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

Paraskevas K. Leivadaros
15225623

Master Information Studies
data science
Faculty of Science
University of Amsterdam

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	UvA Supervisor
Title, Name	PhD candidate, Kyuri Park
Affiliation	University of Amsterdam
Email	k.park@uva.nl

ABSTRACT

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

CCS CONCEPTS

• **Mathematics of computing → Time series analysis.**

KEYWORDS

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

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GITHUB REPOSITORY

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

1 INTRODUCTION

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

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

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

RQ1. Does support for climate policies (like carbon taxes or emissions standards) change during elections? And is this support influenced by personal or community-level perceptions of climate harm?

RQ2. Does willingness to pay for climate solutions vary during elections and what factors influence it?

RQ3. Does political ideology moderate the relationship between perceptions of harm and willingness to pay?

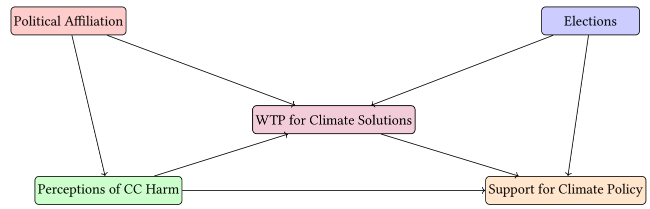

Figure 1: Conceptual Model: Key Relationships Based on Research Questions

2 RELATED WORK

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

Hahnel et al., 2020 [2] found that when political leaders frame climate change as a divisive issue, public opinion becomes polarized on perceptions of climate harm. Similarly, Fisher (2022) [6] found that different ideologies influence how different parties assess climate risks, with left-leaning voters more likely to express concern for vulnerable populations (e.g., poor communities) than right-leaning voters. Given these findings, our study examines whether perceived harm to poor or wealthy communities changes during elections.

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

Schulze et al. (2021) [20] found that willingness to pay (WTP) for climate policies declines in pre-election periods, as voters become more sensitive to financial costs. Research suggests that conservatives are generally less supportive of costly interventions, but may express higher WTP when policies are framed as benefiting local communities or economic stability. Ogami (2024) [15] found that voters tend to prioritize low-cost climate solutions closer to elections due to economic concerns influenced by campaign rhetoric. Based on these findings, our study examines whether elections shape WTP for climate solutions.

The CIRES study on the opinions on climate change during elections [1] found that Democrats consistently express greater support for climate policies, such as carbon taxes, while Republicans remain more resistant. Similarly, Ogami explains that politicians often avoid promoting polarizing policies, such as carbon taxes, in the lead-up to elections to minimize losing voters. The CIRES study also found that people experiencing direct climate impacts, such as extreme weather events, tend to support pro-climate candidates and policy measures. Based on this, our study examines whether support for specific policies changes during elections and whether these shifts are influenced by political affiliation or perceptions of family health and economic well-being.

3 METHODOLOGY

3.1 Resources

Previous research has shown that elections influence climate attitudes and policy support, but the direction and magnitude of these effects are unclear. This study addresses this gap by applying two temporal methods: PVAR and the PCMCI+ algorithm. Although PVAR captures dynamic interdependencies among variables over time under parametric assumptions, PCMCI+ offers a data-driven approach to uncover causal relationships from time series. Using the Tigramite Python package [17], we will try to identify the causal impact of elections on climate perceptions, WTP, and support for climate policies.

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

Variable	Description
Climate Change Perception (cc4_*)	
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
WTP (ccSolve*)	
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)
Climate Policy Support (cc_pol_*)	
cc_pol_tax	Support for a carbon tax
cc_pol_car	Support for stricter car emissions
Political Affiliation and Ideology (pol_*)	
pol_party	Political party identification (Rep, Dem, Ind)
pol_lean	Political party leaning (Lean Rep, Lean Dem)
pol_ideology	Political ideology (Conservative, Moderate, Liberal)
Demographics (dem_*)	
dem_income	Respondent's reported income level
dem_male	Respondent's gender
dem_age	Respondent's age
dem_educ	Respondent's education level

Table 1: Description of Key Variables (raw data)

