interpretation
harm_index × pol_ideology_lag	19.65	High multicollinearity (problematic)
pol_ideology_lag	8.54	Moderate multicollinearity (monitor)
harm_index_lag	8.33	Moderate multicollinearity (monitor)
cc_pol_tax_lag	2.14	Some correlation (acceptable)
cc_pol_car_lag	2.05	Some correlation (acceptable)
dem_income	1.15	Low correlation (no multicollinearity)
dem_educ	1.14	Low correlation (no multicollinearity)
ccSolve_lag	1.07	Low correlation (no multicollinearity)
dem_male	1.06	Low correlation (no multicollinearity)
dem_age	1.04	Low correlation (no multicollinearity)



**Figure 15: Standard errors in the simplified harm index model. The interaction term is more stable, with reduced uncertainty.**

**Table 14: PVAR Model vs Bootstrap - cc\_pol\_car**

Variable	Model p-value	Bootstrap significant?	Notes
const	0.0000	Yes	Agreement
cc4_world_lag	0.0000	Yes	Agreement
cc4_wealthUS_lag	0.0278	Yes	Agreement
cc4_poorUS_lag	0.0011	Yes	Agreement
cc4_comm_lag	0.8296	No	Agreement
cc4_famheal_lag	0.9694	No	Agreement
cc4_famecon_lag	0.4048	No	Agreement
ccSolve_lag	0.4585	No	Agreement
cc_pol_tax_lag	0.0000	Yes	Agreement
cc_pol_car_lag	0.0000	Yes	Agreement
pol_score_lag	0.0286	Yes	Agreement
pol_ideology_lag	0.0277	Yes	Agreement
dem_income	0.2638	No	Agreement
dem_age	0.4348	No	Agreement
dem_educ	0.4778	No	Agreement
dem_male	0.9363	No	Agreement

**Table 15: PVAR Model vs Bootstrap - cc\_pol\_tax**

Variable	Model p-value	Bootstrap significant?	Notes
const	0.0004	Yes	Agreement
cc4_world_lag	0.0000	Yes	Agreement
cc4_wealthUS_lag	0.0800	No	Agreement
cc4_poorUS_lag	0.0532	No	Agreement
cc4_comm_lag	0.4881	No	Agreement
cc4_famheal_lag	0.9730	No	Agreement
cc4_famecon_lag	0.4744	No	Agreement
ccSolve_lag	0.0001	Yes	Agreement
cc_pol_tax_lag	0.0000	Yes	Agreement
cc_pol_car_lag	0.0000	Yes	Agreement
pol_score_lag	0.0000	Yes	Agreement
pol_ideology_lag	0.2071	No	Agreement
dem_income	0.3696	No	Agreement
dem_age	0.1756	No	Agreement
dem_educ	0.0103	Yes	Agreement
dem_male	0.5264	No	Agreement

**Table 16: PVAR Model vs Bootstrap - cc4\_comm**

Variable	Model p-value	Bootstrap significant?	Notes
const	0.0007	Yes	Agreement
cc4_world_lag	0.0020	Yes	Agreement
cc4_wealthUS_lag	0.3777	No	Agreement
cc4_poorUS_lag	0.4075	No	Agreement
cc4_comm_lag	0.0000	Yes	Agreement
cc4_famheal_lag	0.0040	Yes	Agreement
cc4_famecon_lag	0.3456	No	Agreement
ccSolve_lag	0.1687	No	Agreement
cc_pol_tax_lag	0.0888	No	Agreement
cc_pol_car_lag	0.0051	Yes	Agreement
pol_score_lag	0.0044	Yes	Agreement
pol_ideology_lag	0.0193	Yes	Agreement
dem_income	0.0306	Yes	Agreement
dem_age	0.8168	No	Agreement
dem_educ	0.8303	No	Agreement
dem_male	0.8842	No	Agreement

