

# 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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## 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, 14 pages. <https://doi.org/10.1145/nnnnnnn.nnnnnnn>

## 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?

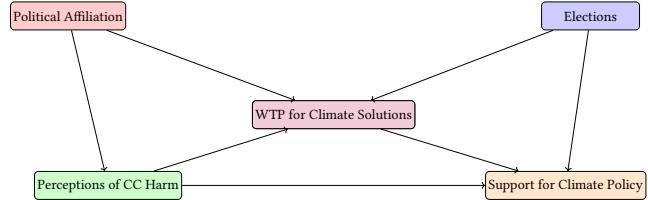


Figure 1: Conceptual Model: Key Relationships Based on Research Questions

## 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 [2] 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) [6] 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) [20] 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) [15] 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 [1] 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 [17], 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

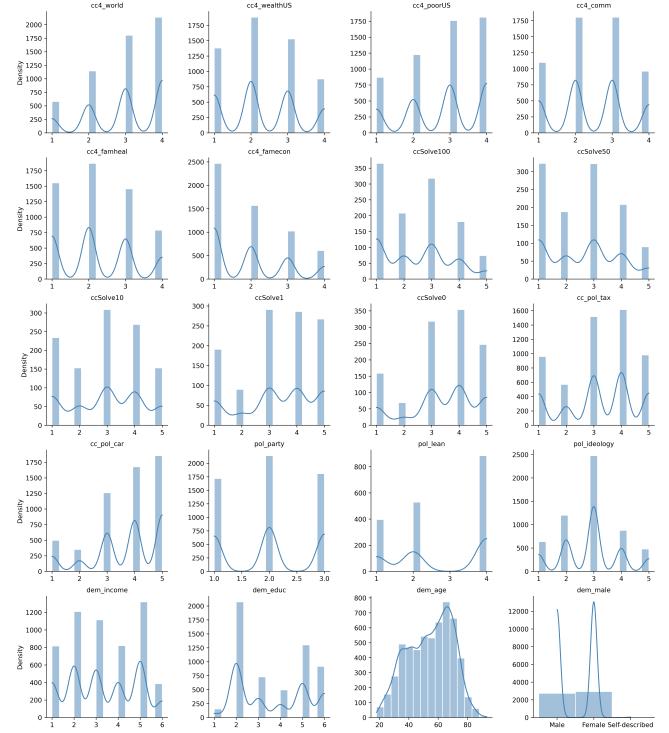
109 **Table 2: Variable coding and response scales (raw data)**

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  
 116 the distribution of key variables (raw data).



117 **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 [10] and the PCMCI+ causal discovery algorithm [18].

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 across time, making it ideal for understanding how climate concern, policy support, and political attitudes influence one another longitudinally [13].

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 CMknn, we use linear partial correlation (Par-Corr) tests, given the short panel length ( $T = 3$ ) in our data [18].

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. Table 5 lists the key packages used throughout the analysis.

### 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.

**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

Tool/Library	Purpose
graphviz [5]	Rendering directed acyclic graphs (DAGs)
matplotlib [11]	Static plotting
networkx [7]	Construction and layout of causal graphs
numpy [9]	Numerical operations and array handling
pandas [14]	Data manipulation and panel structuring
plotly [16]	Interactive network visualizations
seaborn [22]	Statistical graphics for EDA
skimpy [3]	Quick summaries and data diagnostics
statsmodels [21]	PVAR estimation
tigramite [19]	Time-lagged causal discovery (PCMCI+)

Table 5: Software Tools Used in the Analysis. Full citations available in the References section.

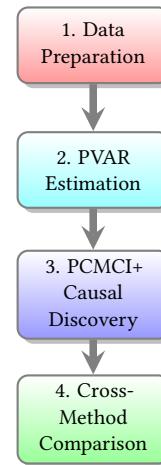


Figure 3: Overview of the main analytical steps in the study

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). 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 6.

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 6: 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 7 summarizes the descriptive statistics of the key variables in the data set after filtering.

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%						
dem_educ	0.00%	Low = 86.1%, High = 13.9%						
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%						

Table 7: Data Summary (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 be viewed as indicative of broader trends rather than as fully generalizable. To mitigate potential bias, demographic variables were inspected for distributional imbalances, and binary groups were constructed to ensure that each category reflected balanced splits.

3.3.2 *PVAR Estimation*. For RQ1, we estimate global PVAR(1) models in which policy support variables are regressed on their 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.