Table 2 summarizes the response options and coding for key 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 disapprove 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

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

Table 3 provides summary statistics for all variables in the dataset prior to filtering. For each variable, the table reports the number and percentage of missing values, as well as key distribution metrics: 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%						

Table 3: Data Summary (raw data)

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

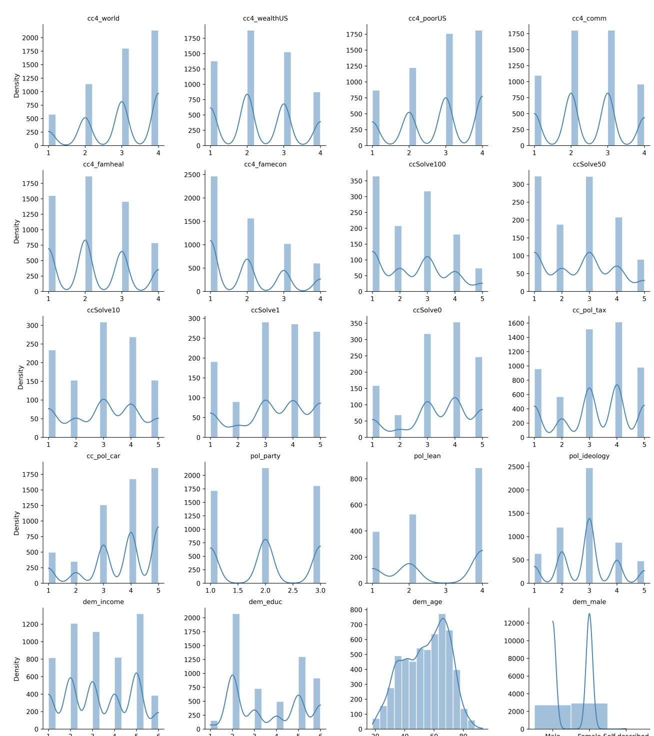

Figure 2: Distributions with Density Overlay (raw data)

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 CMIknn, we use linear partial correlation (ParCorr) 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 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.

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.

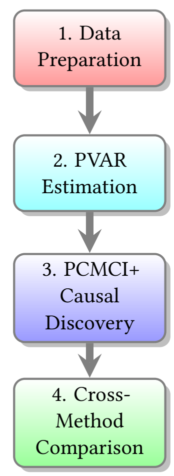

Figure 3: Overview of the main analytical steps in the study

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 (PIDs) 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 PIDs 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.

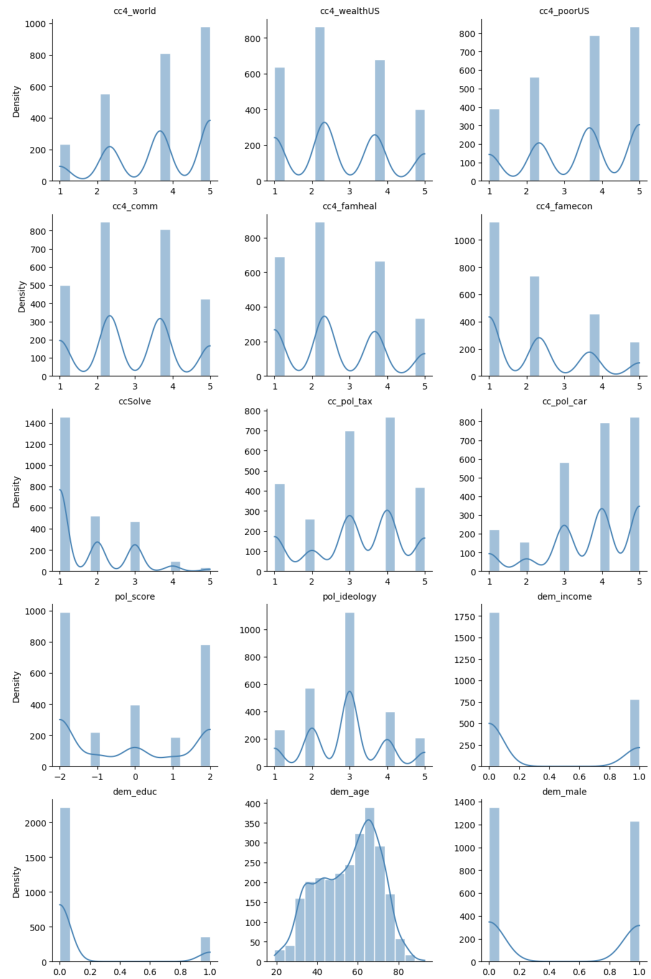

Figure 4: Distributions with Density Overlay (after filtering)