**Table 17: PVAR Model vs Bootstrap – cc4\_famecon**

Variable	Model p-value	Bootstrap significant?	Notes
const	0.0000	Yes	Agreement
cc4_world_lag	0.5872	No	Agreement
cc4_wealthUS_lag	0.2279	No	Agreement
cc4_poorUS_lag	0.8337	No	Agreement
cc4_comm_lag	0.0000	Yes	Agreement
cc4_famheal_lag	0.1431	No	Agreement
cc4_famecon_lag	0.0000	Yes	Agreement
ccSolve_lag	0.9411	No	Agreement
cc_pol_tax_lag	0.0302	Yes	Agreement
cc_pol_car_lag	0.2164	No	Agreement
pol_score_lag	0.0581	Yes	Bootstrap-only
pol_ideology_lag	0.6334	No	Agreement
dem_income	0.5461	No	Agreement
dem_age	0.0064	Yes	Agreement
dem_educ	0.8511	No	Agreement
dem_male	0.6568	No	Agreement

**Table 18: PVAR Model vs Bootstrap – cc4\_famheal**

Variable	Model p-value	Bootstrap significant?	Notes
const	0.0001	Yes	Agreement
cc4_world_lag	0.2266	No	Agreement
cc4_wealthUS_lag	0.5305	No	Agreement
cc4_poorUS_lag	0.3100	No	Agreement
cc4_comm_lag	0.0000	Yes	Agreement
cc4_famheal_lag	0.0000	Yes	Agreement
cc4_famecon_lag	0.0014	Yes	Agreement
ccSolve_lag	0.5812	No	Agreement
cc_pol_tax_lag	0.0003	Yes	Agreement
cc_pol_car_lag	0.8216	No	Agreement
pol_score_lag	0.2093	No	Agreement
pol_ideology_lag	0.1386	No	Agreement
dem_income	0.3400	No	Agreement
dem_age	0.0801	No	Agreement
dem_educ	0.7166	No	Agreement
dem_male	0.1592	No	Agreement

**Table 19: PVAR Model vs Bootstrap – cc4\_poorUS**

Variable	Model p-value	Bootstrap significant?	Notes
const	0.0052	Yes	Agreement
cc4_world_lag	0.0000	Yes	Agreement
cc4_wealthUS_lag	0.1149	No	Agreement
cc4_poorUS_lag	0.0000	Yes	Agreement
cc4_comm_lag	0.0025	Yes	Agreement
cc4_famheal_lag	0.0012	Yes	Agreement
cc4_famecon_lag	0.0597	Yes	Bootstrap-only
ccSolve_lag	0.1808	No	Agreement
cc_pol_tax_lag	0.0264	Yes	Agreement
cc_pol_car_lag	0.0000	Yes	Agreement
pol_score_lag	0.0004	Yes	Agreement
pol_ideology_lag	0.0010	Yes	Agreement
dem_income	0.3656	No	Agreement
dem_age	0.6850	No	Agreement
dem_educ	0.6397	No	Agreement
dem_male	0.5726	No	Agreement

**Table 20: PVAR Model vs Bootstrap – cc4\_wealthUS**

Variable	Model p-value	Bootstrap significant?	Notes
const	0.0013	Yes	Agreement
cc4_world_lag	0.1362	No	Agreement
cc4_wealthUS_lag	0.0000	Yes	Agreement
cc4_poorUS_lag	0.1468	No	Agreement
cc4_comm_lag	0.0000	Yes	Agreement
cc4_famheal_lag	0.2283	No	Agreement
cc4_famecon_lag	0.1026	No	Agreement
ccSolve_lag	0.9218	No	Agreement
cc_pol_tax_lag	0.0001	Yes	Agreement
cc_pol_car_lag	0.4590	No	Agreement
pol_score_lag	0.0340	Yes	Agreement
pol_ideology_lag	0.5162	No	Agreement
dem_income	0.0621	Yes	Bootstrap-only
dem_age	0.0984	No	Agreement
dem_educ	0.6408	No	Agreement
dem_male	0.6390	No	Agreement