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 OLS 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.

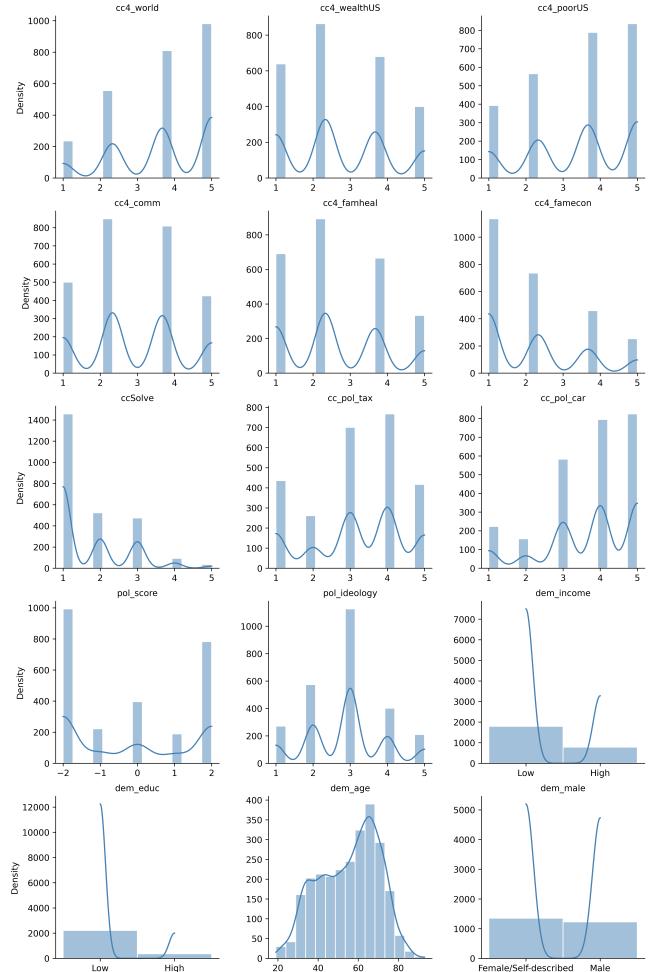


Figure 4: Distributions with Density Overlay (after filtering)

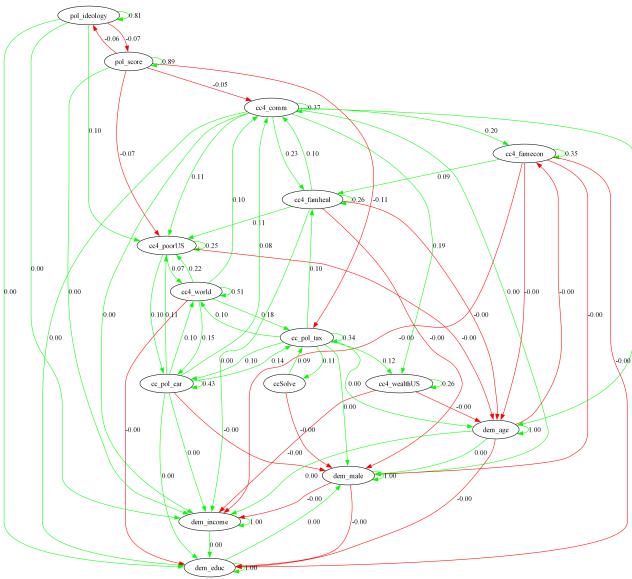
This resampling approach is commonly used in panel data settings [8] [4]. The full bootstrapping procedure is implemented in Python and documented in the project repository. Summary tables of the bootstrap distributions and coefficient intervals are provided in Appendix D.

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 D Table 16, and the code is available in the project repository.

## 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.

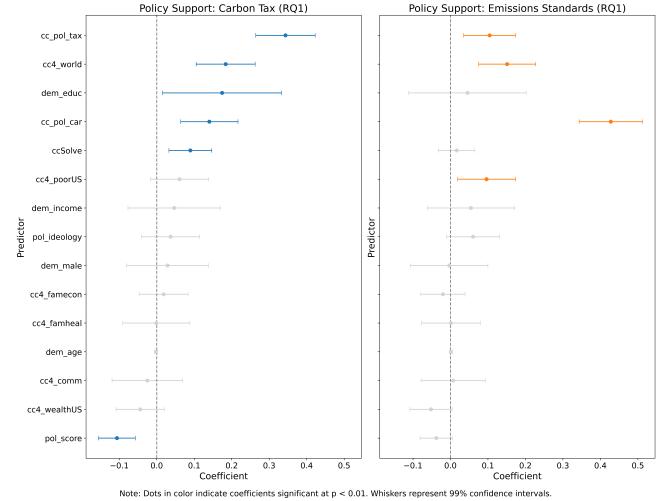


**Figure 5: PVAR Lagged Effects ( $p < 0.01$ ).** Edge labels indicate standardized coefficients from lagged OLS models. Green = positive, Red = negative effects.

