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Contents

Introduction

As highlighted by the most recent Special Reports of the Intergovernmental Panel on Climate Change (IPCC, 2018, 2019a, 2019b), to avert dangerous and irreversible changes to the earth's climate, rapid and comprehensive climate mitigation measures are required, (Rockström et al., 2017; Steffen et al., 2018). Although technological and policy solutions which would allow switching from carbon-intensive to carbon-neutral systems of production and consumption are already available, progress towards decarbonization remains slow. As the literature on socio-technical transitions has highlighted, decarbonization is a multi-dimensional challenge, which requires transforming not only technologies and infrastructures, but also social preferences and behaviors. Challenges to deep decarbonization are shaped by power relations between political, economic and social actors. The feasibility of decarbonization, therefore, depends on context-specific political coalitions, industry interests, and civil society pressures (Geels, Sovacool, Schwanen, & Sorrell, 2017; Hughes & Urpelainen, 2015).

Public attention on climate change and public support for climate policies are key enablers of decarbonization, and they are pivotal aspects to consider when investigating the social and political feasibility of socio-technical transitions. This thesis investigates two key aspects in this context: media coverage of climate change and public support for two rapid decarbonization policies.

The news media have a proven ability to shape social preferences, public attitudes and government policy (Eisensee & Strömberg, 2007; Prat & Strömberg, 2013). Media coverage of climate change can increase the salience of climate change in the public discourse, increase public attention and concern, and increase pressure on policy makers to implement ambitious climate policies (Brulle, Carmichael, & Jenkins, 2012; Carmichael & Brulle, 2017). In Chapter 1 of this thesis, we employ an original dataset of online media coverage of climate change in the 28 countries of the European Union for the period 2014-2019 to analyze trends in media coverage of climate change. Building on behavioral studies showing that temperature abnormalities influence individual climate attitudes and attention, we investigate whether media coverage of climate change is also influenced by temperature abnormalities. This chapter is joint work with Matthew R. Sisco, PhD Candidate at Columbia University, and has recently been published in *Environmental Research Letters*. It is a first step of a broader research project investigating determinants and impacts of media coverage of climate change.

The online news dataset has been constructed employing a web-scraping procedure that allowed us to collect more than 1.7 million online news articles covering climate change in 22 different languages. To the best of our knowledge, this is the first comprehensive dataset of online media coverage of climate change across a wide set of countries and languages. Existing studies of media coverage of climate change focus on the print media. Consumption of print media has however experienced a significant decrease over the last years, and online news are today the key source of information for most citizens. This makes studying online media considerably more valuable.

In this chapter, we show that online media coverage of climate change has significantly increased in the last few years - and soared in 2019 - in all EU countries. We then investigate whether and how the level of media coverage of climate change is influenced by temperature abnormalities. Previous studies of media coverage of climate change have mostly studied the impact of simple measures of temperature, finding null results. Building on studies showing that temperature abnormalities influence climate attitudes and attention, we hypothesize that temperature abnormalities are significant determinants of the level of media coverage of climate change.

To test this hypothesis, we combine our dataset of media coverage of climate change with observed temperature data. We test the impact of different measures of temperature abnormality and find that the strongest determinants of media coverage are positive deviations from short-term average temperatures. Abnormalities with respect to average temperatures in recent years have stronger effects than abnormalities with respect to temperatures in baseline periods that climatologists use to identify changes in climate. These results suggest that media coverage of climate change increases when temperatures are perceived as "warmer than normal" and that the media are more influenced by short-term changes in weather patterns than by scientific accounts of climatic changes.

Another important factor influencing the feasibility of the low-carbon transition are public attitudes towards climate policies. Decarbonization requires the implementation of policies that focus both on supply-side technology solutions and demand-side climate measures. In democracies in particular, governments need to be responsive to their constituencies, and since the likelihood of implementation of policies facing public opposition is low, understanding the drivers of citizens' climate policy preferences is of crucial importance. This is even more relevant given the recently emerged concern about voters becoming an increasing barrier to ambitious climate policies, as occurred for instance in the protest movement of the French Gilets Jaunes, which was fueled by a proposed increase in gasoline taxes.

Chapters 2 and 3 contribute to understanding the determinants of public support for decarbonization. They are part of a research project initiated during my visiting period at the Behavioral Science for Policy Lab at Princeton University, together with Adrian Rinscheid, who was visiting Princeton from St. Gallen University and Elke U. Weber, who hosted us. The project focuses on determinants of public support for two policies that could significantly contribute to rapid decarbonization: the phase-out of fossil fuel cars, and the scale-up of carbon capture and storage (CCS) technologies. These are policy options that would significantly contribute to the deep decarbonization of the transportation and electricity sectors (Rockström et al., 2017) but at the same time raise concerns in terms of social acceptance. They represent fundamentally different mitigation options with different behavioral implications.

CCS is a supply-side solution addressing the supply of fossil fuels via macro-level technology deployment. CCS technologies capture carbon dioxide (CO_2) from a point source or directly from the atmosphere and transport it to a storage site, typically an underground geological formation, where it is deposited. CCS technologies can be combined with fossil fuels-based electricity generation, industrial processes, or with bioenergy production. CCS plays an important role in many climate change mitigation scenarios developed by Integrated Assessment Models compatible with the Paris Agreement's goal of keeping global warming well below 2 degrees (IEA, 2019a; IPCC, 2018). However, CCS deployment has not met projections so far (IEA, 2009; Reiner, 2016), and CCS is on average less supported than other measures to decarbonize the energy system, such as electricity generation from renewable sources (Johnsson, Reiner, Itaoka, & Herzog, 2010).

The transition to low-carbon mobility, on the other hand, has direct demand-side ramifications, and requires the formation of habits compatible with climate change mitigation (Creutzig et al., 2018). Policies to phase out fossil fuel cars are currently being discussed in many countries, several of which (e.g., Norway, France, India, and China) plan to phase out cars with internal combustion engines between 2025 and 2040 (Meckling & Nahm, 2019). A bill to phase out fossil fuel cars was also proposed in the state of California, but it has so far been sidelined. Given their impact on individuals' everyday lives and behaviors and their implications for the automobile industry, these climate mitigation policies can prove particularly challenging to implement, despite their significant pollution co-benefits.

We investigate determinants of public support for policies to phase out fossil fuel cars and to scale up CCS in the United States, a country accounting for 15% of total carbon emissions worldwide, and among the top per capita emitters, where decarbonization is at the same time more necessary and more challenging. To mitigate the problem of social desirability bias that chronically plagues public opinion research on environmental matters, we employ a conjoint experimental design to get insights on the importance of different policy design features in shaping support for decarbonization policies. This allows us to unravel the multidimensionality of policy preferences and to explicitly acknowledge the trade-offs people are confronted with when evaluating various policy proposals. Discrete choice experiments have recently been used to investigate policy preferences in a wide range of policy areas, including climate policy (Bechtel, Hainmueller, & Margalit, 2017; Bechtel & Scheve, 2013; Gampfer, Bernauer, & Kachi, 2014a). In Chapter 2, "Fast track or Slo-Mo? Public support and temporal preferences for phasing out fossil fuel cars in the United States", we focus on public support for policies to phase out fossil fuel cars. This chapter has been published as a paper on *Climate Policy.* Chapter 3, "Carbon Capture and Storage in the United States: Perceptions, Preferences, and Lessons for Policy", focuses on policies to scale up Carbon Capture and Storage technologies, and is at the moment under review at *Energy Policy*.

Together, the three chapters of this thesis attempt to understand the determinants of public attention and public attitudes toward climate change and decarbonization. Focusing on the European Union and the United States, they investigate these determinants in two contexts where climate action is particularly important today.

Chapter 1

A Hot Topic in Hot Times: How Media Coverage of Climate Change is Affected by Temperature Abnormalities

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Abstract

Media coverage of climate change is arguably a fundamental factor shaping climate change attitudes and possibly behaviors, but its trends and determinants are still underinvestigated. In this paper, we analyze a comprehensive dataset representing more than 1.7 million online news articles covering climate change in the 28 countries of the European Union in 22 different languages for the period 2014-2019. We combine our news dataset with observed temperature data to investigate whether and how temperature abnormalities influence media coverage of climate change. We find that the strongest determinants of media coverage are positive deviations from short-term average temperatures. Abnormalities with respect to average temperatures in recent years have stronger effects than abnormalities with respect to temperatures in baseline periods that climatologists use to identify changes in climate. This suggests that the media are less influenced by scientific accounts of climatic changes than by shorter-term changes in weather patterns.

Introduction

Human attention is a scarce resource and without sufficient societal attention to climate change we may not be able to properly address this fundamental challenge. The news media have a unique ability to draw public attention to societal problems like climate change. The media have been shown to have an impact on political outcomes like government policy and voting behavior in different contexts (Eisensee & Strömberg, 2007; Prat & Strömberg, 2013). The impact of media coverage of climate change on public concern has also been investigated in a series of studies (Brulle et al., 2012; Carmichael & Brulle, 2017). Media coverage of climate change could therefore be a crucial factor influencing support for ambitious climate policies or directly influencing climate policy decisions. However, the trends and drivers of media coverage of climate change are not yet well understood. Building on evidence regarding the impact of temperature abnormalities on climate change attitudes and attention (Weber, 2016), we investigate whether and how temperature abnormalities impact media coverage of climate change.

We combine observed temperature data with an unprecedented dataset representing 1.7 million online news articles in 22 different languages covering climate change in the 28 countries of the European Union. Our data span the period from April 2014 through October 2019. To the best of our knowledge, this is the first effort to investigate the impact of temperature abnormalities on media coverage of climate change employing a comprehensive dataset of online news across a wide set of countries. We test the impact of different measures of abnormality and find that the strongest determinants of media coverage of climate change are deviations of temperatures from short-term averages - i.e., average temperatures in the same period of the year over the last few years. In particular, media coverage of climate change increases when temperatures are *warmer* than recent years' averages. Interestingly, media coverage of climate change seems therefore to respond more to short-term temperature abnormalities than to abnormalities with respect to baseline periods that climatologists use to identify changes in climate.

Literature and motivation

Previous studies have presented extensive evidence that temperature abnormalities increase people's climate change belief and concern, at least in the short-term (Bergquist & Warshaw, 2019; Druckman, 2015; Egan & Mullin, 2012; Hamilton & Stampone, 2013; Howe & Leiserowitz, 2013; Kaufmann et al., 2017; Konisky, Hughes, & Kaylor, 2016). Local temperature abnormalities have also been found to influence climate change-related social media activity and internet search activity (Kirilenko, Molodtsova, & Stepchenkova, 2015; Lang, 2014; Sisco, Bosetti, & Weber, 2017).

There are several reasons why attention to climate change may be increased by experienced temperature fluctuations. Noticeable weather abnormalities may simply remind individuals of the problem of climate change due to a mental association between climate change and abnormal weather. Additionally, citizens may look to their own experiences with weather as a direct source of information about the issue. As climate change is a complex phenomenon, individuals may form their climate change attitudes by using personal experiences of local weather in place of more relevant but less accessible information like scientific evidence regarding global climate patterns. The replacement of inaccessible attributes with simpler and more available associated attributes is a cognitive heuristic referred to as attribute substitution and documented in a wide range of decision-making contexts (Gilovich, Griffin, & Kahneman, 2002). Past work has found evidence that attribute substitution is employed in the construction of climate change attitudes (Zaval, Keenan, Johnson, & Weber, 2014). These accounts of how local weather can affect individuals' climate attitudes make evident the possibility that local weather may also affect media attention to the issue.

We investigate how media coverage of climate change is impacted by local temperature trends employing a comprehensive dataset of online media coverage of climate change in the 28 countries of the European Union in the period from April 2014 through October 2019. Very few studies have investigated media coverage of climate change across a wide set of countries and languages. Two notable exceptions are Vu, Liu, and Tran (2019), who investigate frames of climate change in the print press of 45 countries, and Schmidt, Ivanova, and Schäfer (2013), who investigate the country-level determinants of media coverage in 27 different countries.

While previous studies of media coverage of climate change analyze the print media, usually focusing on a relatively small set of newspapers, we present a comprehensive dataset of online media coverage of climate change across a wide set of countries, sources, and languages. The print media are today read by fewer people (in 2018 only 26% of Europeans declared that they read the print media every day) and usually by the most educated sections of the population (Eurobarometer, 2018). Online news are more widely read, with 63% of Europeans reading online news sites according to the most recent Eurostat data (Publications Office of the European Union, 2019). Analyzing online news activity can therefore provide more accurate representations of the news most citizens are currently exposed to.

Previous studies investigating the relationship between temperature and media coverage of climate change mostly tested the impact of present temperature, finding null results (see for instance Schäfer, Ivanova, and Schmidt (2014), but see Shanahan and Good (2000) as an exeption). As climate change is related to changes in temperature, we hypothesize that media coverage of climate change is influenced by temperature abnormalities, rather than by simple temperature levels. Building on studies on the determinants of climate change attention and of perceptions of climate conditions (Ripberger et al., 2017; Sisco et al., 2017), we expect that media coverage of climate change responds in particular to short-term abnormalities - deviations of temperature from recent averages. As climate change is related to temperature increases, we also hypothesize that positive short-term deviations - temperatures *warmer* than recent averages - are comparatively stronger predictors of media coverage of climate change. We expect that long-term abnormalities - deviations from temperature in baseline periods employed by climate scientist to define climatic changes - have a smaller and less significant impact on media coverage of climate change, compared to short-term abnormalities. This mirrors an attribute substitution heuristic: short-term abnormalities are a more available experience than long-term abnormalities, even though the latter more closely mirror scientific definitions of climatic changes.

Data

Our dataset of online media coverage of climate change includes data on 1,703,456 articles published between April 2014 and October 2019 in the 28 countries of the European Union in 22 different languages. It features news mentioning the keywords 'climate change' or 'global warming' translated into the main spoken languages of each country. The translations of these keywords into 22 European languages were completed with the guidance of native speakers from each language (see more details on the dataset and on the translations of keywords in Appendix A).[3] We developed the dataset by employing a script to gather all articles including the keywords among the articles collected by the Europe Media Monitor (EMM). The EMM is a service developed by the European Commission Joint Research Centre, collecting news published on the internet in the world in up to 70 languages. To the best of our knowledge, our dataset is the first comprehensive multi-year dataset of media coverage of climate change across Europe.

We obtain temperature data from the E-OBS dataset, which provides high-resolution daily gridded observational temperature data in Europe since 1950 (Cornes, van der Schrier, van den Besselaar, & Jones, 2018). We first compute daily, weekly and monthly average temperatures at the country level. Second, we compute a series of short-term temperature abnormality measures, defined as the difference between average temperature in each country in each time period (day, week and month of the year) and average temperature in the same country and time period in the previous n years, with N:={1,2,3, ..., 20}. Third, we compute long-term temperature abnormality measures, corresponding to what climate scientists define as changes in climate. Our main long-term abnormality measure is defined as the difference between average temperature in each country in each time period (day, week or month of the year) and average temperature in the same country and time period in the period 1951-1980. This baseline period is employed in most analyses of climatic changes and global surface temperature change (Hansen, Ruedy, Sato, & Lo, 2010). We develop a second measure of long-term abnormality to use in robustness checks, employing the period 1961-1990 as baseline (Hulme et al., 1999; Mitchell & Jones, 2005). Table 1.1 describes the weekly temperature measures employed in the analyses at the weekly level that are presented in the main text of the paper. Table A.2 describes the temperature measures employed in the daily- and monthly-level analyses and reports the

[3] The index of climate change keywords in all European languages we developed for this study is on its own a resource potentially valuable to future studies and we include it in Table A.1

correlations among the temperature variables.