**Table 21: PVAR Model vs Bootstrap – cc4\_world**

Variable	Model p-value	Bootstrap significant?	Notes
const	0.0009	Yes	Agreement
cc4_world_lag	0.0000	Yes	Agreement
cc4_wealthUS_lag	0.1623	No	Agreement
cc4_poorUS_lag	0.0094	Yes	Agreement
cc4_comm_lag	0.2977	No	Agreement
cc4_famheal_lag	0.0107	Yes	Agreement
cc4_famecon_lag	0.4593	No	Agreement
ccSolve_lag	0.2751	No	Agreement
cc_pol_tax_lag	0.0000	Yes	Agreement
cc_pol_car_lag	0.0000	Yes	Agreement
pol_score_lag	0.0176	Yes	Agreement
pol_ideology_lag	0.0102	Yes	Agreement
dem_income	0.9023	No	Agreement
dem_age	0.5480	No	Agreement
dem_educ	0.6456	No	Agreement
dem_male	0.6100	No	Agreement

**Table 22: PVAR Model vs Bootstrap – ccSolve**

Variable	Model p-value	Bootstrap significant?	Notes
const	0.0000	Yes	Agreement
cc4_world_lag	0.0798	No	Agreement
cc4_wealthUS_lag	0.7218	No	Agreement
cc4_poorUS_lag	0.3714	No	Agreement
cc4_comm_lag	0.1418	No	Agreement
cc4_famheal_lag	0.2343	No	Agreement
cc4_famecon_lag	0.2762	No	Agreement
ccSolve_lag	0.0420	No	Partial disagreement
cc_pol_tax_lag	0.0000	Yes	Agreement
cc_pol_car_lag	0.2574	No	Agreement
pol_score_lag	0.7495	No	Agreement
pol_ideology_lag	0.1344	No	Agreement
dem_income	0.2296	No	Agreement
dem_age	0.0562	No	Agreement
dem_educ	0.1646	No	Agreement
dem_male	0.1705	No	Agreement

**Table 23: PVAR Model vs Bootstrap – dem\_age**

Variable	Model p-value	Bootstrap significant?	Notes
const	0.0000	No	Partial disagreement
cc4_world_lag	0.9928	No	Agreement
cc4_wealthUS_lag	0.0000	No	Partial disagreement
cc4_poorUS_lag	0.0096	No	Partial disagreement
cc4_comm_lag	0.0000	No	Partial disagreement
cc4_famheal_lag	0.0000	No	Partial disagreement
cc4_famecon_lag	0.0007	No	Partial disagreement
ccSolve_lag	0.8662	No	Agreement
cc_pol_tax_lag	0.0068	No	Partial disagreement
cc_pol_car_lag	0.7591	No	Agreement
pol_score_lag	0.0508	No	Agreement
pol_ideology_lag	0.0401	No	Partial disagreement
dem_income	0.0175	No	Partial disagreement
dem_age	0.0000	Yes	Agreement
dem_educ	0.4278	No	Agreement
dem_male	0.2873	No	Agreement

**Table 24: PVAR Model vs Bootstrap – dem\_educ**

Variable	Model p-value	Bootstrap significant?	Notes
const	0.0000	No	Partial disagreement
cc4_world_lag	0.0001	No	Partial disagreement
cc4_wealthUS_lag	0.7097	No	Agreement
cc4_poorUS_lag	0.0587	No	Agreement
cc4_comm_lag	0.0000	No	Partial disagreement
cc4_famheal_lag	0.0937	No	Agreement
cc4_famecon_lag	0.0000	No	Partial disagreement
ccSolve_lag	0.1293	No	Agreement
cc_pol_tax_lag	0.3878	No	Agreement
cc_pol_car_lag	0.0023	No	Partial disagreement
pol_score_lag	0.0893	No	Agreement
pol_ideology_lag	0.0046	No	Partial disagreement
dem_income	0.0000	No	Partial disagreement
dem_age	0.0000	No	Partial disagreement
dem_educ	0.0000	Yes	Agreement
dem_male	0.0000	No	Partial disagreement

