Elections and Climate Attitudes: How Do People's Views on Climate Change and Policies Shift During an Election?

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ABSTRACT

This thesis examines the impact of elections on climate change attitudes and policy support. Using a data set of 5,667 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). Although PVAR models the linear dynamic structure of climate-related attitudes, 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. 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, political attitudes

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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 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. We will examine the shifts in climate attitudes before and after the elections to determine how various elements that occur during an election influence the public's opinion. We will focus on specific policies and individuals' willingness to pay (WTP) for climate action. 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?

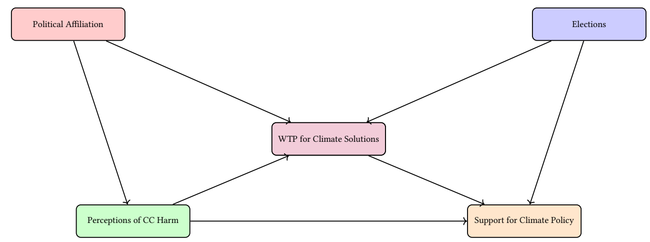

Figure 1: Conceptual Model: Key Relationships Based on Research Questions

2 RELATED WORK

Although prior research has examined the relationship between elections, policies, and climate attitudes, these studies have mainly relied on observation of correlations rather than causal inference. Existing work has shown that elections influence climate attitudes and policy support, but the direction and magnitude of these effects remain unclear. This thesis addresses that gap by applying two complementary temporal methods: PVAR (Panel Vector Autoregression and the PCMCI+ algorithm (Peter and Clark Momentary Conditional Independence). Although PVAR captures dynamic inter dependencies 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 [6], our objective is to identify the causal impact of elections on climate perceptions, willingness to pay for climate solutions, and support for specific climate policies.

This section reviews previous research on the relationship between elections, climate perceptions, and policy support. We focus on three key areas: (1) the methods used to analyze these relationships, (2) the specific research questions addressed, and (3) how these studies help us explore the causal links between elections, willingness to pay for climate solutions, and climate policy support.

Public perceptions of climate change are shaped by political events, particularly elections. Hahnel et al., 2020 [2] found that elections influence climate attitudes, often resulting in political polarization. When political leaders frame climate change as a divisive issue, public opinion becomes polarized, affecting both perceptions of climate harm and support for policies like carbon taxes. Similarly, Fisher (2022) [3] 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 elections amplify these divisions and whether perceived harm to specific groups (e.g., poor vs. wealthy communities) changes during election cycles.

Elections influence public support for climate policies, particularly the costly ones. Schulze et al. (2021) [8] found that willingness to pay 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. Based on these findings, our study examines whether elections shape WTP for climate solutions and whether perceived personal or community-level climate impacts influence WTP during election cycles.

Campaigns and debates reinforce the polarization in climate policy. The CIRES study on the opinions on climate change during presidential elections [1] found that Democrats consistently express greater support for climate policies, such as carbon taxes, while Republicans remain more resistant, particularly during election cycles. Similarly, Ogami (2024) [5] explains that politicians often avoid promoting polarizing policies, such as carbon taxes, in the lead-up to elections to minimize losing voters. These findings suggest that voter preferences and messaging shape climate policy support during elections. Our study builds on this by examining whether support for specific policies increases or decreases during election cycles and whether these shifts are influenced by parties.

Voters who perceive greater personal or community-level harm from climate change are more likely to support climate policies, even in polarized communities. The CIRES study [1] found that people experiencing direct climate impacts, such as extreme weather events, tend to support pro-climate candidates and policy measures. However, research on political identity and climate attitudes suggests that personal experiences with climate events can sometimes shift attitudes beyond political affiliations, but this impact depends on the election context. Based on this, our study examines whether perceptions of family health or economic well-being predict climate policy support during elections, regardless of political affiliation.

Elections shape how voters evaluate the financial trade-offs of climate policies. Ogami (2024) [5] found that voters tend to prioritize low-cost climate solutions closer to elections due to economic concerns influenced by campaign rhetoric. Studies on willingness to pay further indicate that context matters; policies emphasizing immediate community benefits are more likely to gain support. Given this, our study compares support for low-cost versus high-cost climate solutions during election periods and examines whether these preferences are influenced by perceived harm at the global versus local level.

Political beliefs shape the relationship between perceived climate harm and support for policy interventions. Fisher (2022) [3] found that ideological polarization influences whether individuals translate climate risk perceptions into policy preferences. Studies on voter behavior suggest that Democrats are more likely to convert climate concern into higher willingness to pay for solutions compared to Republicans, particularly during election cycles. Building on this, our study investigates whether political affiliation moderates the effect of perceived harm on WTP and whether this effect intensifies during election periods.