Table 1.1: Descriptive Statistics of the Weekly Temperature Measures

Construct	**Measure**	**Mean**	**Std.Dev.**
Short-Term Abnormality	Deviation from previous 5 years' average by country & week	0.41	2.70
Long-Term Abnormality	Deviation from 1951-1980 average by country & week	1.67	2.53
Temperature level	Weekly average temperature by country	10.80	7.82

Methods

To investigate the relationship between temperature abnormalities and media coverage of climate change, we combine our dataset of media coverage with data on observed temperatures in the 28 EU countries. We use regression analysis to test our hypotheses. Media coverage is quantified as the number of articles mentioning climate change or global warming in each country, standardized by the country-specific standard deviation, so that equal weight is assigned to relative variations in different countries. Our main model specification is the following:

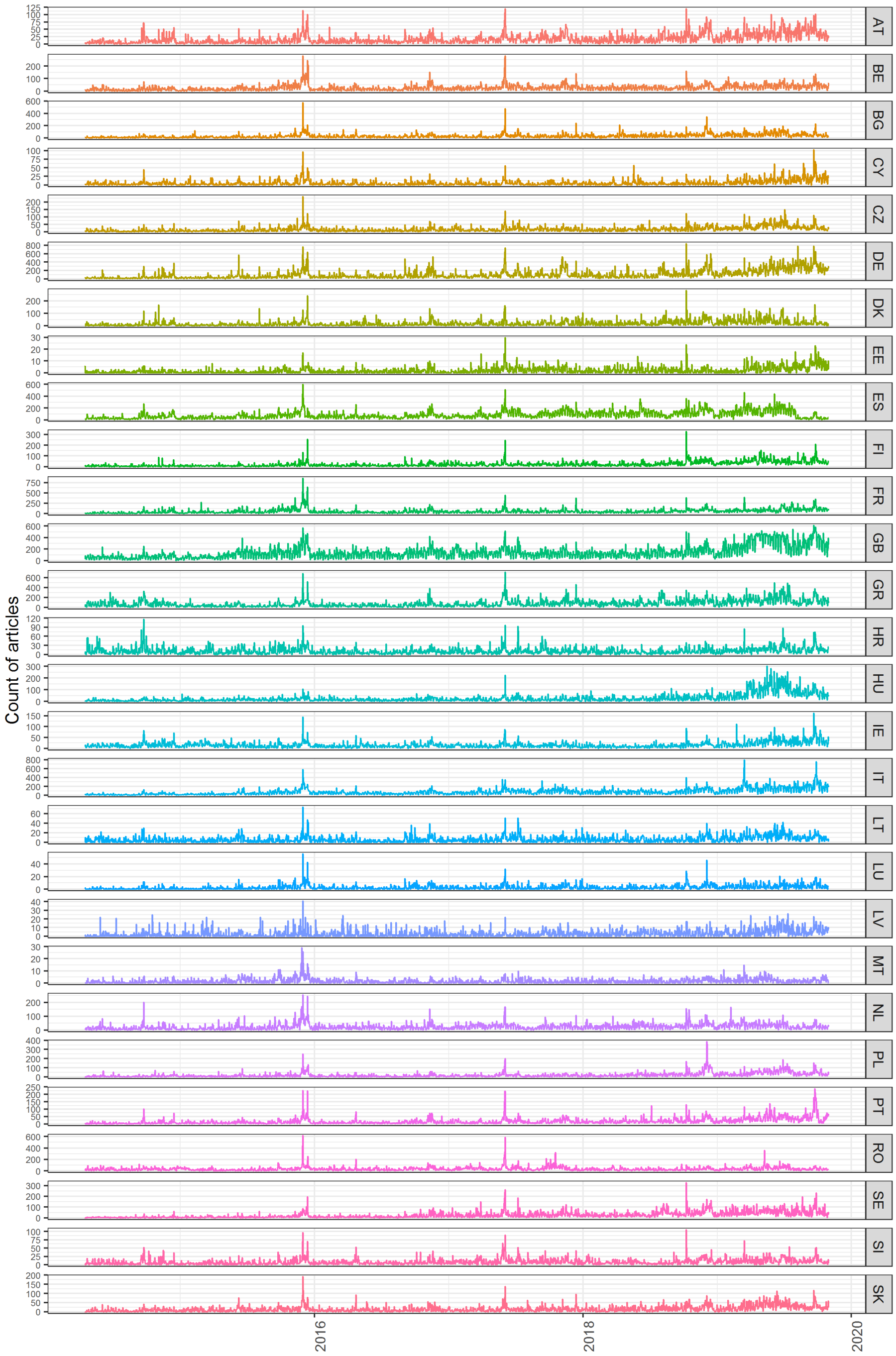
$$Y_{jtm} = \alpha + \beta temp_{jtm} + \phi_c' C_j + \theta t + \psi_{c,t}' C_j t + \zeta_m + \epsilon_{jtm} \tag{1.1}$$

where Y represents the number of articles in country j in time period t in calendar month m, standardized by the country-specific standard deviation, and $temp$ represents the measure of temperature abnormality in in country j in time period t in calendar month m. $\phi'_c C_j$ represent country fixed effects, θt represents a time trend, $\psi'_{c,t} C_j t$ represent country-specific time trends, and ζ_m represents a calendar month fixed effect that controls for seasonality. Together, the latter four terms allow us to control for general time-variant unobserved factors - including the increase in overall media activity over time, time-invariant and time-variant country-level unobserved factors, and for seasonality. The results are essentially unchanged when country-specific time trends and calendar month fixed effects are omitted (see Table A.4 in the Appendix).

Media coverage of climate change in Europe in 2014-2019

Media coverage of climate change has consistently increased since 2014. The average daily number of climate change articles in 2019 is 4.8 times the average in 2014. Examining the overall trend since 2014, peaks of attention to climate change in the media are present in the months of November or December of every year, corresponding to the Conferences of the Parties of the United Nations Framework Convention on Climate Change (see Figure 1.1). Since the beginning of 2018, and in particular in 2019, the rate of increase in media coverage of climate change has significantly risen. This trend is evident in most EU countries.

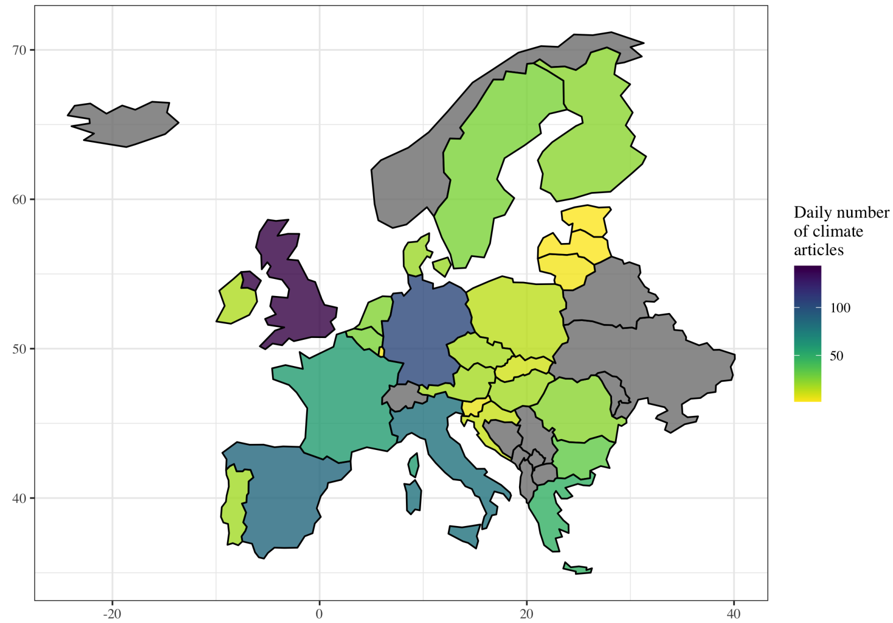
Figure 1.1: The Evolution of Media Coverage of Climate Change in the 28 EU Countries.



Notes: The line plot displays the daily number of articles on climate change in each country for the period April 2014 - October 2019.

Media coverage of climate change is quite heterogeneous across countries, with a 2019 daily average in our data of 304 articles in the United Kingdom, 228 in Germany, 172 in Italy, between 30 and 45 in Austria, Belgium, and Portugal, and of less than 10 in Estonia, Luxembourg and Latvia (see the map in Figure 1.2 and Table A.3 in Appendix A). Population-weighted measures of media coverage suggest that, while country size and population clearly influence the level of media coverage of climate change, they do not fully explain cross-country variability.

Figure 1.2: The Intensity of Media Coverage of Climate Change in Different Countries.



Notes: The map plots the average daily number of climate articles in each country over the whole 2014-2019 time period.

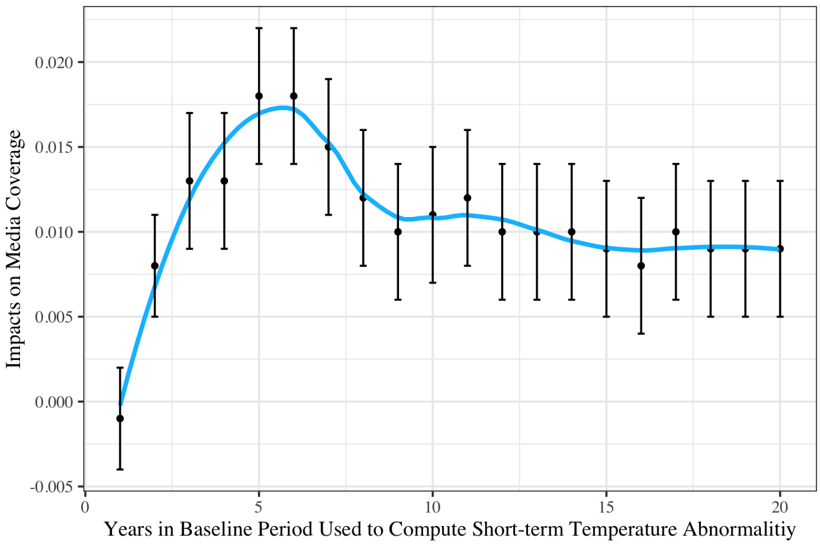
The impact of temperature abnormalities on media coverage of climate change

We first test the impact of short-term temperature abnormalities on media coverage of climate change, examining the differentiated impact of negative and positive abnormalities. We then compare the impacts of short-term abnormalities, long-term abnormalities - which mirror definitions of climatic changes by climate scientists, and temperature levels.

We show below results for data aggregated at the weekly level. In Appendix A, we show that analyses for daily and monthly data present essentially equivalent results (see Tables A.7-A.10). We report analyses with non-standardized measures of media coverage in Tables A.12 and A.13. To support the robustness of our results we also ran placebo tests using future temperature to predict past media coverage and find, as expected, null results (see Tables A.15 and A.16).

Focusing on short-term abnormalities, we compare the impact of abnormalities defined as deviations from average temperatures in the same week of the year over the last 1 to 20 years. As shown in Figure 1.3 and in Table A.14, deviations from temperatures in baseline periods ranging from the previous 2 to 20 years all significantly predict media coverage of climate change. The model that best fits the data and presents the strongest effects is the model with temperature abnormalities computed with respect to the previous 5 years. Effect sizes decrease for somewhat shorter and longer baselines, and are halved for baselines based on the previous 15 to 20 years. Deviations from temperatures in the same time period in the previous year have no statistically significant impact on media coverage of climate change. Media coverage is more impacted by deviations from temperatures in a baseline period that is at the same time recent but not too short. This is probably due to the fact that, in line with the recency effect found in psychological studies, whereby more recent events in a series are remembered more strongly, temperatures experienced more than 8 or 10 years ago are less available in memory (Baddeley & Hitch, 1993). At the same time, recent baseline periods including only the last 2-3 years might be relatively too short to define 'normal' temperature levels.

Figure 1.3: The Effect of Different Measures of Short-term Temperature Abnormalities



Notes: Estimates of the effects of different measures of short-term temperature abnormalities on media coverage of climate change. Abnormalities are computed as the difference between present weekly temperature and temperature in the same week in different baselines, ranging from the previous year to the previous 20 years. Error bars represent +/- one standard error. The blue line is a moving window average of the coefficient estimates over different baseline periods.

As deviations from average temperatures in the previous five years are the strongest determinants of media coverage of climate change, we present in Model (1) of Table 1.2 results of a model testing their impact, controlling for time trend, seasonality, time-invariant and time-variant country-specific unobserved factors.

Having found an impact of short-term temperature abnormalities on media coverage of climate change, the question of how exactly abnormalities impact media coverage remains open. Do all deviations from short-term averages matter equally, or only positive deviations - temperatures *warmer* than short-term averages - have an impact? To investigate the differential impact of positive and negative temperature abnormalities, we construct two variables containing a linear spline of our standard five-year temperature abnormality variable with a knot at 0 (*Negative Temperature Abnormality = Temperature Abnormality if Temperature Abnormality < 0 ; Positive Temperature Abnormality = Temperature Abnormality if Temp.Abnormality > 0*). Model (2) in Table 1.2 shows the impacts of negative and positive short-term temperature abnormalities with respect to the previous five years. The impact of positive abnormalities is positive and significantly bigger in size than the impact of the simple abnormality measure presented in Model (1). Temperatures colder than recent baselines also increase media coverage of climate change, but temperatures warmer than recent baselines have a considerably stronger effect. This suggests that the impact of short-term temperature abnormalities on the media is driven by temperatures perceived as warmer than normal.

Table 1.2: Short-term Temperature Abnormality and Media Coverage of Climate Change

VARIABLES	(1) Coverage	(2) Coverage
Short-term Abnormality	0.018***	
	(0.004)	
Neg. Short-term Abnormality		-0.018***
		(0.005)
Pos. Short-term Abnormality		0.050***
		(0.008)
Constant	0.026	-0.079*
	(0.021)	(0.030)
Observations	8,065	8,065
Adjusted R-squared	0.355	0.358
Country FE × Time trend	✓	✓
Month FE	✓	✓

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Notes: Standard errors are clustered at the country level. Media coverage is measured as the weekly number of climate articles per country divided by the country-specific standard deviation. In Model (1) temperature abnormalities are computed as the difference between average temperature in each country in each week and average temperature in the same country and week over the previous 5 years. In Model (2), negative and positive short-term temperature abnormalities are computed employing a spline of the variable employed in Model (1): *Neg.Temp.Abnormality = Temp.Abnormality if Temp.Abnormality < 0 ; Pos.Temp.Abnormality = Temp.Abnormality if Temp.Abnormality > 0*

We hypothesized that short-term temperature abnormalities are stronger predictors of media coverage compared to long-term abnormalities. To test this hypothesis, we compare the impact of deviations from average temperatures over the previous five years with the impact of deviations from temperatures in the period 1951-1980, which is the baseline period most often employed by climate scientists to define climatic changes. Long-term abnormalities are computed as the difference between average temperature in each country and week and average temperature in the same country and week in the period 1951-1980.

We find that deviations from average temperatures in 1951-1980 have an impact on media coverage of climate change that is approximately half in size compared to that of short-term abnormalities (compare Models (1) and (2) in Table 1.3). Results are equivalent when using 1961-1990 instead of 1951-1980 as baseline period to compute long-term abnormality (see Table A.5). These results suggest that actual climatic changes manifesting as deviations from less recent baseline periods are less significant determinants of coverage of climate change with respect to short-term abnormalities.

As mentioned above, previous studies of media coverage of climate change have mostly tested whether present temperature, rather than temperature abnormalities, impacts the level of attention that the media devotes to climate change. Temperature levels have in general been shown to influence not only economic activities, from agricultural productivity to labor supply (Carleton & Hsiang, 2016), but also a wide range of human behaviors, from aggressive behavior and criminal activity (Baylis, 2020; Ranson, 2014), to performance in math tests (Graff Zivin, Hsiang, & Neidell, 2018) and immigration adjudications (Heyes & Saberian, 2019). Building on such evidence, we test whether present temperature affects online media coverage of climate change.