**Table 25: PVAR Model vs Bootstrap – dem\_income**

Variable	Model p-value	Bootstrap significant?	Notes
const	0.0059	No	Partial disagreement
cc4_world_lag	0.2314	No	Agreement
cc4_wealthUS_lag	0.0037	No	Partial disagreement
cc4_poorUS_lag	0.0118	No	Partial disagreement
cc4_comm_lag	0.0000	No	Partial disagreement
cc4_famheal_lag	0.0000	No	Partial disagreement
cc4_famecon_lag	0.0000	No	Partial disagreement
ccSolve_lag	0.1015	No	Agreement
cc_pol_tax_lag	0.0990	No	Agreement
cc_pol_car_lag	0.0011	No	Partial disagreement
pol_score_lag	0.0000	No	Partial disagreement
pol_ideology_lag	0.0027	No	Partial disagreement
dem_income	0.0000	Yes	Agreement
dem_age	0.0000	No	Partial disagreement
dem_educ	0.8780	No	Agreement
dem_male	0.0000	No	Partial disagreement

**Table 26: PVAR Model vs Bootstrap – dem\_male**

Variable	Model p-value	Bootstrap significant?	Notes
const	0.4530	No	Agreement
cc4_world_lag	0.3646	No	Agreement
cc4_wealthUS_lag	0.0398	No	Partial disagreement
cc4_poorUS_lag	0.0117	No	Partial disagreement
cc4_comm_lag	0.0000	No	Partial disagreement
cc4_famheal_lag	0.0000	No	Partial disagreement
cc4_famecon_lag	0.0000	No	Partial disagreement
ccSolve_lag	0.0000	No	Partial disagreement
cc_pol_tax_lag	0.0000	No	Partial disagreement
cc_pol_car_lag	0.0000	No	Partial disagreement
pol_score_lag	0.1401	No	Agreement
pol_ideology_lag	0.0123	No	Partial disagreement
dem_income	0.3760	No	Agreement
dem_age	0.0000	No	Partial disagreement
dem_educ	0.0045	No	Partial disagreement
dem_male	0.0000	Yes	Agreement

**Table 27: PVAR Model vs Bootstrap – pol\_ideology**

Variable	Model p-value	Bootstrap significant?	Notes
const	0.0000	Yes	Agreement
cc4_world_lag	0.9462	No	Agreement
cc4_wealthUS_lag	0.7204	No	Agreement
cc4_poorUS_lag	0.4194	No	Agreement
cc4_comm_lag	0.4287	No	Agreement
cc4_famheal_lag	0.5793	No	Agreement
cc4_famecon_lag	0.8091	No	Agreement
ccSolve_lag	0.0433	No	Partial disagreement
cc_pol_tax_lag	0.1154	No	Agreement
cc_pol_car_lag	0.8064	No	Agreement
pol_score_lag	0.0000	Yes	Agreement
pol_ideology_lag	0.0000	Yes	Agreement
dem_income	0.9895	No	Agreement
dem_age	0.1613	No	Agreement
dem_educ	0.2698	No	Agreement
dem_male	0.5591	No	Agreement

**Table 28: PVAR Model vs Bootstrap – pol\_score**

Variable	Model p-value	Bootstrap significant?	Notes
const	0.0073	Yes	Agreement
cc4_world_lag	0.0884	No	Agreement
cc4_wealthUS_lag	0.1590	No	Agreement
cc4_poorUS_lag	0.9452	No	Agreement
cc4_comm_lag	0.9441	No	Agreement
cc4_famheal_lag	0.4420	No	Agreement
cc4_famecon_lag	0.1971	No	Agreement
ccSolve_lag	0.4616	No	Agreement
cc_pol_tax_lag	0.0983	No	Agreement
cc_pol_car_lag	0.5311	No	Agreement
pol_score_lag	0.0000	Yes	Agreement
pol_ideology_lag	0.0001	Yes	Agreement
dem_income	0.1056	No	Agreement
dem_age	0.9342	No	Agreement
dem_educ	0.5772	No	Agreement
dem_male	0.2547	No	Agreement