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` → `cc4_world`), each appearing in 100% of the bootstrapped samples. Other non-autoregressive links, such as `cc_pol_tax` → `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_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.

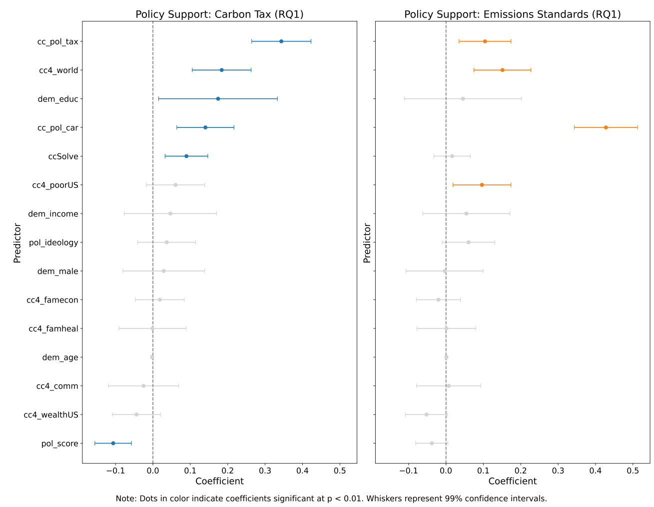

Figure 6: Predictors of support for carbon taxes and emissions standards. The figure displays results from two reduced-form PVAR(1) regressions using dot-whisker plots. Each dot represents a regression coefficient estimate, and the horizontal lines denote 99% confidence intervals. Predictors are ordered 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_pol_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 (`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 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.

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. This shows that personal values and beliefs matter more than things like age, income, or education when it comes to supporting climate rules. 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 overall model uncertainty, as evidenced by their wide confidence intervals in the dot-whisker plots in Figure 6 and elevated standard errors in Appendix C 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 8 in Appendix C shows the number of observations for each subgroup. It should be noted that variance inflation factors (VIFs) for these variables are low (Table 9 in in Appendix C) [12], indicating that multicollinearity is not the primary source of uncertainty. Taken 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.

Overall, the analysis shows that people's views on climate policies do not change during short-term political events such as elections. Instead, people's views are based on long-lasting values and past opinions. This is important for understanding how likely climate action will succeed, especially during elections when politicians are more likely to listen to voters.

4.3 RQ2 – Drivers of WTP for Climate Solutions

The reduced-form 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.