We find that simple measures of present temperature have a marginally significant impact on media coverage of climate change, and that their impact is approximately half in size compared to the effect of short-term abnormalities - and equivalent in size to the impact of long-term abnormalities (compare Models (2) and (3) in Table 1.3). Once short-term temperature abnormality is controlled for, the impact of temperature on media coverage becomes insignificant (see Table A.6). This suggests the impact of short-term abnormality is stronger and more robust than the impact of simple measures of temperatures. While temperature levels do impact a series of human behaviors, the attention that the media devotes to climate change is more strongly influenced by perceptions of abnormal temperatures rather than raw measures of temperature.

Table 1.3: Comparing the Impact of Short-term and Long-term Temperature Abnormalities and Present Temperature on Media Coverage of Climate Change

VARIABLES	(1) Coverage	(2) Coverage	(3) Coverage
Short-Term Abnormality	0.018***		
	(0.004)		
Long-Term Abnormality		0.010**	
		(0.004)	
Present Temperature			0.009*
			(0.004)
Constant	0.026	0.016	0.046*
	(0.021)	(0.022)	(0.020)
Observations	8,065	8,073	8,073
Adjusted R-squared	0.355	0.353	0.353
Country FE × Time trend	✓	✓	✓
Month FE	✓	✓	✓

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Notes: Standard errors are clustered at the country level. Media coverage is measured as the weekly number of climate articles per country divided by the country-specific standard deviation. We compare here the impact of short-term temperature abnormalities, long-term temperature abnormalities, and present temperature on media coverage of climate change. In Model (1) short-term temperature abnormality is computed as the difference between average temperature in each country in each week and average temperature in the same country and week over the previous 5 years. In Model (2) long-term temperature abnormality is computed as the difference between average temperature in each country in each week and average temperature in the same country and week over the baseline period 1951-1980.

Conclusion

In this paper, we investigate whether and how temperature abnormalities influence media coverage of climate change. We employ a comprehensive dataset of media coverage of climate change in the 28 countries of the European Union, with data representing 1.7 million online articles published between April 2014 and October 2019 in 22 different languages. We find that short-term temperature abnormalities - i.e., deviations from temperatures experienced in recent years - significantly increase media coverage of climate change. This effect is driven by positive temperature abnormalities - temperatures warmer than recent years' averages. Interestingly, deviations from temperatures in baseline periods that climatologists use to define climatic changes have a considerably smaller effect compared to that of short-term abnormalities.

Deviations from weather conditions in recent years have also been found to shape discussions about weather on social media (Moore, Obradovich, Lehner, & Baylis, 2019) and to influence perceptions of climatic conditions (Ripberger et al., 2017). Here, we find that temperatures warmer with respect to recent years increase the attention that the media devote to climate change. This effect may be due to an attribute substitution mechanism, with coverage of climate change increasing because temperatures warmer than recent years' averages are interpreted as evidence of climate change. Or climate change might simply become associatively more salient when it is 'warmer than usual'.

Media coverage is driven by both demand and supply. On the one hand, warmer temperatures might increase interest and salience of climate change for editors and journalists, who might consequently increase the coverage of the topic. On the other hand, journalists or editors may be taking advantage of short-term temperature abnormalities to increase coverage of climate change because they anticipate a broader interest among the public. Without readership data, we are unfortunately unable to disentangle these effects in this paper.

The intensity of media coverage and the frames of policy issues present in the media play a key role in influencing public attitudes towards such issues (Bolsen & Shapiro, 2018; Shapiro, Jacobs, & Edwards III, 2011; Zaller et al., 1992). The news media have also been shown to influence a wide range of political outcomes, including public expression, national agendas and policy decisions (King, Schneer, & White, 2017; Strömberg, 2015). Given the fundamental role of the media in the public sphere, investigating determinants of coverage of climate change is extremely important. Providing the first test of the impact of temperature trends on online media coverage of climate change - using data from 28 countries over 6 years, this paper helps answer this question.

Our finding that media coverage of climate change is predicted more by short-term temperature abnormalities than by long-term abnormalities also suggests that long-term future public attention to climate change may not track with objective changes in climate. Based on future climate projections alone, policy makers may be inclined to expect that if we wait to introduce ambitious climate policies we may benefit from higher future public support brought about by higher temperatures due to climate change. Our findings do not support such a strategy of delaying ambitious climate policy implementation as public attention seems to be driven more by short-term fluctuations in temperature than by objective climatic changes.

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Chapter 2

Fast Track or Slo-Mo? Public Support and Temporal Preferences for Phasing Out Fossil Fuel Cars in the United States

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Abstract

Policies to phase out fossil fuel cars are key to averting dangerous and irreversible changes to the earth's climate. Given the potential impacts of such policies on every-day routines and behaviors, the factors that might increase or decrease their public acceptance require investigation. Here we study the role of specific policy design features in shaping Americans' preferences for policy proposals to phase out fossil fuel cars. In light of the urgency of action against climate change, we are specifically interested in citizens' preferences with respect to the timing of phase-out policies. Based on a demographically representative sample of 1,520 American residents rating 24,320 hypothetical policy scenarios in a conjoint experiment, we find that Americans prefer phase-out policies to be implemented no later than 2030. Policy features other than timing are also important: higher policy costs significantly reduce public support; subsidies for alternative technologies are preferred over taxes and bans; and policy co-benefits in terms of pollution reduction increase public support only when they are substantial. The study also investigates the role of individual characteristics in shaping policy preferences, finding that perceived psychological distance of climate change and party identification influence policy preferences. The results of this study have important implications for the political feasibility of rapid decarbonization initiatives like the 'Green New Deal' that are now being discussed in the US and beyond. Among these is the insight that smart sequencing of policies (early implementation of subsidies for low-emission technologies, followed by tax increases and/or bans) might help ensure majority support for a fossil fuel car phase-out.

Introduction

To mitigate the effects of anthropogenic climate change, rapid and comprehensive mitigation measures are required (IPCC, 2018; Rockström et al., 2017; Steffen et al., 2018). With markets alone not providing sufficient incentives for individuals, firms, and entire societies to switch from carbon-intensive to carbon-neutral systems of production and consumption in a timely fashion, public policies are important in steering societal actors into the necessary decarbonization pathways (Fri & Savitz, 2014). In fact, political coalitions have spurred governments around the world to introduce policies for the phase-in of clean technologies in climate-relevant sectors (Meckling, Kelsey, Biber, & Zysman, 2015). While this has opened up new business opportunities, fossil fuel consumption is still rising globally (IEA, 2019a). The problem is that most governments layer support schemes for new technologies on top of existing policies and institutions, instead of dismantling existing fossil fuel systems (Laird, 2016; Stokes & Breetz, 2018). However, to overcome carbon lock-in (Unruh, 2002), phase-out policies will most likely be needed (Geels et al., 2017; Kivimaa & Kern, 2016).

In democracies in particular, governments in charge of designing such policies need to be responsive to their constituencies. Given their desire for re-election, politicians' incentives to enact policies that are opposed by a majority of voters are limited (Downs, 1957; Druckman, 2013). Recently, concern has risen that voters are becoming an increasing barrier to ambitious climate policies, driven by the rise of right-wing populism and post-truth politics (Batel & Devine-Wright, 2018; Fraune & Knodt, 2018; Lockwood, 2018). Opposition to climate policies can arise in particular if these are (perceived to be) poorly designed, as has been seen in the protest movement of the French Gilets Jaunes, which was fueled by a proposed increase in gasoline taxes. Understanding the drivers of citizens' climate policy preferences is therefore of crucial importance for both policymakers and researchers.

Recent climate assessments have stressed the urgency of significant measures to avert irreversible damages to the earth's climate (IPCC, 2018; Research, 2018). Against this background, we specifically investigate citizens' preferences regarding temporal aspects of climate policy implementation, a key factor for assessing the political feasibility of rapid low-carbon transitions. Considering that decarbonization is humanity's first industrial transformation that faces a deadline (Schmitz, 2015), it is important to understand whether citizens support the implementation of decarbonization policies as early as possible or are (still) in favor of postponing them to later dates.

Concretely, our study employs a conjoint experiment to investigate support for policies to phase out fossil fuel vehicles for personal transportation. Decarbonizing the transportation sector is a key element in global efforts to mitigate climate change (Creutzig et al., 2015; Fuglestvedt, Berntsen, Myhre, Rypdal, & Skeie, 2008). The role of citizens is particularly important in transforming this sector, as such transformation efforts not only hinge upon changes in technologies and investment flows, but also on fundamental shifts in user practices, habits, and social norms (Creutzig et al., 2015). In addition to assessing the extent to which citizens' preferences on phase-out policies are affected by the timing of policy implementation, we investigate the impact of other key policy design features, including policy instruments, policy co-benefits in terms of pollution reduction, policy cost, and endorsements by parties and stakeholders. We do so in the context of the US, the second largest CO_2 emitting country in the world.

Our study makes two main contributions. First, while recent research on climate and energy policy has acknowledged the centrality of phase-out of, and divestment from, fossil fuels (Ayling & Gunningham, 2017; Davidson, 2019; Rockström et al., 2017; Rogge & Johnstone, 2017), we are among the first to explore citizens' policy preferences in this realm. Second, given the urgency of more ambitious mitigation action, we investigate the extent to which citizens' preferences are moved by different policy implementation time horizons. As will be explained, our results are significant in suggesting that Americans' proclivity to procrastinate in terms of climate change action is surprisingly low. Earlier policy action is clearly preferred over action enacted later than 2030. However, temporal policy preferences are significantly moderated by individual-level psychological and political characteristics.

Background

Phasing out fossil fuel cars

Phasing out fossil fuel cars is a mitigation option that could substantially contribute to a deep decarbonization of the transportation sector and hence energy systems more broadly. Rockström et al. (2017) indicate that, to limit global mean temperature rise to 2°C, internal combustion engines for personal transportation need to disappear by 2040, as oil has to exit the global energy mix by that time at the latest. In the US, the transportation sector is the largest contributor to greenhouse gas (GHG) emissions, accounting for 29% of total emissions.[4] Overcoming carbon lock-in in the transportation sector is a challenge in multiple ways, but many researchers agree that the main obstacles in the transformation of energy systems are not economic or technological, but socio-political in nature (Diesendorf & Elliston, 2018; Jacobson & Delucchi, 2011; Stokes & Breetz, 2018).

[4]See https://www.epa.gov/greenvehicles/fast-facts-transportation-greenhouse-gas-emissions. Globally, transportation is responsible for 23% of energy-related CO2-emissions (Sims et al. 2014).

Many jurisdictions around the world are discussing and implementing policies to phase out cars with internal combustion engines (IEA, 2019b). While most of the countries that have announced a ban on fossil fuel cars are in Europe (e.g., Norway, France, Great Britain), China and India have also signaled their intent to ban internal combustion engines (see Table B.10 in Appendix B). However, the legal status of these announcements varies significantly, and no country has passed binding legislation so far (Meckling & Nahm, 2019). In the US no significant policy innovation can currently be expected on the federal level, but the state of California in 2018 was the first to discuss a legislative act to ban the registration of new fossil fuel cars starting in 2040. Carbon taxes or fuel tax increases constitute other policy instruments that could contribute to a phase-out. However, taxes can be problematic from a public acceptance perspective. In particular, taxes sometimes face vigorous public opposition if their design does not take potential social inequities into account. Yet, there are also examples of smartly designed environmental taxes that result in increasing public support over time, as in the case of British Columbia, where a carbon tax was introduced in 2008 and is still in effect (Murray & Rivers, 2015). Other policy instruments that ultimately target the same objective, like subsidies for low-emission transportation alternatives, have already been enacted in various places. In the US, the federal government and several states offer financial incentives like tax credits for the purchase of electric vehicles, but polling suggests that awareness of electric vehicles is still extremely low among citizens.[5]

[5] See https://www.greentechmedia.com/articles/read/consumers-lack-ev-awareness-even-in-the-nations-largest-market#gs.2t1aeh

Theoretical framework

Temporal preferences

Research in behavioral science has shown that humans are not particularly good at making forward-looking decisions, but instead tend to be oriented toward immediate benefits (Frederick, Loewenstein, & O'donoghue, 2002) and the status quo (Weber, 2015). When applied to decisions relevant for long-term sustainability, such present bias can threaten the future of humanity (Weber, 2017). When it comes to political preferences, self-interested citizens may not be inclined to accept economic costs if benefits that might accrue from policy action are significantly delayed (Jacobs and Matthews 2012), as is often the case in the context of climate change mitigation. Hence, we can hypothesize that citizens, when faced with the choice of enacting climate policies now versus ten or more years from now, will favor later over immediate action. This expectation is backed by the fact that climate change is still often depicted as a problem with consequences distant in time (Brügger, Dessai, Devine-Wright, Morton, & Pidgeon, 2015), which might lead citizens to perceive the problem as one that can safely be addressed sometime in the future. This of course conflicts with evidence from climate science suggesting that urgent action is required to avoid the crossing of climate tipping points, which could lead to uncontrollable and irreversible climate change (Lenton, 2011; Lontzek, Cai, Judd, & Lenton, 2015).

Psychological distance of climate change and party identification

Preferences for different temporal trajectories of climate action cannot be assumed to be the same across the US population. Some individuals will be more aware of the urgency for climate action and hence support earlier policy implementation. This might be the case especially for citizens who have already personally experienced climate change impacts (Egan & Mullin, 2017; Hainmueller & Hopkins, 2015; Spence, Poortinga, Butler, & Pidgeon, 2011) or expect them in the near future.

This idea ties in with the literature on psychological distance. Psychological distance is defined as the extent to which something is perceived as far away vs. close to the self (Trope & Liberman, 2010). In the context of climate change, psychological distance indicates the extent to which people perceive climate change to be a "threat that is more likely to affect strangers remote in time and space rather than oneself, the people one knows, or nearby places" (Brügger, Morton, & Dessai, 2016). Perceived psychological distance of climate change can therefore be hypothesized to affect temporal policy preferences. Accordingly, citizens who perceive climate change to be proximal should be in favor of earlier policy implementation. Citizens who perceive climate change to be distant, on the other hand, can be expected to prefer policy implementation as far in the future as possible.

In light of the polarization of climate politics in the US (Jasny, Waggle, & Fisher, 2015; Weber & Stern, 2011), we examine citizens' party identification as a second factor potentially moderating their preferences regarding temporal aspects of policy implementation. Given that climate skepticism is far greater among Republicans than Democrats (McCright & Dunlap, 2011), we assume Republicans' support for climate policy action to increase as a function of later implementation dates, while we expect Democrats' support to increase as a function of earlier implementation dates. In the context of phasing out fossil fuel-based technologies, the influence of party identification on temporal preferences has not been investigated so far. Regarding the large group of Americans describing themselves as Independents,[6] our expectation is that their average timing preference is

[6]More than a third of the American electorate consider themselves as Independents (see Gallup 2019). According to data from the Pew Research Center (2018), the share of Independents has increased from

somewhere between Democrats' assumed preference for early policy action and Republicans' assumed preference for later action. Our expectation is based on results of prior research showing that depending on the subject matter, Independents' policy preferences are sometimes closer to those of Democrats and in other cases closer to those of Republicans (Hardisty, Johnson, & Weber, 2010; Leiserowitz, Maibach, Roser-Renouf, & Hmielowski, 2011).