3 METHODOLOGY

3.1 Resources

The primary resource for this study is a data set consisting of survey responses from 1,889 participants collected over 3 waves from June 2020 to August 2021. These longitudinal data capture various aspects of perceptions of climate change, policy support, political affiliation, ideology, and willingness to pay at different time points. Table 1 summarizes the key characteristics of the data set used in this study.

Attribute	Details
Number of recordings	5,667
Number of participants	1,889
Survey waves	3 (June 2020 - August 2021)
Key variables	20
Data structure	Longitudinal (before and after elections)

Table 1: Dataset Characteristics (raw data)

Table 2 provides an overview of the key variables included in the dataset and groups them according to their thematic role in the analysis. Each variable is labeled with a consistent prefix (e.g., `cc4_*`, `ccSolve*`, `pol_*`) to facilitate interpretation and analysis in different models.

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
Willingness to Pay (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 2: Description of Key Variables (raw data)

Table 3 summarizes the response options and coding for key variables used in the analysis.

Table 4 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:

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 3: Variable coding and response scales (raw data)

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%	0.617	3.250	0	0	0	1	77

Table 4: Data Summary (raw data)

mean, standard deviation, and the five-number summary (minimum, 25th percentile, median, 75th percentile, and maximum).

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

3.2 Approach

We use PVAR models (panel vector autoregression) [4] to study how climate-related attitudes evolve over time and influence each other. In this approach, PVAR treats all variables as potentially endogenous (each variable with time-varying value is modeled as a function of its own lag and the lags of other variables in the system). This allows us to examine the dynamic relationships between willingness to pay, policy support, climate harm perceptions, and political identity, without assuming a fixed causal ordering.

This study extends standard PVAR applications by incorporating subgroup modeling across ideological categories and comparing data-driven causal structures using the PCMCI+ algorithm - a combination not previously applied in the context of climate policy attitudes shifts in election periods.

As a complementary analysis, we also applied the PCMCI+ algorithm to the same panel dataset. PCMCI+ is a constraint-based

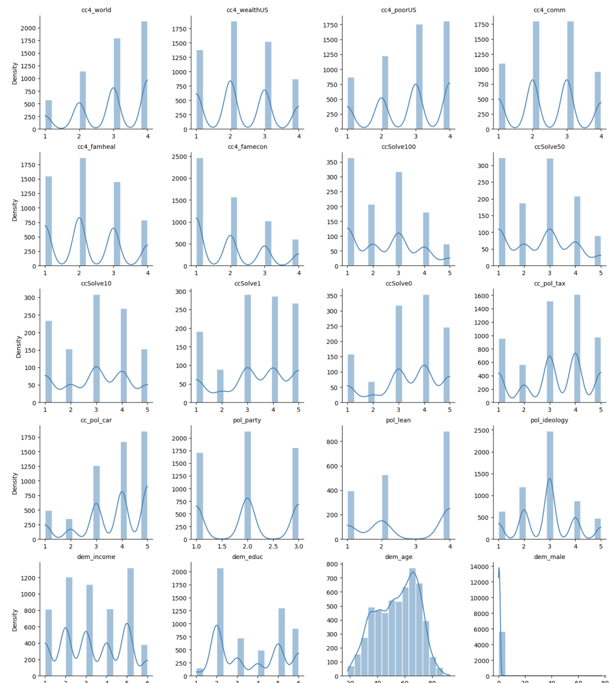

Figure 2: Distributions with Density Overlay (raw data)

causal discovery method designed for high-dimensional time series data. It is capable of identifying potential causal relationships by testing for conditional independencies across temporal lags. While PCMCI+ supports nonlinear and nonparametric causal discovery through conditional independence tests like GPDC and CMIknn [7], our implementation uses the linear partial correlation (ParCorr) test, which is more appropriate given the short time dimension ($T = 3$) of the panel dataset.

The PVAR model produces a directed graph of lagged influences, showing how changes in one variable predict changes in another across survey waves. PCMCI+, in turn, uncovers a temporal causal structure based on conditional independence tests. We qualitatively compare the resulting graphs from both methods to assess the consistency and robustness of the identified associations. This comparative approach enhances the reliability of our findings and deepens our understanding of core dynamics during the election period.