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

To investigate whether support for climate policies fluctuates during elections, and whether such support is shaped by perceptions of climate-related harm, we estimated a reduced-form panel vector autoregression (PVAR(1)) model. The analysis focused on two outcome variables: support for carbon taxes (cc<sub>pol</sub>\_tax) and support for vehicle emissions standards (cc<sub>pol</sub>\_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 and emissions standards.** 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 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 individuals tend to maintain stable preferences. There is also evidence of cross-policy spillover, with prior support for emissions standards (cc<sub>pol</sub>\_car) significantly predicting later support for carbon taxes and vice versa. These findings show that people's views on climate policies remain mostly the same.

Support for carbon taxes is significantly influenced by several attitudinal and demographic predictors. Individuals who perceive that climate change harms the world (cc<sub>4\_world</sub>) 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 (cc<sub>4\_comm</sub>) or family health (cc<sub>4\_famheal</sub>) – do not significantly influence support for carbon taxes at the stricter  $p < 0.01$  threshold. Education level (dem<sub>educ</sub>) is also positively associated with support ( $p = 0.0047$ ), suggesting that 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. The drop in statistical significance is not due to a diminished effect size – the coefficient remains substantial (0.174) – but rather to a relatively high standard error (0.068), which reduces the model's confidence in the estimate. Furthermore, the willingness to financially contribute to climate solutions (ccSolve) significantly predicts support for carbon taxes.

293 In contrast, the political orientation (*pol\_score*) exhibits a negative  
294 significant relationship, with more conservative individuals  
295 being less supportive of carbon taxes.

296 The emission standards model reveals a somewhat different set  
297 of predictors. Again, global harm perception (*cc4\_world*) remains  
298 a significant and positive predictor of support. In addition, concern  
299 about the impact of climate change on the poor in the United States  
300 (*cc4\_poorUS*) is positively associated with support. This suggests  
301 that concerns about fairness, especially how climate change affects  
302 poorer people in the country, influence support for climate rules.  
303 As with the carbon tax model, both autoregressive and cross-policy  
304 predictors are significant. Past support for emissions standards  
305 (*cc\_pol\_car*) and carbon taxes (*cc\_pol\_tax*) each positively influence  
306 current support for emissions standards. Demographic character-  
307 istics do not reach statistical significance in this model. This  
308 shows that personal values and beliefs matter more than things like  
309 age, income, or education when it comes to supporting climate rules.  
310 Unlike carbon taxes, emission standards appear less ideologically  
311 polarized, as political orientation does not emerge as a significant  
312 predictor.

313 Demographic variables such as *dem\_educ\_lag*, *dem\_income\_lag*,  
314 and *dem\_male\_lag* show the highest standard errors in both the  
315 carbon tax and emissions standards models. These predictors con-  
316 tribute disproportionately to overall model uncertainty, as evi-  
317 denced by their wide confidence intervals in the dot-whisker plots  
318 in Figure 6 and elevated standard errors in Appendix C Figure 12.

319 Several factors may explain the imprecision associated with  
320 demographic predictors. First, characteristics such as gender and  
321 education are largely time-invariant, offering limited within-subject  
322 variation across survey waves. Second, some of the high standard  
323 errors for demographic variables such as gender, income, and edu-  
324 cation may be due to small subgroup sizes in the data. For example,  
325 there are only 42 observations from female or self-described respon-  
326 dents with low income and high education, 43 from male respon-  
327 dents with the same traits, and 46 from female or self-described  
328 respondents with high income and high education. These small  
329 groups reduce the ability of the model to estimate precise effects,  
330 likely contributing to the wide confidence intervals observed in  
331 Figures 6 and 12. Table 8 in Appendix C shows the number of obser-  
332 vations for each subgroup. It should be noted that variance inflation  
333 factors (VIFs) for these variables are low (Table 9 in Appendix C)  
334 [12], indicating that multicollinearity is not the primary source  
335 of uncertainty. Taken together, these considerations suggest that  
336 demographic predictors should be interpreted with caution in this  
337 analysis.