Methodology

Sample

We conducted a conjoint experiment implemented in an online survey, which was fielded in October 2018. We contracted with the survey company Lightspeed, with access to approximately 1.3 million respondents in the US. From this panel, a sample that demographically represents the US was drawn based on a matching algorithm. Despite some small deviations, the sample (n = 1,520 American residents) matches the US population well in terms of age, gender, census regions, household income, and party identification (see Table B.1 in Appendix B).[7] This sampling approach is standard in experimental studies of political preferences, in which the estimation of treatment effects is the primary objective (Bolsen, Druckman, & Cook, 2014; Druckman, 2001). As shown by Ansolabehere and Schaffner (2014) (see also Sanders, Clarke, Stewart, & Whiteley, 2007), a carefully conducted matched sampling approach based on opt-in Internet panels also produces accurate population estimates and replicates the basic correlation structures of probability samples. Our study was preregistered at the Open Science Framework and approved by Princeton University's Institutional Review Board.

30 to 37% between 1994 and 2017.

[7]As the sample is taken from a panel of respondents that have given consent to participate in online surveys, it is a nonprobability sample.

Study design

Social scientists have recently adopted conjoint analysis as a method to measure citizens' policy preferences (Bechtel et al., 2017; Gallego & Marx, 2017; Hainmueller, Hopkins, & Yamamoto, 2014). Conjoint analysis simulates a decision situation by exposing people to two or more scenarios – in our case, two hypothetical policy proposals – and asking them to rank and/or rate these scenarios according to their preferences. These scenarios vary on multiple dimensions, in our case different policy attributes. Based on respondents' choices over several rounds, we can simultaneously estimate the individual effects of several policy attributes on policy preferences (Gampfer et al., 2014a). Although respondents might not be able to consciously evaluate the importance they would assign to the different dimensions if asked explicitly, the conjoint analysis, which is based on multiple observed multiattribute choices, allows eliciting the weight respondents attribute to these attributes. Conjoint-based experiments also have the potential to substantially mitigate the problem of social desirability bias that chronically plagues public opinion research on environmental matters, as potential trade-offs that often remain unaddressed in simpler survey questions are explicitly incorporated in the choice alternatives (Hainmueller et al., 2014). In our case, using conjoint analysis reduces the likelihood of overestimating citizens' appetite for ambitious climate policies.

At the beginning of the experiment, participants were made familiar with the context of the policy debate. This included information about the contribution the transportation sector makes to climate change. Moreover, it was highlighted that many climate scientists agree that phasing out fossil fuels is a necessary measure to avert dangerous climate change, and that several countries have already taken measures towards decarbonization of their transportation systems (see Appendix B for the complete information given to respondents). Next, respondents were made familiar with five attributes of a potential policy to phase out fossil fuel cars and the specific levels of the attributes, which we defined based on a screening of the scientific literature and media releases referring to policies to phase out fossil fuel cars. The attributes were explained to respondents in the order in which we present them here. First, different policy types or instruments could be used to initiate a phase-out of fossil fuel cars, such as a ban on new car sales, subsidies for low-emission transportation alternatives, or an increase in fossil fuel taxes. Second, a phase-out would lead to costs for consumers, which we assumed to take on values between \$2 and 14 per month and household. Third, we calibrated the timing attribute using increments of 10 years from 2020 to 2050. Fourth, as a phase-out of fossil fuel cars would not only lead to reductions in CO_2 emissions, but also in particulate matters and other pollutants with adverse health impacts, we defined rough levels of pollution reduction, ranging from 10 to 30% within one year after policy enactment. The final attribute captures endorsement of a policy proposal by different stakeholders. We calibrated this attribute by including endorsements by the Democratic or Republican Party, or by two key visible policy stakeholders, Greenpeace and the US Alliance of Automobile Manufacturers. Table 2.1 provides an overview on all attributes and levels.

After receiving information on the five policy attributes, respondents were exposed to eight consecutive pairs of hypothetical policy proposals to phase out fossil fuel cars. We employed complete randomization: the levels of the five attributes characterizing any given policy proposal varied randomly both within and across the binary comparisons (Hainmueller et al., 2014). The order in which the attributes appeared in the description of proposals was randomized across respondents but fixed for each respondent, to prevent the confounding of attribute effects with order effects while at the same time limiting experimental complexity and cognitive load on respondents. For each choice, respondents indicated their policy preference based on two outcome measures. First, they were asked to choose which scenario they preferred ('forced choice outcome'). Second, simulating a referendum, participants were asked to indicate, on a scale from 0 to 10, how likely they would vote for each proposal if it were the object of a direct democratic vote ('rating outcome'). Apart from the conjoint experiment, the survey included a number of items to measure moderators and covariates of interest. Figure B.1 in Appendix B presents a visualization of a choice task, and Tables B.2 and B.3 provide information on measurement and aggregation of variables.

Table 2.1: Policy attributes and attribute levels for the conjoint experiment

Policy attributes	Level 1	Level 2	Level 3	Level 4
Policy types	Ban on new fossil fuel car sales	Government subsidies for low-emission transportation alternatives	Increase in fossil fuel taxes	-
Policy cost (per household, per month)	$2	$6	$10	$14
Beginning of policy implementation	2020	2030	2040	2050
Pollution reduction within one year after policy enactment	10%	20%	30%	-
Policy endorsement by	US Alliance of Automobile Manufacturers	Greenpeace	Democratic Party	Republican Party

Empirical model

For the analysis of the conjoint experiment, we collapsed the answers from the 11-point ratings into binary measures of policy support, using the median (which is 5) as the cutoff value (see Bechtel et al., 2017). The rationale is that while the rating scale allowed respondents to assess each policy proposal individually and on a fine-grained scale, a political vote (as simulated in the rating task) ultimately boils down to a yes or no. The resulting dependent variable "Vote for Phase-Out" is coded 0 for cases where a respondent rejects a proposal or is neutral about it (values 0 to 5 on the original scale) and 1 for cases where a respondent supports a proposal (values 6 to 10 on the original scale). Since respondents were exposed to eight consecutive pairs of policy proposals, our analyses rely on a total of 24,320 observations. As Bansak, Hainmueller, Hopkins, and Yamamoto (2018) show, marginal effects derived from conjoint experiments are robust to a large number of choice tasks (as much as 30), which is why satisficing is unlikely to degrade respondents' response quality in our setting.

In the first step, we are interested in the average marginal effects of attribute levels on policy support. As our experiment is based on a fully randomized conjoint design, the causal effects of policy attributes on policy support are non-parametrically identified (Bechtel & Scheve, 2013). Hence, as Hainmueller et al. (2014) show, with a fully randomized design, a simple difference-in-means estimator yields unbiased estimates. This means that average marginal effects for individual attribute levels can be estimated by fitting a simple regression of the dependent variable, which is policy support, on a set of dummy variables capturing the attribute levels of interest. These dummy variables take the value one if the respective attribute level was present in a policy proposal, and zero otherwise. For each attribute, one level is fixed as a baseline against which to compare the marginal effects, so that the regression coefficient for each dummy variable corresponds to the average marginal effect of the respective attribute level relative to the omitted reference level of the same attribute. Hence, we estimate the following main model:

$$Y_{ijk} = \beta X_{ijk} + e_{ijk} \tag{2.1}$$

where a respondent i's vote y for proposal k in task j is modeled as a function of X_{ijk}, which represents a vector containing the attribute levels of the policy proposal presented to i in k. To account for within-respondent correlations in responses, we cluster standard errors e by respondent. By estimating this model, we obtain marginal effects b for all attribute levels simultaneously.

As we are also interested in exploring whether the marginal effects vary across the theoretically relevant subgroups specified in the Theoretical Framework section, we additionally compute marginal effects conditional on respondents' level of psychological distance of climate change and party identification. As these characteristics are not affected by the experimental treatments, the conditional effects are also non-parametrically identified given the fully randomized design (Bechtel & Scheve, 2013).

Results and discussion

Pre-experimental support for phase-out policies

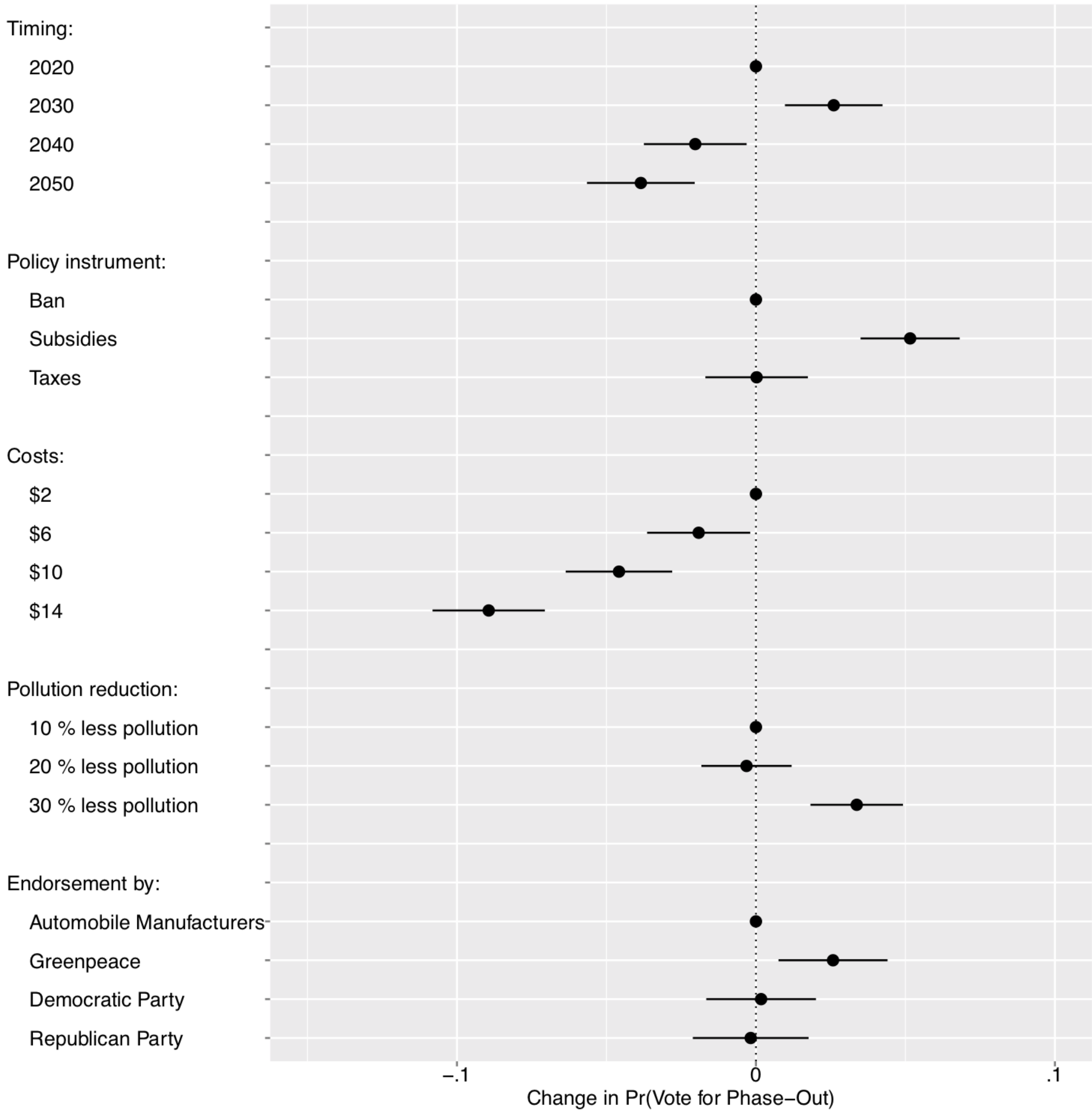
After being provided with basic facts about the climate impact of fossil fuel-based transportation systems and policy initiatives announced by several countries, but before receiving information about the attributes and attribute levels that characterized potential policy proposals in the conjoint experiment, respondents were asked about the extent to which they support policies to phase out fossil fuel cars. Mapping the results from the original 6- point scale (from "Do not support at all" to "Strongly support") onto the probability scale, the average support level (M = .63; SD = .26) indicates that most respondents seem to support such policies in principle. About 34% of respondents stated that they (strongly) support policies to phase out fossil fuel cars (corresponding to '5' or '6' on the six point scale), while 20% stated that they (strongly) oppose such measures

('1' or '2'; see Figure B.9 in Appendix B). However, assessing policy support this way is likely to overestimate the public's enthusiasm and does not tell us anything about more specific dimensions of support, such as the preferred timing and policy instruments. More fine-grained insights about citizens' policy preferences can be derived from our conjoint experiment.

Insights from the conjoint experiment

Figure 2.1 shows the marginal effects associated with each attribute level. The horizontal lines represent their 95% confidence intervals. For each of the five attributes, one level serves as the baseline category, which is shown without confidence interval. As our interest lies primarily with the temporal dimension of policy implementation, Figure 2.1 shows the effects of different implementation years first, followed by all other attribute levels.

Figure 2.1: Average effects of policy attributes on respondents' policy preference to phase out fossil fuel cars.



Notes: Each dot represents an average marginal effect of an individual attribute level on a respondent's probability to choose a hypothetical policy proposal in relation to a proposal with the reference level for the same attribute. The horizontal bars represent the associated 95% confidence intervals. Dots without bars represent the reference level for each policy attribute. Calculations are based on linear regression analyses with dichotomized rating outcomes and standard errors grouped at the level of the individual (clustered standard errors (see Figure B.4 in Appendix B). N = 24,320 policy proposals.

For the timing attribute, we see that the temporal distance of policy implementation clearly impacts citizens' appraisal of policies. Policy implementation in 2030 significantly increases the probability that respondents support the proposal, compared to implementation in 2020. While this is in line with our expectation that citizens prefer later over immediate action, implementation dates later than 2030 significantly decrease the probability to support a proposal, compared with the baseline category of immediate policy action (i.e., in 2020). The probability that voters support policies implemented in 2040 is 4.6 percentage points lower than the probability to support policies implemented in 2030. Below we further explore whether this partly surprising finding can be explained by a perceived urgency to act on climate change.

As for the second attribute, policy instrument, proposals including the provision of subsidies for low-emission transportation alternatives have higher probabilities to be supported than bans on new fossil fuel car sales or increases in fossil fuel taxes. Trying to achieve decarbonization of the transportation system with subsidies instead of a ban or an increase in gasoline taxes leads to a 5.2 percentage point increase in the probability that citizens will support the proposal. These results are in line with earlier research showing that citizens prefer subsidies over taxes (Cherry, Kallbekken, & Kroll, 2012) and tend to be reluctant to accept 'hard regulations' like bans and tax increases (Attari et al., 2009) in the transportation sector.

Not surprisingly, the cost induced by a policy leads to an (almost) monotonic decrease in a proposal's probability to be supported. The probability to support a policy that would come at a monthly cost of $14 per household is 8.9 percentage points lower than the probability to support a policy with a monthly cost of $2 per household. Roughly, every dollar in monthly household cost leads to a decrease in policy support of 0.75 percentage points. Our analysis hence confirms that keeping the costs citizens have to bear for decarbonization within reasonable limits is essential to ensuring public support.

The co-benefits of phase-out policies in terms of pollution reduction lead to significant changes in public support only when they are substantial. While policy support is equivalent for policies that lead to 10 or 20% of pollution reduction, achieving a 30% reduction results in a substantial increase in the probability to support a policy of 3.4 percentage points compared to the baseline level of 10%.

Finally, when investigating the whole sample, endorsements by stakeholders do not seem to strongly influence average public support, apart from the increase in the probability to support policies induced by Greenpeace's endorsement when compared with endorsement of the Automobile Alliance. The seemingly low influence of endorsements is not surprising, as it is known that perceived trustworthiness is a requirement for elite cues to play an effective role in the formation of political preferences (Druckman, 2001; Nicholson, 2011). We therefore conducted additional analyses to explore whether trust in stakeholders moderates this relationship. As we show in the Appendix B (Figure B.2), stakeholder endorsements do indeed have sizeable effects within certain subgroups. In particular, endorsement by political parties significantly increases policy support among respondents who perceive the respective party as trustworthy, and significantly decreases support by respondents who perceive it as not trustworthy.