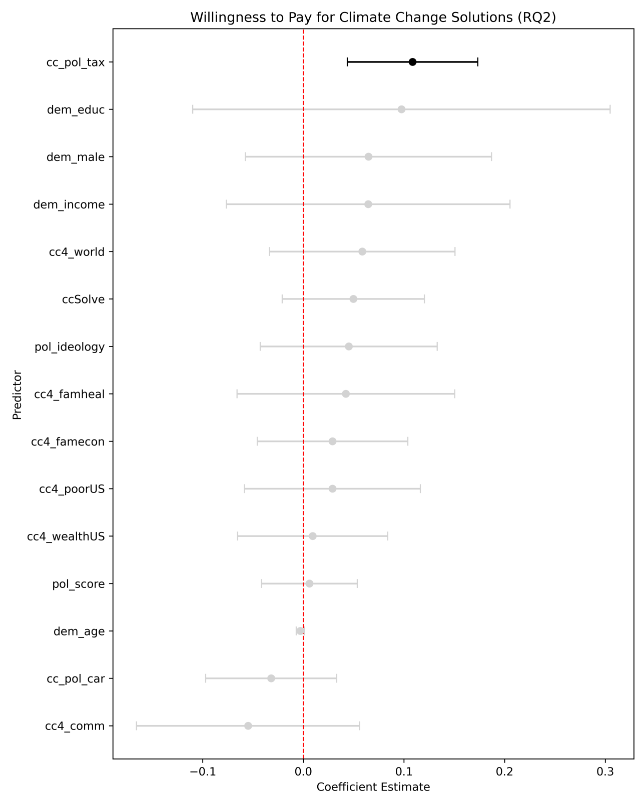

Figure 7: Predictors of willingness to pay for climate change solutions (`ccSolve`). Dot-whisker plots show coefficient estimates with 99% confidence intervals. Only prior support for carbon tax (`cc_pol_tax`) is statistically significant ($p < 0.01$), shown in black.

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 C). 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 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.

4.4 RQ3 – Moderating Role of Political Ideology

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

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

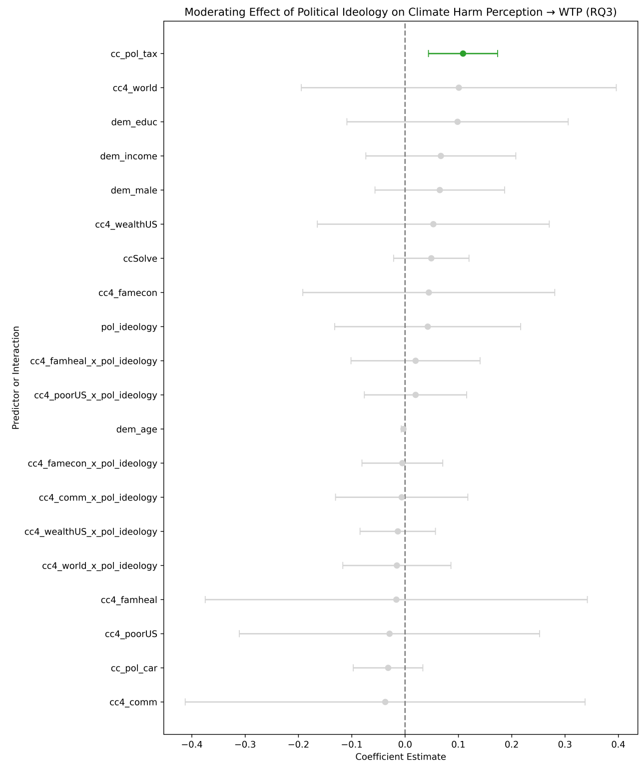

Figure 8: Moderation model with interaction terms between harm perceptions and political ideology. Only prior support for a carbon tax is significant ($p < 0.01$).

None of the interaction terms between harm perceptions and political ideology — such as `cc4_world × pol_ideology`, `cc4_poorUS × pol_ideology`, or `cc4_famheal × pol_ideology` — achieve statistical significance. This suggests that political ideology does not meaningfully alter how people translate climate risk perceptions into willingness to act financially.

The full interaction model exhibits substantial multicollinearity, especially between harm perception variables and their interaction terms. Standard errors for main harm predictors such as `cc4_famheal`, `cc4_comm`, and `cc4_world` exceed 0.10, with variance inflation factors (VIFs) for interaction terms ranging from 40 to 80 — well above acceptable thresholds (see Table 11 in Appendix C). This collinearity inflates standard errors, reduces statistical power, and makes it difficult to isolate individual effects (see Figure 14 in Appendix C).

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

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

The results of both the full interaction and simplified harm index models suggest that political ideology does not significantly moderate the relationship between climate harm perceptions and willingness to pay. However, simplifying the model structure substantially improved the statistical clarity. The harm index approach yielded lower multicollinearity, narrower confidence intervals while preserving the conclusion that prior climate policy support remains the strongest and most consistent predictor of financial engagement with climate solutions.