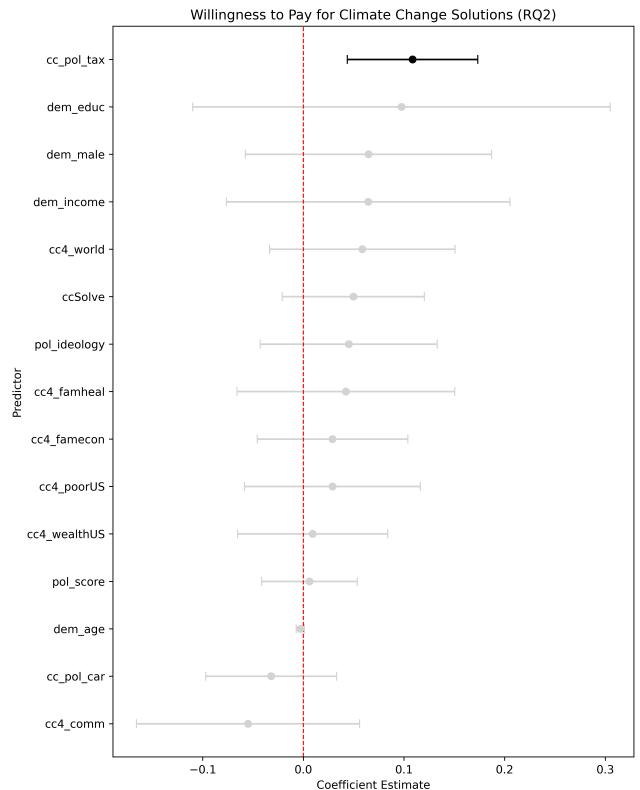
338 Together, these results suggest that support for climate policy  
339 during elections is primarily shaped by global environmental con-  
340 cern, policy consistency, and - especially in the case of emissions  
341 standards – concern for social fairness. In contrast, perceptions of  
342 local or familial harm do not play a statistically significant role in  
343 shaping support, contrary to some expectations in the literature.  
344 The difference in how political views affect support for the two  
345 policies suggests that carbon taxes are more politically divisive  
346 than policies like emissions standards.

347 Overall, the analysis shows that people’s views on climate poli-  
348 cies do not change during short-term political events such as elec-  
349 tions. Instead, people’s views are based on long-lasting values and

350 past opinions. This is important for understanding how likely cli-  
351 mate action will succeed, especially during elections when politi-  
352 cians are more likely to listen to voters.

### 353 4.3 RQ2 – Drivers of WTP for Climate Solutions

354 The reduced-form PVAR(1) model for ccSolve (willingness to pay  
355 for climate action) reveals that attitudes remain highly stable through-  
356 out the election period. Among all lagged predictors, only one vari-  
357 able - prior support for a carbon tax (*cc\_pol\_tax*) – emerges as a  
358 statistically significant predictor at the  $p < 0.01$  level. This finding  
359 indicates that individuals who previously expressed support for  
360 carbon pricing are more likely to report a willingness to pay for  
361 broader climate solutions in subsequent waves. Figure 7 displays  
362 the estimated coefficients using dot-whisker plots, highlighting  
363 statistically significant predictors at the  $p < 0.01$  level with 99%  
364 confidence intervals.



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

370 An inspection of the standard errors reveals that *dem\_educ\_lag*,  
371 *dem\_income\_lag*, and *dem\_male\_lag* exhibit the largest standard  
372 errors among all predictors (see Figure 13 in Appendix C). These  
373 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 likely 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 across survey waves, reducing within-subject variability. In particular, the variance inflation factors (VIFs) for these predictors are low (see Table 10 in Appendix C), indicating that multicollinearity is not a primary concern in this model.

#### 381 4.4 RQ3 – Moderating Role of Political Ideology

382 To explore this question, we extended the PVAR(1) model to include  
383 interaction terms between perceived climate harms and the political  
384 ideology of the respondents. The aim was to test whether the  
385 effect of harm perceptions on the willingness to financially support  
386 climate solutions varies across the ideological spectrum.