Standard approaches such as pooled OLS or fixed-effects regression could model the average association between predictors and outcomes over time. However, these methods assume unidirectional relationships and do not capture the dynamic feedback between attitudes, policy support, and perceived harm. PVAR extends beyond these baselines by treating variables as jointly endogenous and explicitly modeling their temporal structure. Likewise, PCMCI+ enables causal discovery without relying on strong parametric assumptions. The inclusion of both methods allows us to go beyond static associations and explore potential causal dynamics in the context of elections and climate attitudes.

To summarize the modeling strategies used in the study, Table 5 provides a high-level overview of the methods and their respective roles in the analysis.

Method	Why It's Used
PVAR (global)	Captures how all variables influence each other over time in a multivariate system
Subgroup PVAR	Examines effects across ideological groups (conservatives vs liberals)
PCMCI+	Identifies causal links using time-lagged conditional independence tests
Demographics	Accounts for income, gender, age, and education
Political Identity	Models the influence of party affiliation and ideology

Table 5: Overview of Methods and Their Purpose

Table 6 maps each survey wave to the research questions it informs, highlighting the panel structure's value for temporal and subgroup analyses.

Wave	Research Questions Addressed
Wave 2	Provides baseline values for all lagged predictors. Initiates modeling for policy support (RQ1) and willingness to pay (RQ2).
Wave 3 (Election)	Captures dynamics during the election period. Key wave to assess attitudinal shifts related to elections (RQ1 and RQ2).
Wave 4	Allows continued observation of attitudes after the election. Used in subgroup analysis to test ideological moderation (RQ3).

Table 6: Timeline structure and relevance of each wave

The implementation relied entirely on open-source Python packages. Table 7 lists the key packages used throughout the analysis pipeline.

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

Table 7: Software Tools Used in 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. Subgroup analysis is then used to examine ideological differences, followed by the application of a causal graph algorithm in the final step. An overview of these main stages is provided in Figure 3.

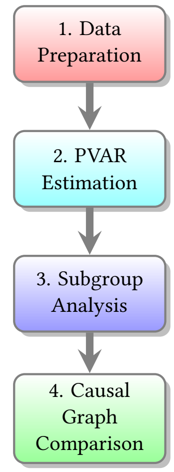

Figure 3: Overview of the main analytical steps in the study

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). Respondents who identified as Democrats or Republicans were assigned scores of −2 and 2, respectively. For those who identified as Independents (`pol_party` = 3), their placement depended on their lean: 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.

Seven variables had missing values, particularly in the climate policy support and willingness-to-pay (WTP) items. 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 8.

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 8: 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 to enable PVAR and causal modeling.

Table 9 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%	0.3043	0.4602	0	0.00	0.00	1.00	1
dem_educ	0.00%	0.1409	0.348	0	0.00	0.00	0.00	1
dem_age	0.00%	55.47	14.80	19	43.00	58.00	67.00	93
dem_male	0.00%	0.4766	0.4995	0	0.00	0.00	1.00	1

Table 9: Data Summary (after filtering)

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

Sample Bias and Representativeness
While the dataset includes 861 respondents in three waves, it may not fully represent the broader US population. To mitigate potential bias in age, income and education, demographic variables were inspected for distributional imbalances, and binary groups were constructed to ensure that each category reflected balanced splits and meaningful comparisons. This reduces the risk of biased estimates due to skewed sampling. Although demographic controls are included in the analysis, the results should be viewed as indicative of broader trends rather than as fully generalizable to the national population.

2. PVAR Estimation
Estimate global PVAR(1) models. The model for *RQ1 (whether support for climate policies changes during elections and whether it is influenced by harm perception)* focuses on policy support (`cc_pol_tax`, `cc_pol_car`) as dependent variables and uses all the variables as predictors (including the dependent variables). The model for *RQ2 (how willingness to pay is shaped by related attitudes over time)* focuses on willingness to pay (`cc_Solve`) as the dependent variable and uses all the variables as predictors (including the dependent variable).

3. Subgroup Analysis
Estimate subgroup PVAR(1) models for liberals and conservatives based on the `pol_ideology` variable. This directly addresses *RQ3 (whether political ideology moderates the relationship between perception of harm and willingness to pay).*