4.5 PCMCI+ Causal Discovery

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

4.6 PVAR and PCMCI+ Comparison

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

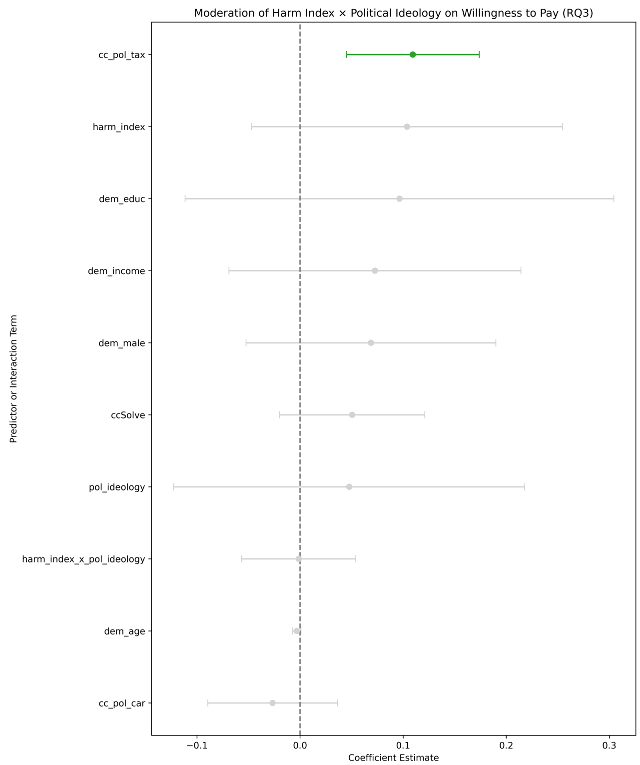

Figure 9: Moderation model using a composite harm index. Interaction with political ideology is not significant, but more precisely estimated.

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]).

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

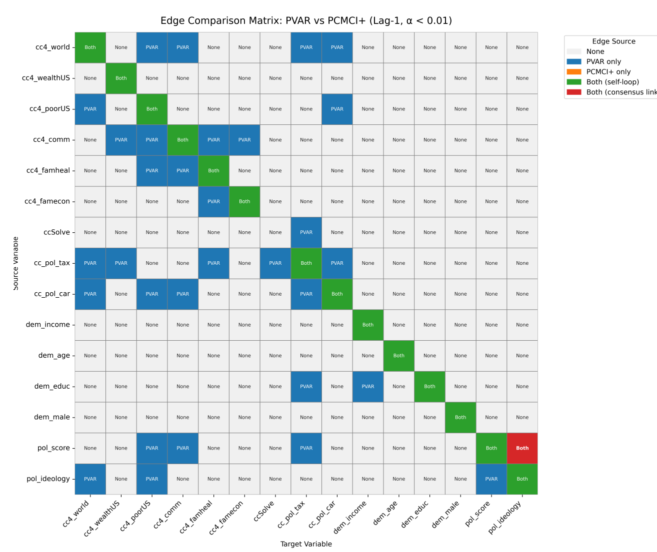

Figure 11: Edge Comparison Matrix: Directed lag-1 edges detected by PVAR and PCMCI+. Only statistically significant links at $\alpha < 0.01$ are displayed.

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 standards, highlighting that fairness considerations (Fisher (2022)) influence regulatory policy support more than taxation.

Contrary to expectations from the CIRES study (2024), personal and local harm perceptions (community, family) are not significant predictors of either 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 sizea. 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+ yields a sparser, more conservative network that isolates direct causal links. Fewer shared edges highlight differing inference logics: predictive vs conditional independence. 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 shows that political identity plays a key role in how people form views on climate issues and policies.

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 with PCMCI+

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

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

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

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 RESULTS

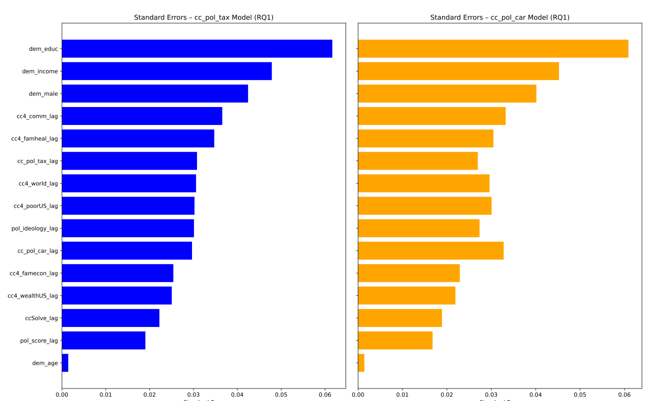

Figure 12: Standard errors for predictors in the carbon tax model (`cc_pol_tax`, left) and emissions standards model (`cc_pol_car`, right). In both cases, the demographic variables — education, income, and gender — exhibit the highest standard errors