387 Figure 8 presents the results of the full interaction model. Among  
388 all predictors and interaction terms, the only variable that is sta-  
389 tistically significant at the  $p < 0.01$  level is prior support for a  
390 carbon tax (`cc_pol_tax`). This confirms a consistent pattern seen  
391 in previous models: individuals who already support specific cli-  
392 mate policies are more likely to express a willingness to pay for  
393 climate solutions in general.

394 None of the interaction terms between harm perceptions and po-  
395 litical ideology – such as `cc4_world`  $\times$  `pol_ideology`, `cc4_poorUS`  
396  $\times$  `pol_ideology`, or `cc4_famheal`  $\times$  `pol_ideology` – achieve sta-  
397 tistical significance. This suggests that political ideology does not  
398 meaningfully alter how people translate climate risk perceptions  
399 into willingness to act financially.

400 The full interaction model exhibits substantial multicollinearity,  
401 especially between harm perception variables and their inter-  
402 action terms. Standard errors for main harm predictors such as  
403 `cc4_famheal`, `cc4_comm`, and `cc4_world` exceed 0.10, with  
404 variance inflation factors (VIFs) for interaction terms ranging from 40  
405 to 80 – well above acceptable thresholds (see Table 11 in Appen-  
406 dix C). This collinearity inflates standard errors, reduces statistical  
407 power, and makes it difficult to isolate individual effects (see Fig-  
408 ure 14 in Appendix C).

409 To address multicollinearity, we constructed a `harm_index` to  
410 summarize all six harm perception variables into a single factor,  
411 which was then interacted with political ideology. The simplified  
412 specification resulted in improved model stability. All variance  
413 inflation factors (VIFs) for the harm index model remained below  
414 the conventional threshold of 10 (see Table 12 in Appendix C),  
415 and standard errors for key predictors and interaction terms were  
416 substantially reduced (see Figure 15 in Appendix C).

417 Figure 9 presents the results of the simplified moderation model  
418 using the `harm_index`.

419 The results of both the full interaction and simplified harm in-  
420 dex models suggest that political ideology does not significantly  
421 moderate the relationship between climate harm perceptions and  
422 willingness to pay. However, simplifying the model structure sub-  
423 stantially improved the statistical clarity. The harm index approach

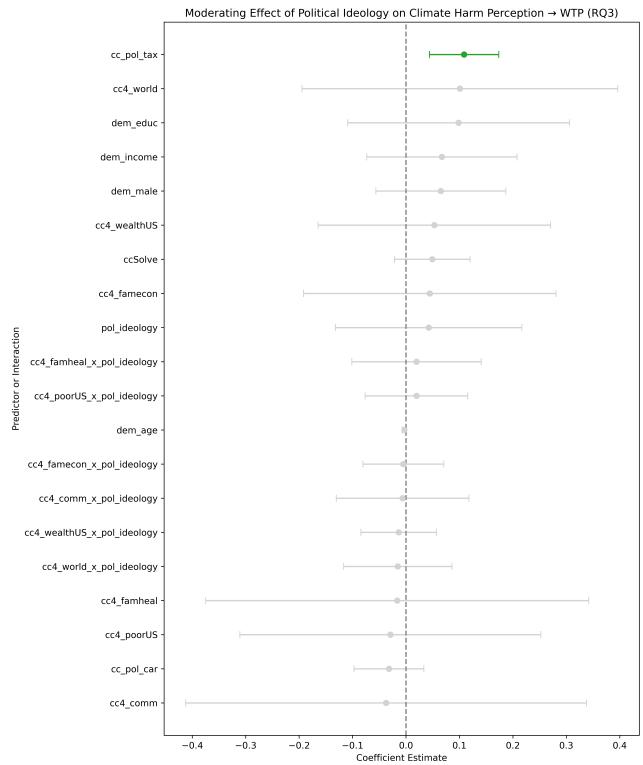


Figure 8: Moderation model with interaction terms between harm perceptions and political ideology. Only prior support for a carbon tax is significant ( $p < 0.01$ ).