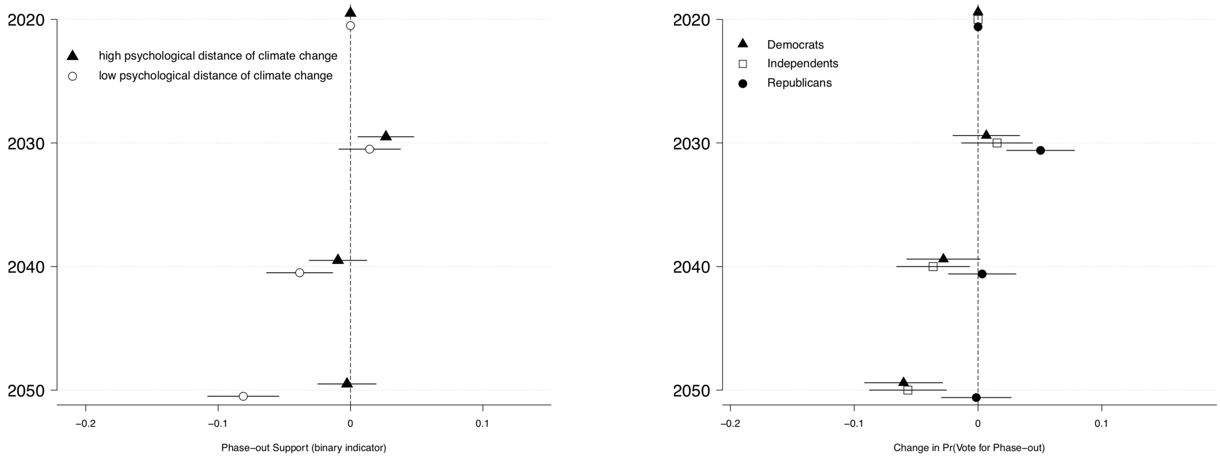
We ran several robustness checks with the conjoint experiment data. First, we re-estimated the effects using logit models, and the results remain unchanged. Moreover, neither exclusion of respondents who completed the experiment exceptionally fast nor replicating the analysis based only on the first three choice tasks each respondent completed lead to substantially different results (see Figure B.4).

Temporal preferences for climate policy implementation: Conditional effects

To better understand temporal preferences for policy implementation, we investigate two factors that we hypothesized to be relevant for perceptions of urgency of climate change action: perceived psychological distance of climate change, and party identification. As shown in Figure 2.2a, psychological distance moderates the impact of policy timing on policy support.[8] We find that, in the subgroup of respondents with high perceived distance, the malleability of policy support as a function of different implementation times is limited. Implementation in 2030 leads to higher support than implementation in 2020, but the differences between implementation in 2020, 2040 or 2050 are statistically indistinguishable from zero. Policy support by individuals with a low psychological distance, on the other hand, is not significantly influenced by implementation in 2020 versus 2030, but their probability to support a policy option significantly decreases by 5.5 (9.5) percentage points if implementation is delayed to 2040 (2050), compared to 2030.

[8] Perceived psychological distance was measured with five items. Using factor analysis, one latent factor was extracted (see Table B.2 in Appendix B). We took a median split on the factor variable to generate subgroups for high versus low perceived psychological distance of climate change

Figure 2.2: Average effects of timing attribute on respondents' policy preference by psychological distance of climate change and party identification



(a) (b)

Notes: Symbols represent average marginal effects for the policy attribute "beginning of policy implementation", conditional on psychological distance of climate change (a) and party identification (b). Subgroups for perceived psychological distance of climate change were generated by taking a median split on the original factor variable. Partisan subsamples represent 545 self-identified Democrats, 495 self-identified Independents, and 480 self-identified Republicans. Calculations are based on linear regression analyses with dichotomized rating outcomes, the full set of attribute values as predictors, and clustered standard errors (see Tables B.5 and B.6 in Appendix B). N = 24,320 policy proposals.

Party identification is also systematically related to temporal policy preferences.[9] The time horizon of policy implementation plays a role in determining each partisan group's preferences, but in different ways (see Figure 2.2b). Republicans' support increases for policies implemented in 2030, while immediate (2020) or later (from 2040 onward) implementation are supported to the same extent. This is different for Democrats and Independents, whose preferences are influenced in similar ways by different time horizons. In both groups, policy support is similar for implementation in 2020 and 2030, but support decreases significantly if implementation takes place only in 2040 or later (with the difference between 2020 and 2040 slightly failing to attain statistical significance for Democrats). However, these effects about relative differences in policy support as a func-

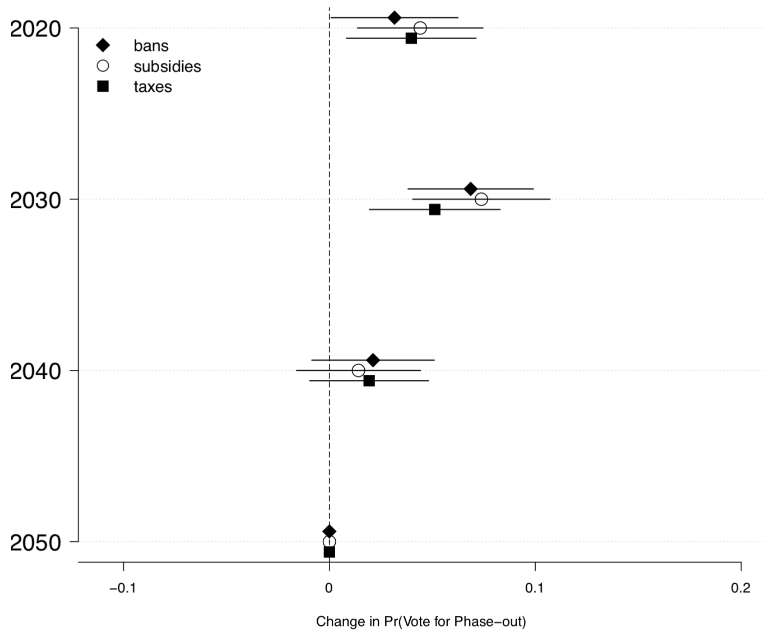
[9]Party identification was measured with one item, using a seven-point scale from "Strong Democrat" to "Strong Republican." Based on this, we created three subgroups for Democrats, Independents and Republicans. See Table B.2 for details.

tion of implementation time should not be mistaken with absolute support. In Appendix B, we show simulation results to predict absolute levels of support, indicating that average policy support among Democrats is about 68 to 69% for measures implemented in 2020 or 2030, while support is considerably lower among Independents (47% for 2020 / 48% for 2030) and Republicans (51 / 55%; see Table B.7 in Appendix B).

Do temporal preferences interact with policy instrument preferences?

Knowing that both the timing of policy implementation and instrument choice have an influence on Americans' preferences for phase-out policies, policymakers may be interested to know whether the two attributes interact in shaping preferences. Recent research on strategies for decarbonization has proposed smart sequencing of climate policies as an effective way to avoid political dead-ends in the decarbonization of energy systems (Meckling, Sterner, & Wagner, 2017). For instance, subsidies for the purchase of electric vehicles could be introduced early on and be combined with taxes that are ratcheted up over time, while a ban on newly registered cars with an internal combustion engine could be enacted later. However, there has been little effort so far to assess whether these ideas of policy sequencing resonate with public preferences.

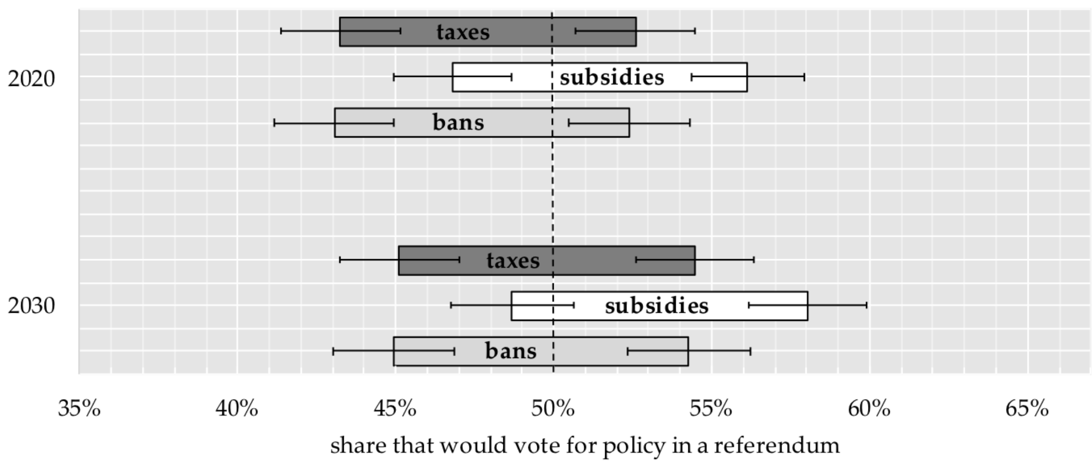
Figure 2.3: Interaction of policy instrument and timing attribute.



Notes: Symbols represent estimates of the effects of the policy attribute "beginning of policy implementation" on phase-out support conditional on policy instruments. Calculations are based on linear regression analyses with dichotomized rating outcomes, the full set of attribute values as predictors, and clustered standard errors (see Table B.8 in Appendix B). N = 24,320 policy proposals.

Figure 2.3 shows that respondents' preferences are not driven by such an interaction. This illustration is based on a regression model that interacts the policy timing attribute and the policy instrument attribute. Taking 2050 as reference category, we see that Americans prefer each type of policy to be implemented in 2020 or 2030 when compared to 2050, with the differences between policy instruments being negligible and statistically nonsignificant. In light of our previous finding that subsidies are generally preferred over other policy instruments (see Figure 2.1), it may be tempting for policymakers to disregard hard regulations as complementary measures. However, subsidies for low-emission alternatives alone are not likely to ultimately phase out internal combustion engines, which is why tax increases and bans may still be considered. To further explore the prospects of smartly sequenced measures beyond subsidies gaining public support, we compute (absolute) support levels based on predicted values. Here, we take advantage of the fact that we posed the rating task as a probabilistic question, asking respondents to indicate how likely they would vote for each proposal in a direct vote. Rescaling the policy ratings and mapping them onto the set [0, 100] allows us to predict levels of support for specific policy proposals by (first) estimating the effect of policy attributes on the rescaled rating variable, and (second) computing predicted values for policy proposals of interest (Bechtel & Scheve, 2013).

Figure 2.4: Bandwidths of predicted phase-out policy support



Notes: Bars include all predicted levels of public support for implementation of different policy instruments in 2020 and 2030, contingent on other policy features. Lower bounds represent scenarios with lowest predicted support for each instrument x timing combination (including 95% confidence intervals), and upper bounds represent scenarios with highest predicted support for each instrument x timing combination (including 95% confidence intervals). Predicted values are based on rating outcomes from N = 24,320 policy proposals.

Figure 2.4 contains the bandwidths of all predicted values for the three policy instruments in 2020 and 2030.[10] While support for all policy instruments is generally higher if implemented in 2030 than in 2020, the bandwidths of predicted support include the pivotal 50% threshold for all instruments already in 2020. For example, the predicted level of support for an increase in fossil fuel taxes implemented in 2020 ranges from 43.2 to 52.6%

[10]Here, we focus on public support within the timeframes identified as crucial for policy action by climate scientists (e.g., Rockström et al., 2017); i.e, we do not include years later than 2030.

in our sample, depending on the calibration of other attributes. Given the differences in absolute support levels between the policy instruments, Figure 2.4 provides evidence that there is indeed a case for policy sequencing also from a public opinion perspective. For subsidies, the majority of predicted values derived from our sample is above 50% already for implementation in 2020, while about half of policy scenarios that include bans or tax increases attain majority support if implemented in 2030. However, these numbers should be approached with caution given the mixed reliability of stated preference approaches when it comes to estimating absolute levels of preferences (Hainmueller, Hangartner, & Yamamoto, 2015). In general, getting the policy design "right" will be decisive in ensuring majority support for decarbonization policies.

Explaining policy support

In the final step of our empirical analysis, we broaden our perspective by investigating factors that explain support for phase-out policies. Our dependent variable is average policy support, computed by averaging over the 16 individual ratings given by each respondent in the conjoint tasks. We regress this policy support measure (M = .49; SD = .24) on several independent variables (for further details, see Table B.3 in Appendix B). As Table 2.2 shows, the strongest predictor of policy support is perceived psychological distance of climate change. Support is also significantly and positively related to pro-environmental behavior, younger age, urban place of residence, and not owning a car. Moreover, there is a positive effect for Democrats and a negative effect for Independents (both significant), with Republicans as baseline. We also find a significant but very small effect of gender, with males providing more policy support.

Table 2.2: Explaining support for phase-out policies

	Support for phase-out policies (1)
Age	-0.0233***
	(0.0031)
Gender (baseline female)	0.0212*
	(0.0101)
Income	-0.0015
	(0.0027)
Rural (baseline urban)	-0.0300***
	(0.0076)
Car ownership	-0.0113*
	(0.0053)
Democrat (baseline Republican)	0.0391**
	(0.0127)
Independent (baseline Republican)	-0.0341**
	(0.0129)
Pro-environmental behavior	0.0335***
	(0.0059)
Psych. distance of climate change	0.1034***
	(0.0060)
Energy knowledge	0.0034
	(0.0051)
Constant	0.5934***
	(0.0267)
N	1,511
R2	0.388

Notes: Coefficients from OLS regressions; standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependent variable is average policy support as obtained through the rating outcome of the conjoint analysis. For measurements of predictor variables, see Tables B.2 and B.3 in Appendix B. Age was recoded to 6 groups (18-29; 30-39; 40- 49; 50-59; 60-69; 70+). Party identification is captured with two dummy variables for Democrats and Independents, respectively. Continuous predictor variables were standardized before conducting the analysis (Mean = 0; SD = 1)

Limitations

Using a conjoint design allowed us to investigate the role of different policy attributes and how they interact with respondents' characteristics in shaping policy preferences. Compared to standard surveys, conjoint experiments are less vulnerable to demand effects and social desirability bias (Wallander, 2009). Indeed, we find that measuring phase-out policy support with a simple question before the conjoint experiment suggests that support is higher than when it is obtained through the conjoint ratings. The levels of support derived from the conjoint experiment are most likely more realistic than measures based on simpler survey questions.

At the same time, our study design entails a number of limitations. The choice to fully randomize policy scenarios implies that respondents were sometimes confronted with relatively far-fetched scenarios, such as Republicans advocating for tax increases. While including such atypical scenarios does not pose a threat to internal validity, they might threaten external validity (Hainmueller et al., 2014). Following the procedure proposed by Hainmueller et al. (2014), we tested whether the presence of atypical scenarios seriously distracted respondents. As Figure B.5 in Appendix B shows, while marginal effects of respondents that were exposed to less versus more atypical scenarios differ somewhat, these differences do not compromise our general interpretations. We also tested whether being exposed to a higher number of partisan endorsements (as opposed to endorsements by interest groups) distracted respondents, but as Figure B.6 in Appendix B shows, the results of corresponding subgroup analyses do not differ substantially from those obtained from the full sample. Another concern refers to hypothetical bias, the problem that while respondents might indicate voting in favor of a specific policy proposal in the hypothetical choice situation of our experiment, some of them would probably cast a no-vote in a real ballot. We cannot exclude this possibility. However, our study is not primarily interested in voting behavior. Rather, we use this outcome as an easily accessible way to experimentally investigate the extent to which specific policy characteristics influence support for phase-out policies in the transportation sector more generally.