**Table 29: Model vs Bootstrap – RQ1 Tax Model**

Variable	Model <i>p</i> -value	Bootstrap significant?	Notes
const	0.0002	Yes	Agreement
cc4_world_lag	0.0000	Yes	Agreement
cc4_wealthUS_lag	0.0790	No	Agreement
cc4_poorUS_lag	0.0451	Yes	Agreement
cc4_comm_lag	0.4927	No	Agreement
cc4_famheal_lag	0.9732	No	Agreement
cc4_famecon_lag	0.4677	No	Agreement
ccSolve_lag	0.0001	Yes	Agreement
pol_score_lag	0.0000	Yes	Agreement
pol_ideology_lag	0.2216	No	Agreement
cc_pol_tax_lag	0.0000	Yes	Agreement
cc_pol_car_lag	0.0000	Yes	Agreement
dem_income	0.3301	No	Agreement
dem_educ	0.0047	Yes	Agreement
dem_male	0.4951	No	Agreement
dem_age	0.1442	No	Agreement

**Table 30: Model vs Bootstrap – RQ1 Car Model**

Variable	Model <i>p</i> -value	Bootstrap significant?	Notes
const	0.0000	Yes	Agreement
cc4_world_lag	0.0000	Yes	Agreement
cc4_wealthUS_lag	0.0176	Yes	Agreement
cc4_poorUS_lag	0.0014	Yes	Agreement
cc4_comm_lag	0.8257	No	Agreement
cc4_famheal_lag	0.9675	No	Agreement
cc4_famecon_lag	0.3778	No	Agreement
ccSolve_lag	0.3830	No	Agreement
pol_score_lag	0.0242	Yes	Agreement
pol_ideology_lag	0.0272	Yes	Agreement
cc_pol_tax_lag	0.0001	Yes	Agreement
cc_pol_car_lag	0.0000	Yes	Agreement
dem_income	0.2275	No	Agreement
dem_educ	0.4565	No	Agreement
dem_male	0.9318	No	Agreement
dem_age	0.4233	No	Agreement

**Table 31: Model vs Bootstrap – RQ2 Model**

Variable	Model <i>p</i> -value	Bootstrap significant?	Notes
const	0.0000	Yes	Agreement
cc4_world_lag	0.1016	No	Agreement
cc4_wealthUS_lag	0.7496	No	Agreement
cc4_poorUS_lag	0.3938	No	Agreement
cc4_comm_lag	0.2018	No	Agreement
cc4_famheal_lag	0.3138	No	Agreement
cc4_famecon_lag	0.3175	No	Agreement
pol_score_lag	0.7426	No	Agreement
pol_ideology_lag	0.1861	No	Agreement
cc_pol_tax_lag	0.0000	Yes	Agreement
cc_pol_car_lag	0.2054	No	Agreement
ccSolve_lag	0.0701	No	Agreement
dem_income	0.2384	No	Agreement
dem_educ	0.2259	No	Agreement
dem_male	0.1727	No	Agreement
dem_age	0.0548	Yes	Bootstrap-only

**Table 32: Bootstrap Results for PCMCI+**

Source	Target	Lag	Frequency
cc4_world	cc4_world	1	1.00
cc4_wealthUS	cc4_wealthUS	1	1.00
cc4_poorUS	cc4_poorUS	1	1.00
cc4_comm	cc4_comm	1	1.00
cc4_famecon	cc4_famecon	1	1.00
cc_pol_tax	cc_pol_tax	1	1.00
cc_pol_car	cc_pol_car	1	1.00
dem_income	dem_income	1	1.00
dem_age	dem_age	1	1.00
dem_educ	dem_educ	1	1.00
dem_male	dem_male	1	1.00
pol_score	pol_score	1	1.00
pol_ideology	pol_ideology	1	1.00
cc4_famheal	cc4_famheal	1	0.79
ccSolve	ccSolve	1	0.55
cc_pol_car	cc_pol_tax	1	0.10
cc_pol_tax	ccSolve	1	0.10
pol_score	pol_ideology	1	0.06

Note: Frequency indicates the proportion of bootstrap samples (out of 100) in which the edge was found to be statistically significant by PCMCI+ with  $\alpha = 0.01$ . All autoregressive edges (variable  $\rightarrow$  itself at lag 1) appeared in 100% of the samples.