4. Causal Graph Comparison

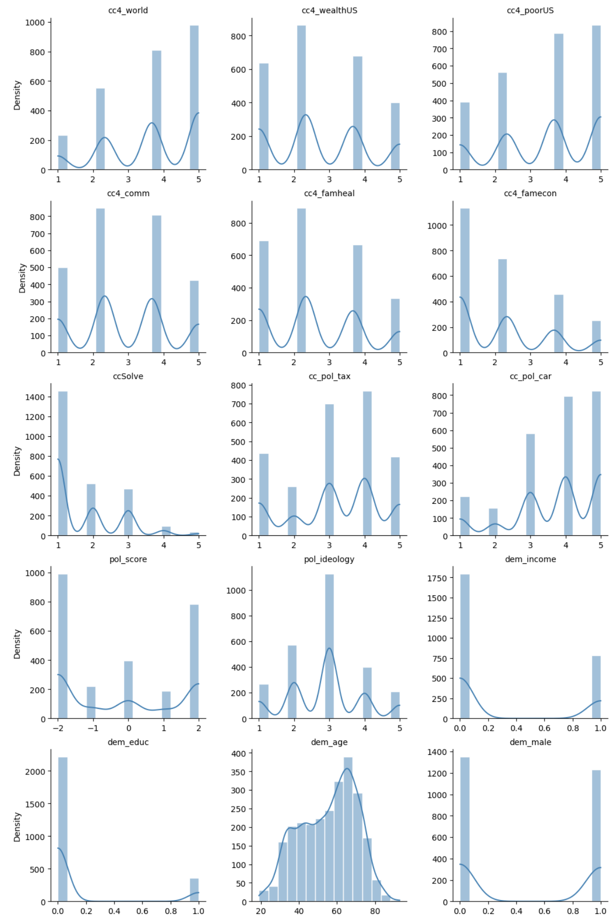

Figure 4: Distributions with Density Overlay (after filtering)

Apply the PCMCI+ algorithm using the Tigramite Python package. This method identifies potential causal links through time-lagged conditional independence tests, providing a complementary, data-driven perspective to the PVAR results.

3.4 Evaluation

The evaluation of results is organized around three research questions and uses a combination of global PVAR(1) models, subgroup analysis by political ideology, and causal graph discovery. These models allow us to examine how climate attitudes, political identity, and demographic factors influence support for climate policies and willingness to pay over time, including the election period.

Policy Support Shifts and the Role of Harm Perception (RQ1): First, estimate global PVAR(1) models where the dependent variables are support for carbon taxes and emissions standards (`cc_pol_tax`, `cc_pol_car`). Second, include as predictors the lagged values of all the variables such as harm perception variables (`cc4_*`), willingness to pay (`ccSolve`), political identity (dummy-coded `pol_party` and `pol_ideology`), and demographic controls (`dem_income`, `dem_male`, `dem_age`, `dem_educ`). Third, estimate all variables as jointly endogenous within each equation, using pooled

OLS with clustered standard errors. Finally, assess how policy support evolves over time and whether it is influenced by perceptions of harm, especially during the election wave (wave 3).

Willingness to Pay Over Time (RQ2): First, estimate a global PVAR(1) model where `ccSolve` is the dependent variable and is regressed due to its own lag, lagged policy support, perception of harm, political identity, and demographics. Second, evaluate the stability of the willingness to pay over time and whether it changes throughout the election period. Third, identify which predictors (e.g., policy support, perception of global harm, ideology) consistently explain variation in WTP.

Ideological Moderation (RQ3): First, estimate a pooled OLS model with interaction terms between political ideology and each harm perception variable. Second, assess whether the strength of the relationship between perceived climate harm and willingness to pay varies by ideological group. Third, determine if liberals, moderates, or conservatives respond differently to perceived climate threats when forming their willingness to financially support solutions.

Cross-Method Comparison: Start by applying the PCMCI+ algorithm using the Tigramite package to estimate a time-lagged causal graph from the panel data. And finish by comparing the structure and direction of key paths (e.g. harm → support, ideology → WTP) with those found in the PVAR models to assess consistency and gain deeper insight into causal structure.

Robustness
To assess the reliability of our causal estimates, we performed robustness checks using bootstrapping to assess the stability of the results. In particular, since causal discovery algorithms like PCMCI+ are sensitive to small changes in the data, running the algorithm on bootstrapped subsets helped verify whether the resulting causal graphs are consistent. While both PCMCI+ and PVAR are inherently limited by the low number of time periods ($T = 3$), we used bootstrapping to assess the robustness of PCMCI+'s causal links and to validate the consistency of PVAR's estimated coefficients.

This evaluation strategy provides a detailed view of how climate attitudes and policy support evolve over time. It also allows us to assess the role of ideology, demographics, and perceived harm, and to validate findings across both data-driven approaches.

3.5 Expectations

We expect that policy support will remain relatively stable over time, but will be shaped by global harm perception and political identity. Willingness to pay is expected to be more dynamic and moderated by ideology.