Lastly, an alternative explanation of our result that citizens on average prefer phase-out policies to be implemented in 2030 is that people might generally prefer climate policies that are always 'just 10 years away'. To borrow from Trope and Liberman (2010), a decade's remove might provide just the right balance of concreteness and abstraction. While it would be beneficial to further investigate this hypothesis, it is worth noting that the patterns of timing preferences vary considerably among subgroups. It is also likely that the temporal distance of policy implementation that maximizes public support depends on the behavioral relevance of climate policies. While our study is about policies that entail implications for most citizens' everyday behaviors, temporal preferences for climate policies in sectors that carry less behavioral relevance might differ. For instance, Rinscheid and Wüstenhagen (2019) found that Germans prefer a phase-out of coal-fired power plants by 2025 over 2030 or later dates. Taken together, these findings call for further research on temporal perceptions in the field of climate policy and beyond.

Conclusion and Policy Implications

The decarbonization of the transportation sector is a key element of global attempts to tackle climate change and avert irreversible damages to planet earth. However, the needed transformation will most likely not occur without the enactment of far-reaching public policies to phase out fossil fuel cars. Contributing to the literature on the social acceptance of climate and energy transition policies, we employ a conjoint experiment to study how various policy attributes influence Americans' support for policies to phase out fossil fuel cars. Our aim is to examine causal connections between experimental treatments (the attributes of policy proposals) and the outcome of interest (policy support), rather than quantifying the level of climate policy support in the US population (Howe, Mildenberger, Marlon, & Leiserowitz, 2015; Motta, Chapman, Stecula, & Haglin, 2019).

Given the urgency of climate action, we focus in particular on preferences with respect to the temporal dimension of policy implementation. Based on the ratings of 24,320 hypothetical policy scenarios, we find that Americans' support for policies to phase-out fossil fuel cars is maximized if these are implemented in 2030. On average, later implementation dates significantly decrease policy support, although the preferences of certain groups (Republicans; people with a high psychological distance relative to climate change) are much less influenced by implementation timing. In an additional exploratory analysis documented in the Appendix B (see Figure B.7), we find that the perceived feasibility of phasing out fossil fuel cars is another factor that moderates citizens' preferences. While perceiving the phase-out to be infeasible is associated with preferences for later policy action, higher perceived feasibility links up with preferences for an early phase-out (i.e., no later than 2030).

Taken together, our study suggests that status quo bias is less pronounced than expected, providing further evidence that such bias is a transient and malleable phenomenon (Weber, 2015). Our results also suggest that the coming decade might provide a window of opportunity for adopting effective phase-out policies for fossil fuel cars that find public support. However, our conjoint analysis also highlights that majority support for policies may depend on how they will eventually be designed. For instance, we find that Americans prefer subsidies over hard regulations. Although the results indicate no interaction between policy instrument and timing, predicted levels of public support suggest that a sequencing approach that starts with introducing incentives for alternative technologies (subsidies) and proceeds with hard regulations (bans, taxes) might obtain wider public acceptance. We would like to encourage future studies to more thoroughly investigate citizens' understanding of policies that will take internal combustion engines off the road, including their understanding of policy co-benefits (e.g., less pollution, less noise) and potentially more challenging side effects (e.g., changes in user practices).

In light of concerns about voter backlash against ambitious climate policies, the finding that our respondents show low willingness to postpone phase-out policies to after 2030 is encouraging. Phasing out internal combustion engines for newly registered cars by 2030 would in fact follow the roadmap for rapid decarbonization compatible with the Paris Agreement sketched by Rockström et al. (2017). These results have important implications for the political feasibility of initiatives like the Green New Deal that are now being discussed in the US and beyond. The Green New Deal currently focuses mostly on a "carrot" approach, based on subsidies and industrial policy.[11] In fact, existing incentive schemes at the state and federal levels, like the US federal "Qualified Plug-In Electric Vehicle Tax Credit"[12], are important first steps in the decarbonization of the transportation sector. As consumer choices are often based on a comparison of upfront costs, using subsidies to bring these down for low- emissions alternatives is a key element in modifying the relevant choice architecture (Kunreuther et al., 2014; Kunreuther & Weber, 2014; Yoeli et al., 2017). However, subsidies alone might be insufficient to speed up the transformation at the needed pace and do also bear some risks like rent capture and costly lock-in (Meckling et al., 2017). Hard regulations will most likely be necessary to reach required mitigation goals. As our analysis shows, a smart sequencing of carrot and stick policies may be a promising strategy to increase their public acceptance.

[11]See, e.g., https://www.congress.gov/116/bills/hres109/BILLS-116hres109ih.pdf (in particular p. 9)
[12]https://www.energy.gov/eere/electricvehicles/electric-vehicles-tax-credits-and-other-incentives

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Chapter 3

Carbon Capture and Storage in the United States: Perceptions, Preferences, and Lessons for Policy

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Abstract

Although Carbon Capture and Storage (CCS) technologies can potentially play an important role in climate change mitigation efforts, commercial CCS projects are still rare. Knowledge about the technical challenges of these technologies is rapidly advancing, but the challenges related to their public acceptance are still underinvestigated. Here we try to close this research gap by investigating public perceptions of CCS and public attitudes towards policies to scale up these technologies in the United States, where most existing industrial-scale CCS projects are operating. Based on a demographically representative sample of US residents, we find that awareness of CCS is extremely low. Using a conjoint experiment, we show that policies that outlaw the construction of new fossil fuel power plants without CCS find higher public acceptance than CCS subsidies and increases in taxes on unabated fossil fuel power generation. Public acceptance decreases with rising costs of CCS deployment and decreasing minimal distance requirements of CCS plants from residential areas. Our results provide insights into the political feasibility of a large-scale deployment of CCS and show that specific policy design choices play an important role in influencing US public support for policies to scale up these technologies.

Introduction

Rapid decarbonization is essential to reach the Paris Agreement goal of limiting global average temperature increase to well below two degrees above pre-industrial levels, and to avoid the most adverse impacts of climate change (IPCC, 2018; Rockström et al., 2017). Beside greenhouse gas emission reductions, technologies that allow removing greenhouse gases from the atmosphere or preventing their release have increasingly drawn attention as complementary decarbonization strategies. These include negative emission technologies (NETs) and Carbon Capture and Storage (CCS). CCS technologies capture carbon dioxide (CO_2) at the source of production, transport it, and store it in suitable underground geological formations for permanent storage. Despite the limited development of CCS projects to date, the technology plays an important role in several climate change mitigation scenarios. Most scenarios produced by Integrated Assessment Models compatible with the Paris Agreement goal of limiting warming to well below 2 degrees Celsius feature a high amount of emissions mitigated trough CCS (Edenhofer, 2015; IPCC, 2018; Kriegler et al., 2014). However, the expansion of CCS has not met expectations so far (IEA, 2009; Viebahn & Chappin, 2018), and the massive scale-up of CCS present in many model scenarios is at odds with current CCS deployment levels (Minx et al., 2018; Rogelj et al., 2016).

This has produced debates regarding the technical, economic, social and political feasibility of a large-scale deployment of CCS in the energy sector (Anderson & Peters, 2016; Buck, 2016; Williamson, 2016). Research on this topic is rapidly expanding (Minx et al., 2018) and the technical literature has highlighted some factors hampering the scale-up of CCS, such as high costs, storage capacity issues, and injection rates constraints (Lane, J.L., Greig, C., & Garnett, A., 2020; Martinez Arranz, 2016; Viebahn, Vallentin, & Höller, 2014, 2015). However, research on its social and political feasibility is relatively less developed, even though at least as important (Viebahn & Chappin, 2018). This mirrors general patterns regarding the (mis-)allocation of climate research funding: according to a recent estimate, only 0.12% of all funding for climate change mitigation research is spent on social science research, with the natural and technical sciences receiving the bulk of research funding (Overland & Sovacool, 2020).

L'Orange Seigo, Dohle, and Siegrist (2014), Viebahn and Chappin (2018) and Tcvetkov, Cherepovitsyn, and Fedoseev (2019) comprehensively review studies of public perceptions of CCS. Most studies are based on stakeholder elicitation processes or focus groups (see for instance Lock, Smallman, Lee, and Rydin (2014) and Upham and Roberts (2011)). The results of national surveys of CCS perceptions and their determinants have been published for China (Chen et al., 2015; Li et al., 2014), Germany (Arning et al., 2019), Canada (Boyd, Hmielowski, & David, 2017), and Japan (Saito, Itaoka, & Akai, 2019). Data on CCS perceptions in the United States (US) are provided in Whitmarsh, Xenias, and Jones (2019)'s cross-country study of the impact of framing effects on CCS support. Cox, Spence, and Pidgeon (2020) provide data on perceptions of emerging carbon dioxide removal technologies in the United Kingdom and the United States. Existing national surveys all report very low awareness of CCS among the general population and find that low levels of CCS acceptance are related to perceptions of CCS as a risky technology. Other studies have highlighted the role of trust (Terwel, Harinck, Ellemers, & Daamen, 2011; Yang, Zhang, & McAlinden, 2016), community compensation (ter Mors, Terwel, & Daamen, 2012) and communication (Bruin, Mayer, & Morgan, 2015; Vercelli et al., 2013) in increasing public acceptance of CCS.

In this study, we contribute to the literature on the political feasibility of scaling up CCS by investigating attitudes towards CCS in a demographically representative sample of 1,520 United States (US) residents. As most existing industrial-scale CCS projects are operating in the US (Global CCS Institute, 2019) and the country could be a leader in CCS deployment, understanding perceptions of and attitudes towards these technologies among the American public is particularly important (Tcvetkov et al., 2019). We present data collected in 2018 on CCS awareness and perception. We focus on technologies that capture CO_2 produced by industrial processes and fossil fuel power plants, as they are the most widely employed CCS technologies (Global CCS Institute, 2019). Our study delivers an assessment of risk and benefit perceptions of CCS and investigates individual characteristics that explain heterogeneities in these perceptions. To foreshadow our results, we find that awareness and knowledge of CCS are extremely low and that respondents with previous awareness of CCS perceive the benefits of the technology to be higher.

Moreover, drawing from political science investigations into the determinants of policy support (Bechtel & Scheve, 2013; Fesenfeld, Wicki, Sun, & Bernauer, 2020), we employ a conjoint experiment to assess how support for policies to scale up CCS depends on specific policy design features. Investigating determinants of public support for policies to scale up CCS is crucial to understand the political feasibility of a large-scale deployment of these technologies, but this aspect has not received sufficient attention in the literature so far. CCS policies can take various forms, such as bans on the construction of new fossil fuel power plants without CCS, government subsidies for CCS development, or increases in taxes on unabated fossil fuel power generation. We find that bans are significantly more supported than subsidies and tax increases. As for the impact of other key policy design features, policy support linearly decreases with policy costs and increases with minimal distance requirements of CCS plants from residential areas. Interestingly, policy implementation in 2020 or 2030 is preferred over later implementation.

Research design and method

Our study is based on an online survey which included a conjoint experiment. The survey was part of a longer questionnaire focused on public attitudes toward rapid decarbonization policies that we developed and employed for the studies in Chapters 2 and 3 of this dissertation (see details in the Appendix). It was preregistered at the Open Science Framework and administered to a demographically representative sample of 1,520 American residents between the 1st and 18th of October 2018 (see Table C.1 in Appendix C for a comparison of the distribution of key socio-demographic variables in our sample and the US population).

Respondents first received a description of CCS technologies and information on how these technologies might contribute to climate change mitigation. The first section of the survey assessed public attitudes towards CCS, including knowledge of CCS and perceptions of CCS risks and benefits. The second section presented a conjoint experiment, which allows us to investigate the role of specific policy design features in shaping support for CCS policies. Conjoint experiments have been used to examine policy preferences in different contexts, including energy and climate policy (Bechtel & Scheve, 2013; Gampfer, Bernauer, & Kachi, 2014b; Hainmueller et al., 2014). They allow observing respondents' preferences over a series of multidimensional policy scenarios and estimating the impacts of different attributes on policy support (Hainmueller et al., 2014).

Respondents were informed that policy proposals to scale up CCS in their state may vary on a number of attributes and received information on five policy attributes and their levels. They then were shown eight consecutive pairs of state-level policy proposals, with each proposal defined on the five attributes. For each pair of proposals, respondents were required to choose the proposal they preferred (forced-choice outcome) and to rate on a scale from 0 to 10 their probability of voting for each proposal in a hypothetical direct democratic vote (rating outcome). Details on the conjoint experiment are provided in section I of Appendix C, and Figure C.1 shows an example of a choice screen.

The attribute levels were fully randomized within and across policy pairs, which guarantees the non-parametrical identification of the causal effects of the policy attributes (Bechtel & Scheve, 2013). To estimate the average marginal effect of each attribute level (ACMEs) on policy support, we ran a regression with dummy variables for different attribute levels. For each attribute, we define one level as baseline with respect to which we compute the marginal effect of the other levels. The model we estimate is therefore the following:

$$y_{ijk} = \beta X_{ijk} + \epsilon_{ijk} \tag{3.1}$$

where y_{ijk} is the vote by respondent i for proposal k in task j and X_{ijk} is a vector of attribute levels of the policy proposal presented to i in k. Standard errors are clustered by respondent to account for within-respondent correlations in responses.

We selected five pertinent policy attributes based on a survey of the scientific and policy literature related to CSS, focusing on the following dimensions: policy instrument, policy cost, timing, space, and stakeholder endorsement. Table 3.1 displays the five policy attributes and their levels.

Table 3.1: Policy attributes and attribute levels for the conjoint experiment

Policy attributes	Level 1	Level 2	Level 3	Level 4
Policy type	Ban on the construction of new fossil fuel power plants without CCS	Government subsidies for CCS	Increase in taxes on fossil fuel power generation without CCS	-
Policy cost (per household, per month)	$4	$9	$14	$19
Beginning of policy implementation	2020	2030	2040	2050
Required distance to residential areas	2 miles	5 miles	10 miles	50 miles
Policy endorsement by	Carbon Capture Coalition	Greenpeace	Democratic Party	Republican Party

As public support for public policies has been shown to crucially depend on policy instruments, our first attribute of interest is the specific policy instrument employed to scale up CCS. In our experiment we included three policy instruments that have either been implemented or discussed in the policy debate (BÃ€ckstrand, Meadowcroft, & Oppenheimer, 2011; von Stechow, Watson, & Praetorius, 2011): (1) Bans on the construction of new unabated fossil fuel power plants (i.e., without CCS); (2) Government subsidies for CCS; (3) Increase in taxes on unabated fossil fuel power generation. We did not assess support for more ambitious policies to scale up CCS that are however not presently considered at the political level, such as a phase-out of existing unabated fossil fuel plants. Given that Americans have been shown to be sensitive to the cost of energy solutions (Ansolabehere & Konisky, 2014), we include cost as a second attribute likely to shape preferences towards CCS policies. We selected four different policy cost levels (\$4, \$9, \$14, \$19) defined as monthly cost per household, in order to make these amounts tangible to respondents. The timing of policy implementation is a third key element of policy proposals. It is particularly relevant in the context of climate policies and CCS, as postponing mitigation action has fundamental implications for our ability to achieve rapid decarbonization. The timing attribute levels we selected include a beginning of policy implementation in 2020, 2030, 2040, and 2050. The fourth policy attribute is required distance of plants employing CCS from residential areas, and its levels are 2, 5, 10 and 50 miles. Building on studies of public opposition to energy technology developments near communities and homes and on previous studies of CCS perceptions finding opposition to CCS developments close to residential areas (Saito et al., 2019; Tcvetkov et al., 2019), we hypothesized that place attachment might cause proximity of CCS plants to exert a significant negative influence on policy support (Devine-Wright, 2009). Finally, as endorsements by key political and social actors can influence citizens' policy preferences (Lupia, 1994), we selected policy endorsement as the fifth attribute. Its levels are policy endorsement by the Democratic party, by the Republican party, and by two organizations with official positions in favor of CCS (the Carbon Capture Coalitions) and against CCS (Greenpeace).