Appendix D BOOTSTRAPPING

We do not include a separate table of bootstrap results for RQ3, as the estimated effects and their stability closely mirror those reported for RQ2. The bootstrap results for RQ3 are available in the 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)

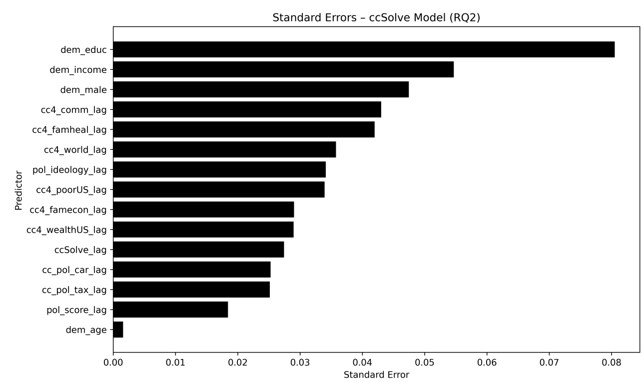

Figure 13: Standard errors of predictors in the `ccSolve` model. Variables with the highest uncertainty are shown at the top.

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)

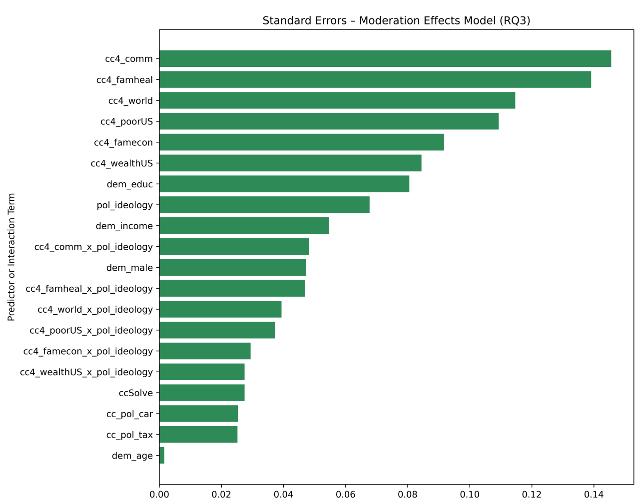

Figure 14: Standard errors for predictors in the full interaction model (RQ3). Harm perception variables and their interaction terms exhibit the largest uncertainty.

Table 12: VIF - Harm Index Moderation Model (RQ3)

Variable	VIF	Interpretation
harm_index × 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)

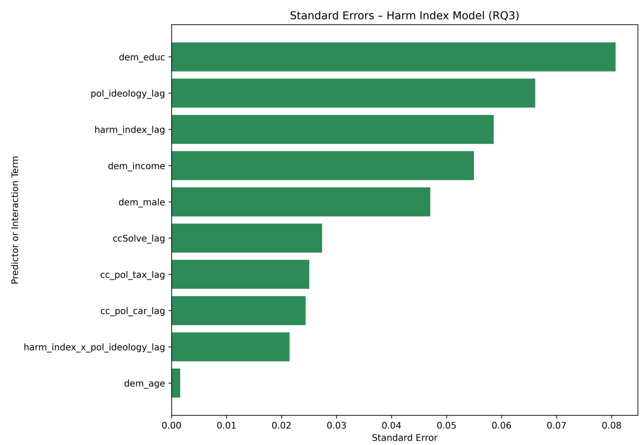

Figure 15: Standard errors in the simplified harm index model. The interaction term is more stable, with reduced uncertainty.

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 p-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 p-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 $\longrightarrow$ itself at lag 1) appeared in 100% of the samples.