4 RESULTS

4.1 RQ1 – Drivers of Support for Climate Policy During Elections

To investigate whether support for climate policies fluctuates during election periods, 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 of 15 demographic and attitudinal predictors, and standard errors were clustered at the respondent level. Figure 5 displays the estimated coefficients using dot-whisker plots, highlighting statistically significant predictors at the $p < 0.01$ level with 99% confidence intervals.

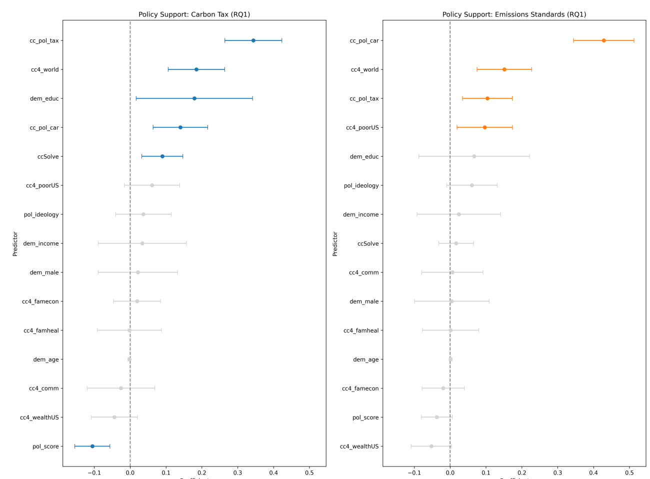

Figure 5: Predictors of support for carbon taxes and emissions standards. The figure displays results from two reduced-form PVAR(1) regressions using dot-whisker plots. Each dot represents a regression coefficient estimate, and the horizontal lines denote 99% confidence intervals. Predictors are ordered 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. This visualization helps identify which attitudinal, demographic, and political variables are most strongly associated with support for climate policies during election periods.

A clear pattern emerges across both models: Support for climate policies exhibits strong persistence 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. The consistency of cross-policy policies is also evident: past support for one policy positively predicts current support for the other. These findings show that people's views on climate policies remain mostly the same, even during election time.

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 over self-interested or localized risk perception. Education level (`dem_educ`) is also positively associated with support, suggesting that more educated respondents are more receptive to market-based climate solutions.

Furthermore, the willingness to financially contribute to climate solutions (`ccSolve`) significantly predicts support for carbon taxes. There is also evidence of cross-policy spillover, with prior support for emissions standards (`cc_pol_car`) significantly predicting later support for carbon taxes. In contrast, political orientation (`pol_score`) exhibits a negative significant relationship, with more conservative individuals being less supportive of carbon taxes.

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.

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 for 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.

In particular, demographic characteristics, including education, income, age, and gender, 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 (Figure 5) and elevated standard errors (Figure 6).

Several factors may explain this imprecision. First, demographic characteristics like gender and education are largely time-invariant, offering limited within-subject variation across survey waves. Second, small subgroup sizes — particularly combinations of traits like income and gender — may reduce the model's ability to detect robust effects. Notably, variance inflation factors (VIFs) for these variables are low (Table 10), indicating that multicollinearity is not the primary driver of uncertainty. These considerations suggest that while conceptually important, 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 rules like emissions standards.

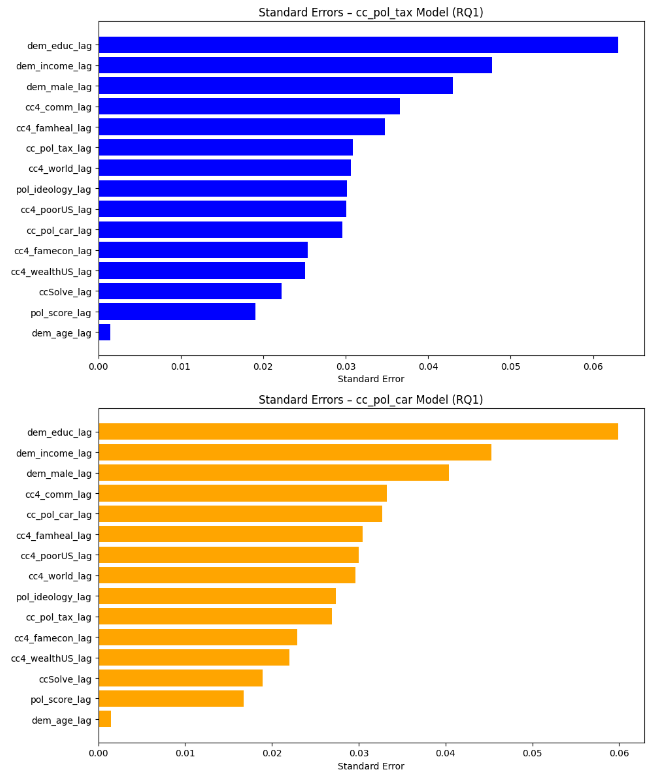

Figure 6: Standard errors for predictors in the carbon tax model (`cc_pol_tax`, top) and emissions standards model (`cc_pol_car`, bottom). In both cases, the demographic variables — education, income, and gender — exhibit the highest standard errors, indicating considerable uncertainty in their estimated effects.