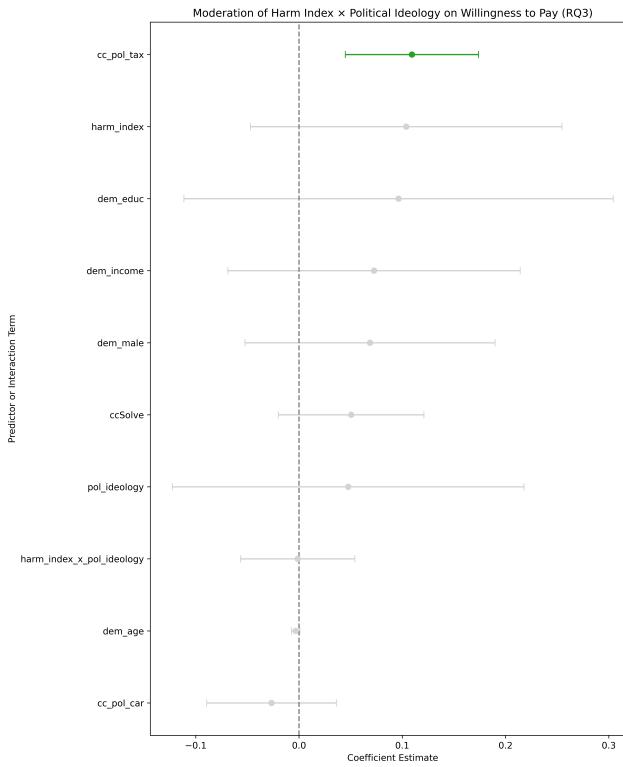
424 yielded lower multicollinearity, narrower confidence intervals while  
425 preserving the conclusion that prior climate policy support remains  
426 the strongest and most consistent predictor of financial engagement  
427 with climate solutions.

#### 428 4.5 PCMCI+ Causal Discovery

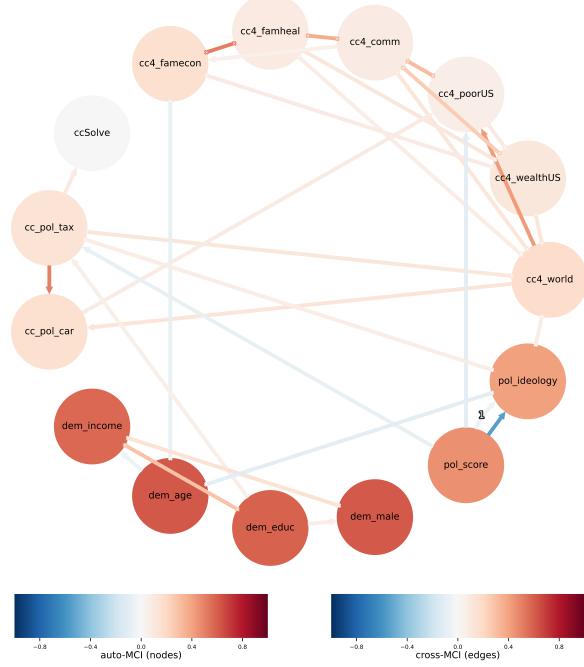
429 Figure 10 shows the graph generated by PCMCI+, which uses par-  
430 tial correlation as the CI test to isolate direct causal links. Edge  
431 colors represent momentary conditional information (MCI), with  
432 red indicating positive effects and blue indicating negative effects.  
433 The color intensity reflects the strength of the dependency. This  
434 PCMCI+ graph shows that most variables are strongly influenced  
435 by their own past values. We can tell this from the dark red colors  
436 of the nodes, which represent strong self-dependence (auto-MCI).  
437 There are only a few meaningful connections between different  
438 variables. One example is that `pol_score` has a small but statis-  
439 tically significant effect on `pol_ideology`, suggesting that when  
440 someone's political score changes, their reported ideology tends to  
441 shift slightly in the opposite direction at the next time point.

#### 442 4.6 PVAR and PCMCI+ Comparison

443 To understand the temporal and causal structure of climate attitudes,  
444 we compare PVAR and PCMCI+. Both rely on longitudinal panel  
445 data, but differ in their underlying assumptions and inference logic.



**Figure 9: Moderation model using a composite harm index. Interaction with political ideology is not significant, but more precisely estimated.**



**Figure 10: PCMCI+ causal graph. Nodes are colored by auto-MCI (self-dependence), and edges reflect causal strength.**



**Figure 11: Edge Comparison Matrix: Directed lag-1 edges detected by PVAR and PCMCI+. Only statistically significant links at  $\alpha < 0.01$  are displayed.**

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

To directly compare results, Figure 11 presents a matrix of lag-1 edges detected by each method at  $\alpha = 0.01$ . PVAR identifies 46 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 [1] and Ogami (2024) [15], 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) [2], Fisher (2022) [6]). 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 voters' financial commitment to climate action is slow to change in elections (Schulze et al., (2021) [20]).