Inattentive individuals who failed an attention check were removed from the sample and from the analyses. All analyses were replicated on a sample excluding 64 respondents that completed the survey in less than 33.4 percent of median completion time with identical results (see Table C.5 in Appendix C).

CCS perceptions

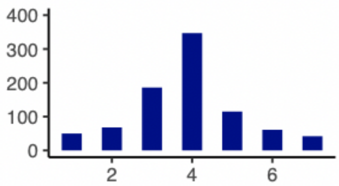
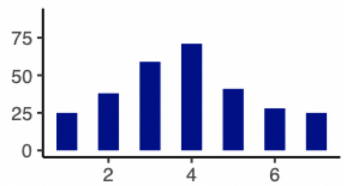
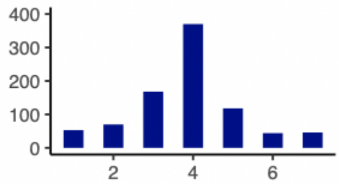
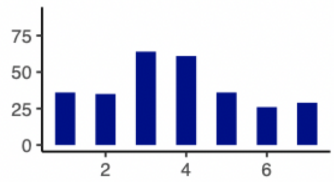
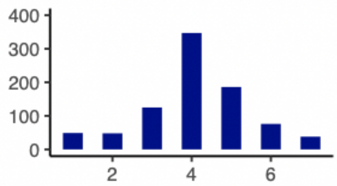
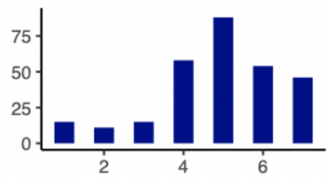
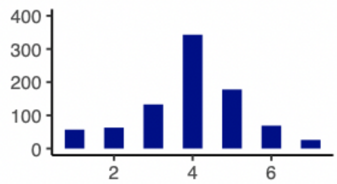
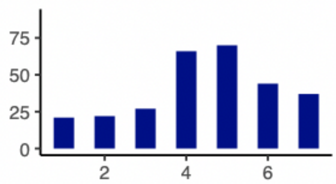
Awareness of CCS

Consistent with results from other countries (Arning et al., 2019; Chen et al., 2015; Saito et al., 2019; Tcvetkov et al., 2019), we find very low awareness of CCS technologies among respondents in our sample. 57 percent of respondents declared that they had never heard about CCS before taking the survey, 24 percent were not sure and only 19 percent stated that they had heard about CCS before. These results suggest that the US population is not very familiar with CCS technologies. This is not surprising given the extremely low coverage of CCS in the mass media and in the national political debate (Dowd, Ashworth, Rodriguez, & Jeanneret, 2012; Feldpausch-Parker et al., 2013).

Perceptions of CCS risks and benefits

After providing information on CCS (see details in Appendix C), we measured respondents' perceptions of risks and benefits associated with these technologies. Table 3.2 displays the survey items and the distribution of responses separately for the subsample of respondents that had never heard of CCS before taking the survey and for the subsample of respondents that had already heard of CCS before. Figure 3.1 shows average perceptions of CCS for the same two subsamples.

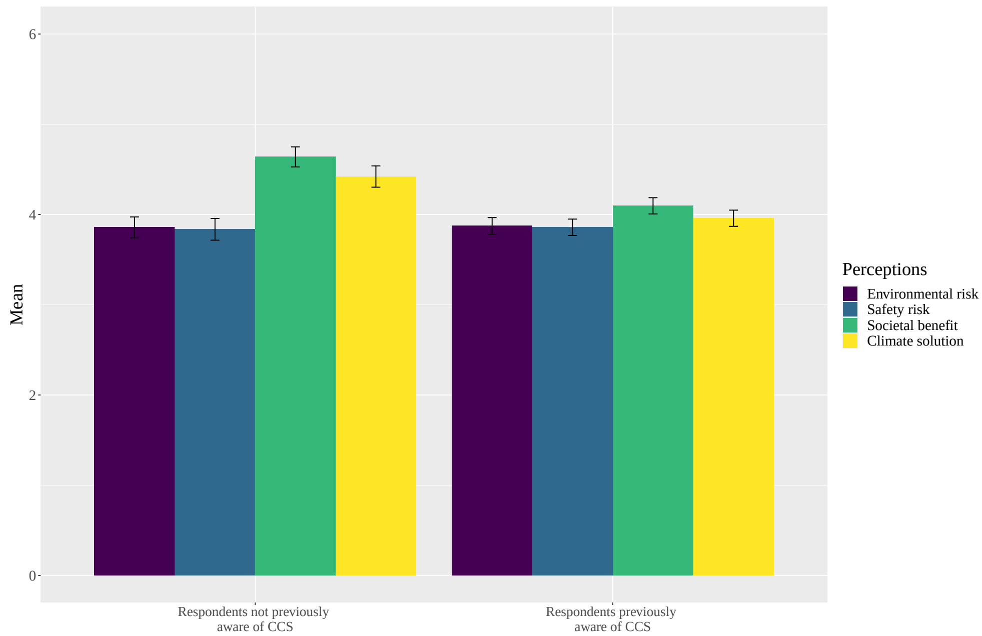
Table 3.2: Perceptions of risks and benefits of CCS

Survey Questions	Distribution of values for respondents with no previous CCS awareness	Distribution of values for respondents with previous CCS awareness
Q1. "To what extent do you think that CCS has a negative impact on the environment?"		
Q2. "To what extent do you think that CCS has a negative impact on your safety?"		
Q3. "To what extent do you think that CCS entails benefits for society?"		
Q4. "To what extent do you think that CCS is a good solution to the challenge of climate change?"		

Notes: Survey items measuring perceptions of CCS technologies and distribution of responses for the subsamples of respondents with no previous awareness of CCS and with previous awareness of CCS. Responses based on a 7-point Likert scale from "Not at all" to "Very much". Respondents who were not sure they heard of CCS before are not included in the plots.

Perceptions of the negative impacts or risks of CCS are similar for respondents with previous awareness of CCS and for respondents with no previous awareness. Perceptions of environmental risks (Q1) are moderate and equivalent for the two groups (mean value of 3.87 on a 7-point scale) and perceptions of safety risks (Q2) are also moderate and similar (mean values of 3.77 for the 'aware' and 3.86 for the 'non aware'). Perceptions of societal benefits of CCS (Q3) are higher among respondents with previous awareness of the technology compared to respondents with no previous awareness (mean values of 4.88 and 4.10 respectively), and perceptions of CCS as a good solution to climate change (Q4) are also higher among the former than among the latter group (mean values of 4.47 for the 'aware' and 3.96 for the 'non aware'). The differences in perceptions of benefits among the two groups are statistically significant (p-value of t-test $< .001$). Overall, most likely due to the extremely limited debate on CCS in the public sphere and non-expert environments, perceptions of CCS are not extreme. However, interestingly, respondents who are more familiar with CCS have more positive perceptions of this technology.

Figure 3.1: Perceptions of risks and benefits of CCS



Notes: Perceptions of risks and benefits associated with Carbon Capture and Storage technologies. Average values for the subsample of respondents with no previous awareness of CCS (n = 869) and for the subsample of respondents with previous awareness of CCS (n = 287). Respondents that declared they were not sure if they had heard of CCS before are excluded from this comparison. Error bars represent 95% confidence intervals.

We investigated the variation in perceptions of CCS by means of regression analysis, after constructing an index composed of the four perception items. Higher values of the index indicate more positive perceptions of CCS (we reversed the risk perception items to construct this index). Our battery of independent variables comprises socio-demographic variables (age, gender, educational attainment, income, urban versus rural place of residence), political orientation, previous awareness of CCS, and psychological distance of climate change, which is an index measuring whether respondents perceived climate change to be close to them on several dimensions (details on the index and other variables are presented in Table C.2 in Appendix C). Consistent with our descriptive analyses above, respondents with previous awareness of CCS have more positive perceptions of CCS. Respondents perceiving climate change as closer to themselves have more positive views of CCS. Having a higher income, being male and residing in urban areas is associated with more positive perceptions of CCS, while age and education are not significant predictors. Interestingly, Democrats have more positive perceptions of CCS than Republicans. The more positive perceptions of CCS among Democrats and among people with lower psychological distance to climate change might be in part due to the fact that CCS was explicitly presented as a climate change mitigation technology in our survey. This suggests that different ways of describing or framing of CCS policies might have different impacts on policy support among different subgroups of citizens, in particular among Republicans or people with lower concern for climate change.

Table 3.3: Regression analysis of predictors of CCS perceptions

	(1) CCS Perceptions
Age	-0.008
	(0.007)
Gender	0.514*
	(0.220)
Education	-0.106
	(0.121)
Income	0.222***
	(0.063)
Urban / rural	-0.495**
	(0.163)
Partisan orientation	-0.154*
	(0.062)
Psych. distance	0.819***
	(0.239)
Constant	14.103***
	(0.697)
Observations	1,511
R-squared	0.041

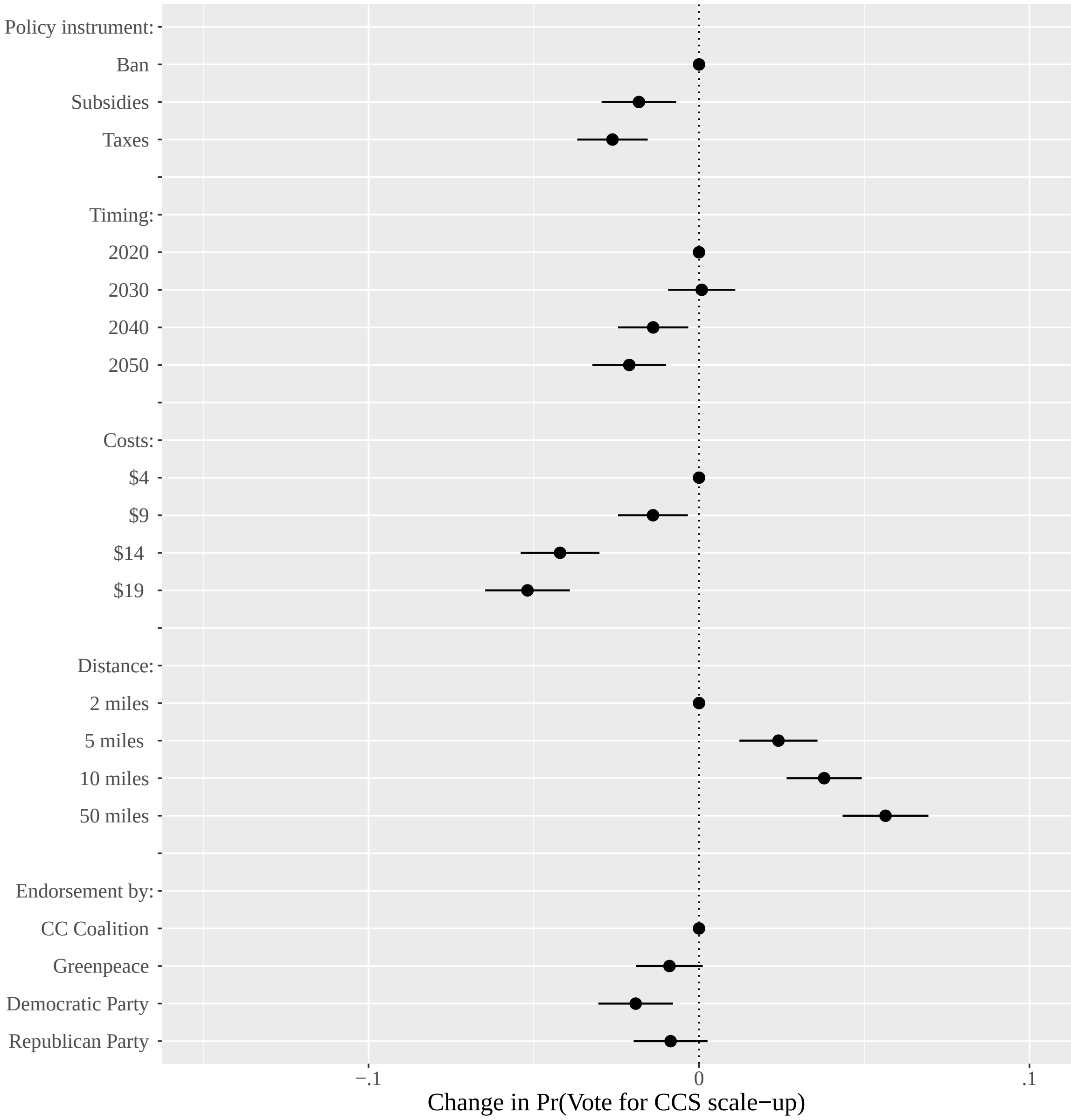
Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Notes: Regression analysis of predictors of CCS perceptions. The outcome variable is an index constructed as the arithmetic sum of the four items measuring perceptions of risks and benefits of CCS presented in Table 3.2. Higher values of the outcome variable indicate more positive perceptions of CCS. Urban/Rural takes the values 1 = Urban; 2 = Suburban; 3 = Rural. Partisan orientation is a 7-point scale from 1 = Strong Democrat to 7 = Strong Republican. Psychological distance is a binary variable which is equal to 0 for the subsample of respondents with higher psychological distance to climate change and to 1 for the subsample of respondents with lower psychological distance to climate change. This variable is based on a dichotomization of an index combining different survey items measuring distance to climate change on different dimensions (see details in Table C.2 in Appendix C). Previous CCS awareness is equal to 0 for respondents who had never heard of CCS before, 0.5 for respondents who said they maybe heard of CCS before, and 1 for respondents who had heard of CCS before. See details on survey items and descriptive statistics in Table C.2 in Appendix C.

Conjoint experiment results

Figure 3.2 shows the results of the conjoint experiment, displaying marginal effects of attribute levels with the associated 95% confidence intervals. One level per attribute is selected as baseline category (shown without confidence intervals). We report here results based on the rating outcome. The corresponding regression table is presented in Table C.3 in Appendix C. Results based on logistic regression using the forced choice outcome are reported in Table C.4 and are qualitatively equivalent.

Figure 3.2: Average effects of CCS policy attributes on policy support



Notes: Each dot represents an average marginal effect of an attribute level on the probability of voting for a policy proposal in relation to a proposal with the reference level for the same attribute. The horizontal bars represent the associated 95% confidence intervals. Dots without bars represent the reference level for each policy attribute. Calculations are based on linear regression analyses using policy rating as outcome variable. Standard errors are clustered for respondents. N = 24,320 policy proposals.

Figure 3.2 shows that policies that ban the construction of new plants without CSS are more supported than subsidies for CCS and increases in taxes on unabated fossil fuel power generation. Subsidies are more supported than taxes, although this difference is not significant.

Policy support also depends on the timing of policy implementation. Policies implemented in 2020 and 2030 find higher support than policies implemented in 2040 and 2050 (note that the difference between 2030 and 2040 is not significant). These results are in line with studies by (Rinscheid, Pianta, & Weber, 2020; Rinscheid & Wüstenhagen, 2019), who have shown that citizens in the US and Germany on average favor earlier implementation of decarbonization policies over later policy action.

As predicted, policy costs are another significant determinant of policy support, with support almost linearly decreasing with an increase in policy costs. Policy support also increases with stricter minimal distance requirements between plants employing CCS and residential areas. This is in line with findings of previous studies of CCS perceptions and of perceptions of energy technologies in general.