Table 10: Variance Inflation Factors (VIF) for Predictors in the RQ1 Models

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)

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

4.2 RQ2 – Drivers of Willingness to Pay for Climate Policy During Elections

The reduced-form PVAR(1) model for `ccSolve` (willingness to pay for climate action) reveals that attitudes remain highly stable across 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.

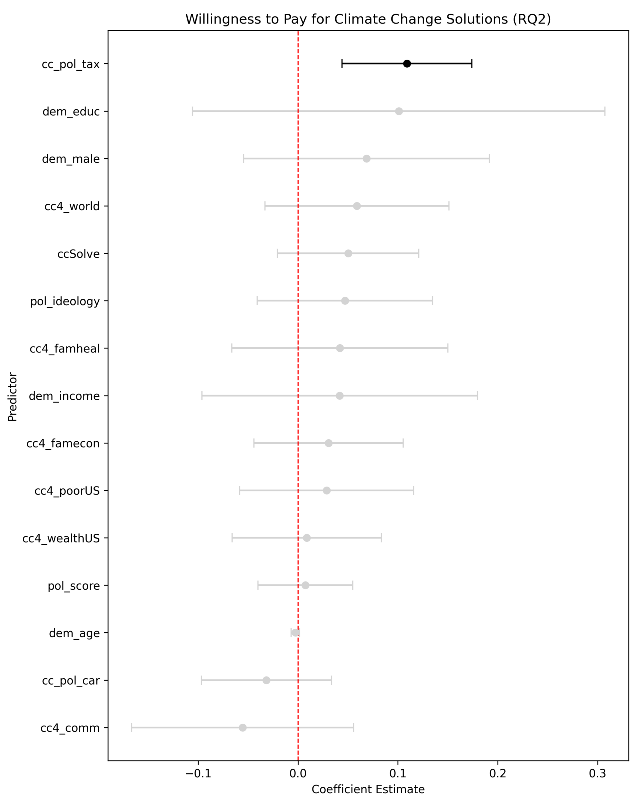

Figure 7: Predictors of willingness to pay for climate change solutions (`ccSolve`). Dot-whisker plots show coefficient estimates with 99% confidence intervals. Only prior support for carbon tax (`cc_pol_tax`) is statistically significant ($p < 0.01$), shown in black.

No other variables show statistically significant effects. As such, willingness to pay appears resilient to short-term political cycles and is primarily anchored in prior climate policy support rather than shifting external or ideological factors.

An inspection of standard errors reveals that `dem_educ_lag`, `dem_income_lag`, and `dem_male_lag` exhibit the largest standard errors among all predictors (see Figure 8). These three demographic variables contribute most to overall model uncertainty, 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.

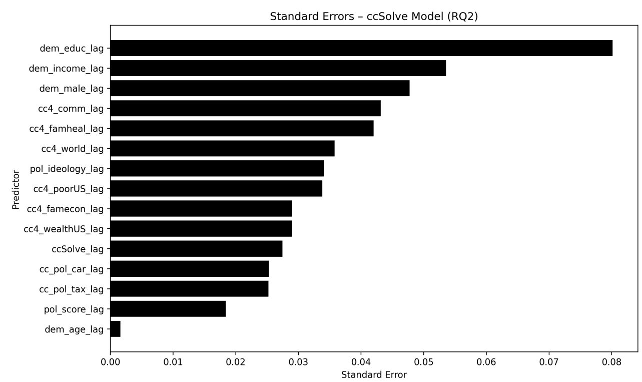

Figure 8: Standard errors of predictors in the `ccSolve` model. Variables with the highest uncertainty are shown at the top.

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. Notably, the variance inflation factors (VIFs) for these predictors are low (see Table 11), indicating that multicollinearity is not a primary concern in this model.

Table 11: Variance Inflation Factors (VIF) for Predictors in the RQ2 Model

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)

4.3 RQ3 – Moderating Role of Political Ideology on Climate Harm Perceptions and Willingness to Pay for Climate Solutions

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

Figure 9 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.