- 473 standards, highlighting that fairness considerations (Fisher (2022))  
 474 influence regulatory policy support more than taxation.  
 475 Contrary to expectations from the CIRES study (2024), personal  
 476 and local harm perceptions (community, family) are not significant  
 477 predictors of either policy support or WTP. This finding challenges  
 478 the assumptions that direct exposure or proximity to harm is a  
 479 primary driver of climate action support.  
 480 Political ideology does not significantly moderate how climate  
 481 harm perceptions translate into WTP, contradicting parts of the  
 482 literature (Fisher (2022)). Even after improving model stability  
 483 through a harm index, no moderation effect emerged thus indicat-  
 484 ing that ideological commitments shape climate action indirectly  
 485 rather than interactively.  
 486 High standard errors for demographic variables (especially gen-  
 487 der, income, and education) reflect time-invariant traits and small  
 488 subgroup sizea. These predictors should be interpreted with cau-  
 489 tion. There is no evidence of multicollinearity for demographics  
 490 (low VIFs), so imprecision probably is a result of data sparsity, not  
 491 model redundancy.  
 492 PVAR detects broader temporal correlations. PCMCI+ yields a  
 493 sparser, more conservative network that isolates direct causal links.  
 494 Fewer shared edges highlight differing inference logics: predic-  
 495 tive vs conditional independence. The shared edge (pol1\_score →  
 496 pol1\_ideology) found by both PVAR and PCMCI+ suggests that  
 497 people's political identity, such as whether they lean Democrat  
 498 or Republican, strongly influences how they describe themselves  
 499 ideologically. The fact that this link appears in both models makes  
 500 it more reliable and shows that political identity plays a key role in  
 501 how people form views on climate issues and policies.
- 520 **6 CONCLUSION**
- 531 This study examined how public support for climate policies and  
 532 willingness to pay (WTP) for climate solutions evolve during elec-  
 533 tions. Applying both Panel VAR and PCMCI+ models, we found  
 534 that climate attitudes are remarkably stable over time. Prior sup-  
 535 port for climate policies, especially carbon taxes, strongly predicts  
 536 both policy support and WTP, while global perceptions of climate  
 537 harm (e.g., harm to the world) are more influential than localized  
 538 or personal concerns.  
 539 While ideology shapes overall policy preferences, it does not  
 540 appear to influence how people translate climate risks into financial  
 541 support contrary to previous studies. These findings suggest that  
 542 values, not elections, drive climate attitudes thus highlighting the  
 543 importance of long-term engagement strategies over short-term  
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## 590 Appendix A RISK ASSESSMENT

### 591 A.1 Computational Challenges with PCMCI+

592 **Risk:** The PCMCI+ algorithm can be computationally intensive,  
593 especially with large datasets and multiple time lags.

594 **Mitigation:** Start with a subset of data to test and optimize  
595 the PCMCI+ implementation. Use cloud computing resources if  
596 necessary or the Snellius Dutch National supercomputer.

597 **Plan B:** If issues persist, consider simplifying the model.

### 598 A.2 Ethical Considerations

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

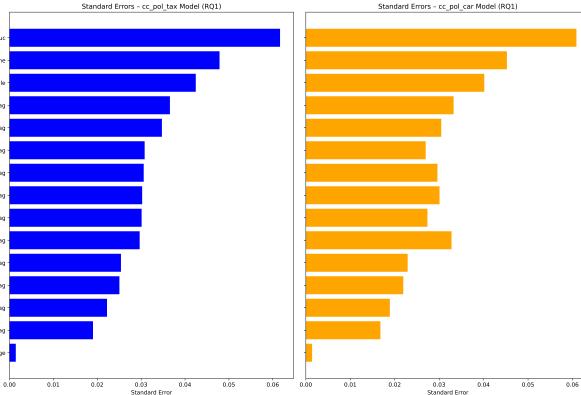
600 **Mitigation:** Clearly state the limitations of the study and provide  
601 guidelines for ethical use of the results in the thesis and repository.

602 **Plan B:** Include an "Ethical Use" section, outlining specific sce-  
603 narios of appropriate and inappropriate use of the findings.