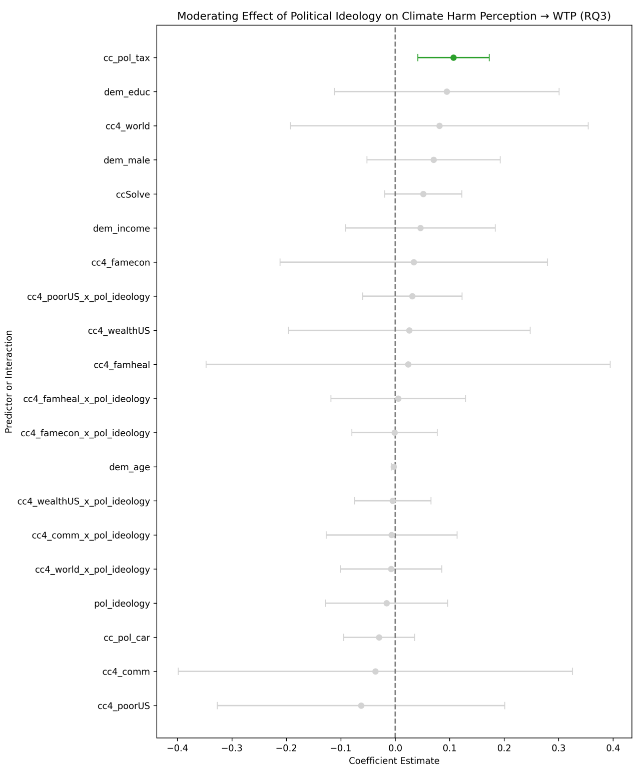

Figure 9: Moderation model with interaction terms between harm perceptions and political ideology. Only prior support for a carbon tax is significant ($p < 0.01$).

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.

Despite its theoretical appeal, 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 12). This collinearity inflates standard errors, reduces statistical power, and makes it difficult to isolate individual effects (see Figure 10).

Table 12: Variance Inflation Factors (VIF) for the Full Interaction Model (RQ3)

Variable	VIF	Interpretation
cc4_comm_x_pol_ideology	87.39	High multicollinearity (problematic)
cc4_famheal_x_pol_ideology	78.85	High multicollinearity (problematic)
cc4_poorUS_x_pol_ideology	73.07	High multicollinearity (problematic)
cc4_world_x_pol_ideology	66.68	High multicollinearity (problematic)
cc4_comm	47.98	High multicollinearity (problematic)
cc4_famheal	43.39	High multicollinearity (problematic)
cc4_wealthUS_x_pol_ideology	38.33	High multicollinearity (problematic)
cc4_famecon_x_pol_ideology	34.82	High multicollinearity (problematic)
cc4_poorUS	31.96	High multicollinearity (problematic)
cc4_world	25.22	High multicollinearity (problematic)
cc4_wealthUS	23.99	High multicollinearity (problematic)
cc4_famecon	23.80	High multicollinearity (problematic)
pol_ideology	4.03	Some correlation (acceptable)
cc_pol_car	2.18	Some correlation (acceptable)
cc_pol_tax	2.16	Some correlation (acceptable)
dem_income	1.15	Low correlation (no multicollinearity)
dem_educ	1.14	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)

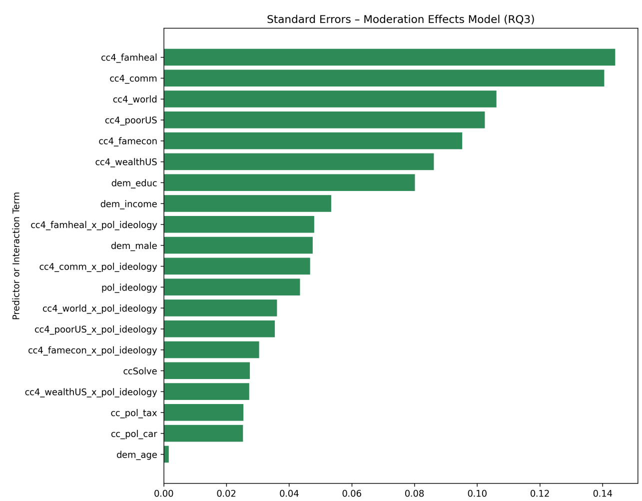

Figure 10: Standard errors for predictors in the full interaction model (RQ3). Harm perception variables and their interaction terms exhibit the largest uncertainty.

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 13), and standard errors for key predictors and interaction terms were substantially reduced (see Figure 11).

Table 13: VIF Values - Harm Index Moderation Model

Variable	VIF	Interpretation
`harm_index × pol_ideology`	8.64	Moderate multicollinearity (monitor)
`harm_index`	4.80	Some correlation (acceptable)
`pol_ideology`	3.66	Some correlation (acceptable)
`cc_pol_tax`	2.13	Some correlation (acceptable)
`cc_pol_car`	2.04	Some correlation (acceptable)
`dem_income`	1.14	Low correlation (no multicollinearity)
`dem_educ`	1.13	Low correlation (no multicollinearity)
`ccSolve`	1.07	Low correlation (no multicollinearity)
`dem_male`	1.05	Low correlation (no multicollinearity)
`dem_age`	1.04	Low correlation (no multicollinearity)

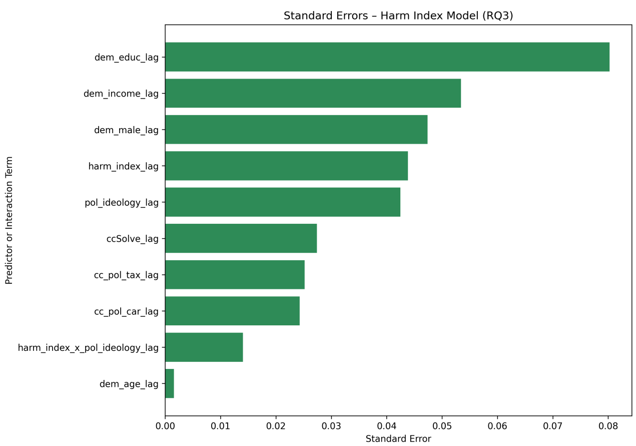

Figure 11: Standard errors in the simplified harm index model. The interaction term is more stable, with reduced uncertainty.

Figure 12 presents the results of the simplified moderation model using the `harm_index`.

The results from 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 statistical clarity. The harm index approach yielded lower multicollinearity, narrower confidence intervals, and greater interpretability — while preserving the conclusion that prior climate policy support remains the strongest and most consistent predictor of financial engagement with climate solutions.

5 DISCUSSION

6 CONCLUSION

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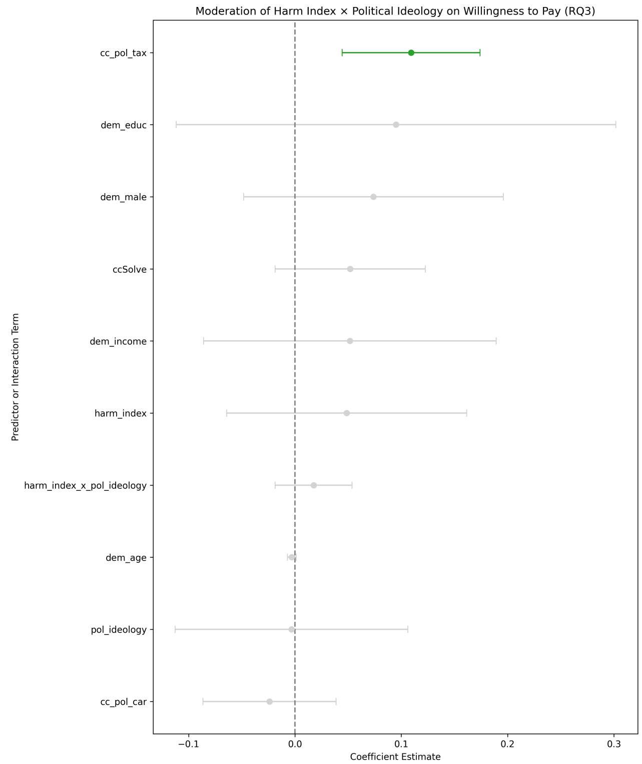

Figure 12: Moderation model using a composite harm index. Interaction with political ideology is not significant, but more precisely estimated.

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Appendix A RISK ASSESSMENT

A.1 Data Quality and Completeness

Risk: While the dataset is largely complete, there are missing values in 7 out of the 20 key variables. Although these are considered insignificant, unexpected data quality issues may arise during analysis.

Mitigation: Perform detailed exploratory data analysis early in the project. Prepare multiple imputation methods for the missing data.

Plan B: If data quality issues persist, focus analysis on the most complete variables and consider omitting the variables that have missing data.

A.2 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 computational issues persist, consider simplifying the model or using alternative causal inference methods such as Granger causality or vector autoregression (VAR) models.

A.3 Software Dependencies

Risk: The Tigramite package or its dependencies may have compatibility problems or bugs.

Mitigation: Set up the software environment early and run multiple tests.

Plan B: Search for alternative Python packages as backups.

A.4 Ethical Considerations

Risk: Potential misuse of the findings for political purposes or biased interpretations.

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

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