## 604 Appendix B GENERATIVE AI

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

## 614 Appendix C RESULTS



615 **Figure 12: Standard errors for predictors in the carbon tax  
616 model (cc\_pol\_tax, left) and emissions standards model  
617 (cc\_pol\_car, right). In both cases, the demographic variables  
618 – education, income, and gender – exhibit the highest stan-  
619 dard errors**

## 620 Appendix D BOOTSTRAPPING

621 We do not include a separate table of bootstrap results for RQ3,  
622 as the estimated effects and their stability closely mirror those  
623 reported for RQ2. The bootstrap results for RQ3 are available in the  
624 project code repository.

Table 8: 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 9: 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)

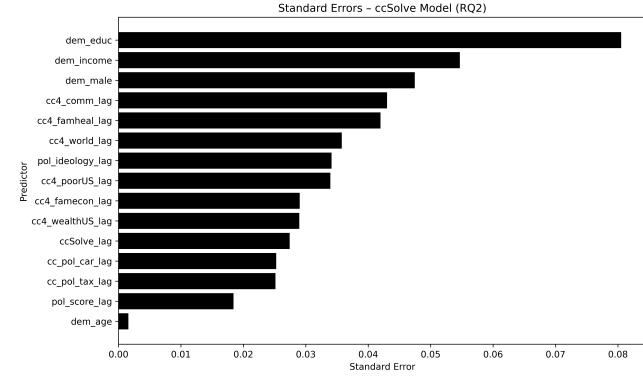


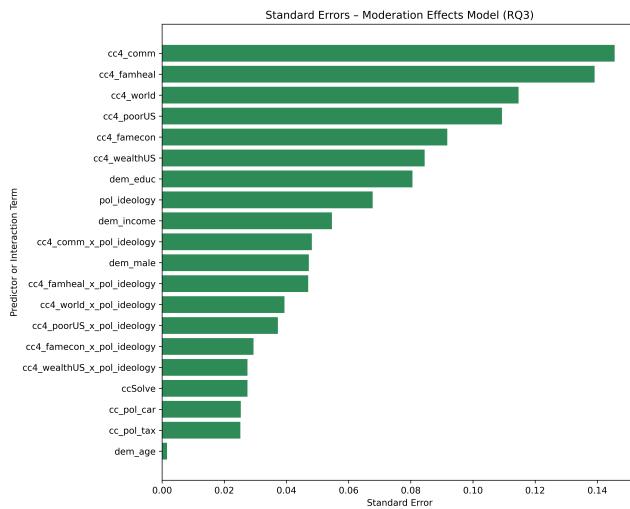
Figure 13: Standard errors of predictors in the ccSolve model. Variables with the highest uncertainty are shown at the top.

**Table 10: 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 11: VIF - Full Interaction Model (RQ3)**

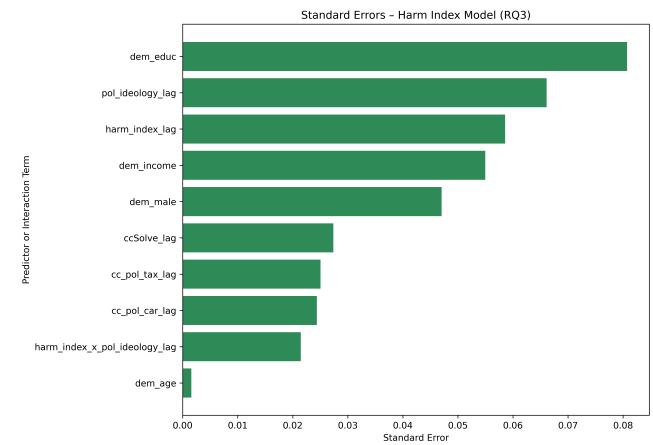
Variable	VIF	Interpretation
cc4_comm_x_pol_ideology	86.92	High multicollinearity (problematic)
cc4_world_x_pol_ideology	77.89	High multicollinearity (problematic)
cc4_famheal_x_pol_ideology	76.56	High multicollinearity (problematic)
cc4_poorUS_x_pol_ideology	71.04	High multicollinearity (problematic)
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 12: VIF - Harm Index Moderation Model (RQ3)**

Variable	VIF	Interpretation
harm_index_x_pol_ideology_lag	19.65	High multicollinearity (problematic)
pol_ideology_lag	8.54	Moderate multicollinearity (monitor closely)
harm_index_lag	8.33	Moderate multicollinearity (monitor closely)
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 13: Model vs Bootstrap Comparison – Tax Model**

Variable	Model p-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 14: Model vs Bootstrap Comparison – 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 15: Model vs Bootstrap Comparison – 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 16: 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 → itself at lag 1) appeared in 100% of the samples.