Policy endorsement by key political and societal actors does not have a clear and sizable impact on average support on our full sample of respondents. These results are not surprising, as the impact of policy endorsements can reasonably be expected to have a differentiated impact depending on different respondents' perception of endorsers. When assessing heterogeneous effects for respondents with different perceptions of these societal actors, we see that endorsement by the Republican (Democratic) party have a significant and sizable positive impact on policy support among Republicans (Democrats), and that endorsements by Greenpeace and the Carbon Capture Coalition significantly increase policy support among respondents with high levels of trust in these actors, although such effects are lower than those of political parties (see Figure C.3 in Appendix C).

Support for illustrative policy scenarios

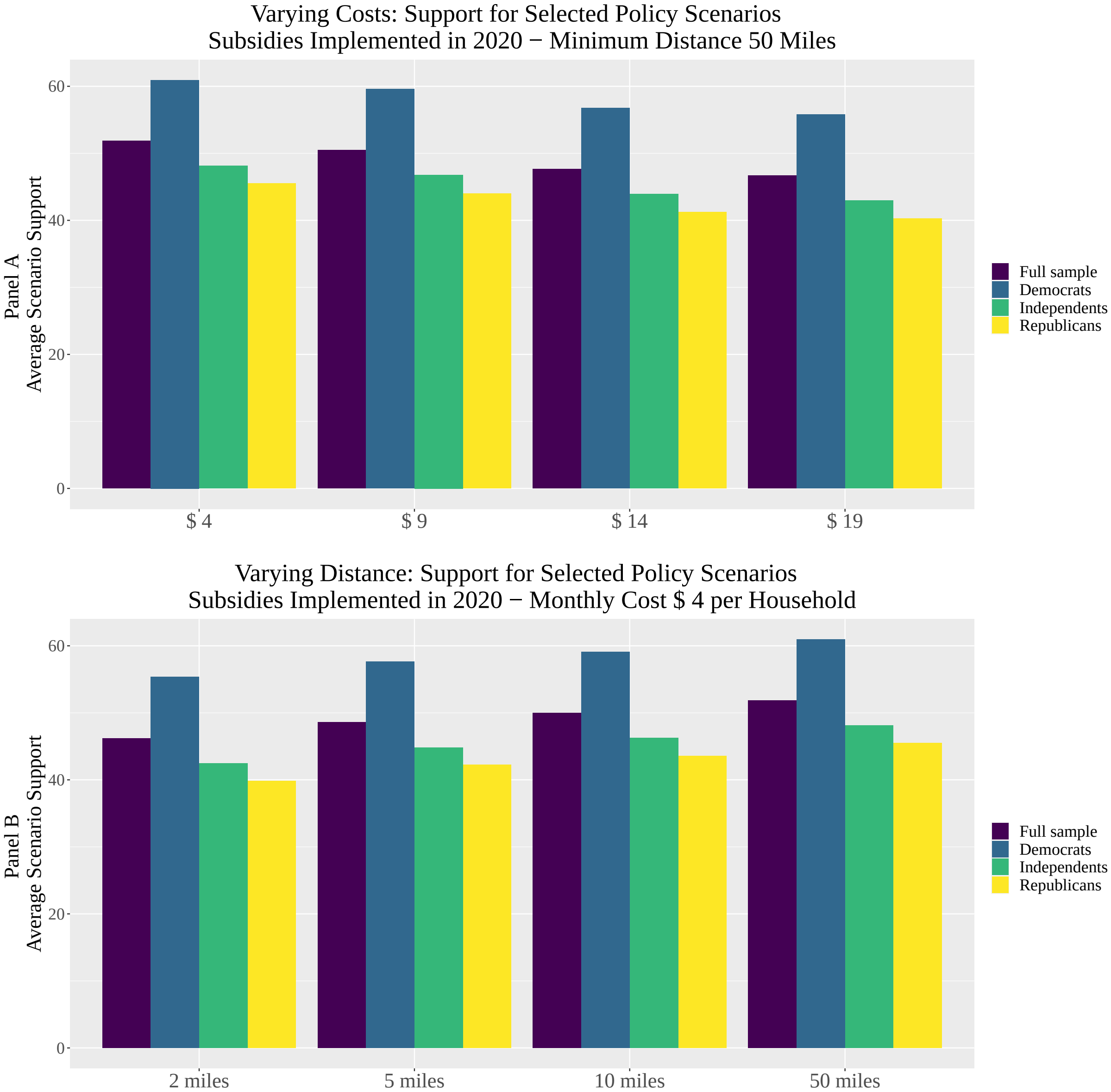
The conjoint design allows us to simulate support for specific policy scenarios. This can be done using the estimated effects of attribute levels on policy support and computing predicted values for specific policy scenarios. Figure 3.3 displays support for a series of policy scenarios, showing how support varies with two key attributes: policy costs and distance from residential areas. Because partisan orientation is an important determinant of perceptions of CCS – average policy support across all our policy scenarios is 55 percent among Democrats and 38 percent among Republicans – we present policy support levels for the whole sample of respondents (in purple), but also separately for Democrats (in blue), Independents (in green) and Republicans (in yellow). These predicted values can be interpreted as the share of support a policy receives in the respective population (i.e., full sample, Democrats, Independents, and Republicans).

Panel A of Figure 3.3 shows how policy support varies with policy costs. All scenarios in panel A are based on CCS subsidies that are implemented in 2020 and include a minimal distance from residential areas of 50 miles, averaged across the policy endorsement attribute levels. Policy support decreases with the increase of costs, and policies with a cost of \$4 or \$9 per household per month are supported by more than 50 percent of our sample. It is important to note that here support levels are relatively high because the distance attribute is fixed at 50 miles for all policy scenarios.

Panel B shows how policy support varies with distance requirements from residential areas. All scenarios in panel B are based on subsidies that are implemented in 2020 with a cost of \$4 per household per month, averaged across the policy endorsement attribute levels. Policy support increases with the increase of distance requirement from residential areas. Policies with minimal distance requirements of 50 miles find support among 50 percent of our sample. Here too support levels are relatively high because the cost attribute is fixed at $4 for all policy scenarios.

Among Democrats, average support for all policies in Figure 3.3 is higher than 50 percent, and often higher than 60 percent, while among Republicans support is always lower than 50 percent. Support levels of Independents are between those of Republicans and those of Democrats for all policies. It is important to note that our study is based on a non-probability but demographically representative sample of American residents. While the support levels found in our study may not perfectly mirror support in the American population, the differences in support levels are a robust indication about the extent to which changes in policy attributes move citizens' support for CCS policies.

Figure 3.3: Predicted levels of policy support for a selection of policy scenarios



Notes: This figure presents predicted levels of policy support for a selection of policy scenarios varying with respect to policy costs (Panel A) and distance from residential areas (Panel B). Predicted values of support are based on estimated effects of attribute levels. Scenarios in panel A are based on CCS subsidies implemented in 2020 with minimal distance from residential areas of 50 miles. Scenarios in panel B are based on CCS subsidies implemented in 2020 with a cost of $4 per household per month. Results for the full sample of respondents are presented in purple, results for Democrats in blue, results for Independents in green and results for Republicans in yellow. Predicted values can be interpreted as the share of policy support the respective population (full sample, Democrats, Independents, and Republicans).

Conclusion and Policy implications

Based on a survey and a conjoint experiment administered to a demographically representative sample of American residents, we investigated perceptions of CCS technologies and factors that influence the support for policies to scale up CCS. The study documents that awareness of these technologies, which play a major role in many Integrated Assessment Model scenarios compatible with the Paris Agreement's goal of limiting global warming to well below 2 degrees, is rather low. However, individuals who perceive climate change to be closer to themselves on multiple dimensions have more positive views of CCS. Also, people who are familiar with CCS tend to perceive its societal and climate change-related benefits to be higher. Several factors move support for policies to scale up CCS, including the type of policy instrument, cost, timing, and distance requirements. Moreover, support for CCS policies varies with political orientation, being stronger among Democrats.

Our results have three key policy implications. First, support for policies to scale up CCS is sensitive to the choice of policy instruments. We found that bans on the construction of unabated fossil fuel plants are more supported than subsidies for CCS and taxes on unabated power generation. This is consistent with evidence of tax-aversion, in particular among Americans, present in the economics and behavioral literature (Hardisty et al., 2010; Kessler & Norton, 2016). Therefore, taking citizens' preferences into account, policymakers may wish to push legislation into this direction. Second, required distance of CCS infrastructure from residential areas is a key attribute influencing policy support. This suggests that opposition to local CCS infrastructure might emerge during project development, mirroring opposition to other local energy infrastructure such as nuclear power plants, windmills or hydropower plants. CCS infrastructure might therefore have higher chance of political survival in less densely populated areas. Third, policy support is considerably different among people with different partisan orientation, with Democrats having on average higher support levels. This dimension should be taken into due account when proposing and implementing policies to scale up CCS.

Future research may assess whether different frames of CCS policies have a different impact on policy support among individuals with different partisan orientation. Moreover, we cannot asses here whether the correlation between higher familiarity with CCS and more positive perceptions of these technologies is caused by the fact that available information on CCS is mostly produced by CCS promoters presenting CCS as a powerful climate mitigation. Future studies might attempt to assess whether providing more information on CCS produces more positive perceptions and decreases wariness about these relatively new technologies.

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Conclusion

This thesis addresses a set of questions relating to public attention and attitudes toward climate change and decarbonization policies. Chapter 1 focuses on media coverage of climate change and Chapters 2 and 3 address public support for climate change policies. They investigate factors that influence the social and political feasibility of climate action and decarbonization.

Chapter 1 shows that media coverage of climate change has significantly increased in the last few years, skyrocketing in 2019. It employs an original dataset of media coverage of climate change in the 28 countries of the European Union, with data representing 1.7 million online articles published between April 2014 and October 2019 in 22 different languages. It shows that media coverage of climate change is influenced by temperature abnormalities, and in particular by deviations of temperatures from recent years' averages. Deviations from temperatures in baseline periods that climatologists use to define climatic changes have only a marginally significant impact on media coverage of climate change, and this effect is considerably smaller than that of short-term abnormalities. These results suggest that media coverage of climate change follows a mechanism similar to individual climate attention.

The behavioral literature has shown that individuals form their climate attitudes following an attribute substitution heuristic, using personal experiences of local weather instead of more accurate but less accessible scientific evidence on global climate patterns. While long term abnormalities – changes with respect to climate in 1950-1980 – are not directly experienced, average temperatures in the last few years seem to form a baseline of "normal" weather, and deviations from these averages - in particular positive deviations - may be heuristically employed as evidence of climate change, or may make more salient climate change due to a cognitive association between climate change and warmer weather.

Short-term abnormalities have been found to shape discussions about weather on social media (Moore et al., 2019) and to influence perceptions of climatic conditions (Ripberger et al., 2017). Our paper shows that they also influence media coverage of climate change. This effect may be driven by editors and journalist following the same attribute substitution mechanism highlighted in studies of individual climate attitudes. They may be covering climate change more when they experience temperatures that are different from normal - using temperature in recent years to construct a measure of normal weather - because they interpret these short-term abnormalities as evidence of climate change. On the other hand, journalists or editors may be taking advantage of short-term temperature abnormalities to increase coverage climate change because they anticipate a broader interest among the public.

This chapter focuses on one factor influencing media coverage of climate change. Further studies should shed light not only on other determinants of media coverage of climate change, but also, perhaps more importantly, on the impact of media coverage of climate change on individual attitudes and behaviors, and on climate policy decisions.

In chapter 2 and 3 we investigate what shapes public attitudes towards two rapid decarbonization policies. Decarbonizing the energy and transportation sectors is required to address climate change and avert irreversible damages to planet earth. However, this transformation will not occur without the enactment of ambitious public policies. This has opened a discussion on rapid decarbonization strategies, which would contribute to achieve substantial transformations in a relatively short time. Two key policies in this sense are the phase-out of fossil fuel cars and the scale-up of Carbon Capture and Storage (CCS) technologies. Both these policies could contribute to the achievement of ambitious decarbonization goals, but are at the same time controversial, for different reasons. It is therefore important to understand public attitudes towards them, and in particular to shed light on the determinants of public support or opposition. Building on extensive evidence on the importance of specific policy design features in influencing policy support, we designed two conjoint experiments to study how various policy attributes influence Americans' support for policies to phase out fossil fuel cars and to scale up CCS. We administered the experiments to a demographically representative sample of United States residents. Investigating public support for these policies among Americans is essential, because the United States is one of the top per capita emitters and could be a leader in CCS development.

A first important finding of our studies is that support for policies to phase out fossil fuel cars and to scale up CCS is maximized if these are implemented in 2030. This suggests that status quo bias is less pronounced than expected, and that the coming decade might provide a window of opportunity for adopting effective decarbonization policies. Banning the sale of new fossil fuel cars by 2030 would in fact follow the roadmap for rapid decarbonization compatible with the Paris Agreement sketched by Rockström et al. (2017).

Our conjoint analysis highlights that majority support for policies depends on how they will eventually be designed. First, policy costs are a key determinant of policy support. Second, soft regulations are overall preferred over hard ones. In the case of policies to phase out fossil fuel cars, predicted levels of public support suggest that a sequencing approach that starts with introducing incentives for alternative technologies (subsidies) and proceeds with hard regulations (bans, taxes) might obtain wider public acceptance. In the case of CCS, bans on the construction of unabated fossil fuel plants are more supported than subsidies for CCS and taxes on unabated power generation. The finding that taxes are the least preferred policy instrument is consistent with evidence of tax-aversion present in the behavioral and economic literature. Policy support also considerably varies across people with different partisan orientation, with Democrats presenting substantially higher support levels both for policies to phase out fossil fuel cars and for policies to scale up CCS.

We also investigate the impact of policy co-benefits or perceived risks on policy support. For the phase-out of fossil fuel cars, the co-benefits in terms of pollution reduction lead to significant increases in public support only when they are substantial. As to policies to scale up CCS, required distance of CCS infrastructure from residential areas is a key attribute influencing policy support. These results on the leveraging effect of these policy features provide important insights for policy design.

These results yield concrete implications for policymakers concerned with the question of how to achieve the decarbonization of energy and mobility systems. Shedding light on the determinants of public support, they also provide insights on how public opposition to climate policies can be mitigated and how public support can be strengthened. The results of these studies have important implications for the political feasibility of rapid decarbonization initiatives like the Green New Deal discussed in the United States and the European Green Deal currently discussed in the European Union.

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Appendices

Appendix A

Supplementary Material: Chapter 1

Dataset of media coverage of climate change in Europe

Our dataset of online media coverage of climate change includes data on 1,703,456 articles published between April 2014 and October 2019 in the 28 countries of the European Union. To the best of our knowledge, it is the first comprehensive multi-year dataset of media coverage of climate change across Europe. It gathers all articles including the keywords "climate change" or "global warming" among the articles collected by the Europe Media Monitor (EMM).

The EMM is a service developed and maintained by the Competence Centre on Text Mining and Analysis of the European Commission Joint Research Centre (JRC). It collects news published on the internet in the world, gathering over 280.000 reports per day in 70 languages. It collects data by monitoring over 20000 RSS feeds and HTML pages from 7000 news portals world-wide (`https://ec.europa.eu/jrc/en/scientific-tool/europe-media-monitor-newsbrief`).

We employ a script to gather, among the items collected by EMM, all articles published in the 28 EU countries (including the United Kingdom) including the keywords "climate change" or "global warming" translated into the main spoken languages of each country. The translations of these keywords into 22 European languages were completed through a two step process. Fist, the authors identified all possible translations of the expressions "climate change" and "global warming" employing their personal knowledge and the online dictionary Glosbe (`http://www.glosbe.com/`). Glosbe is a multilingual dictionary that provides translation memories with examples of translated sentences based mostly on published free parallel corpora (e.g. European Union documents that have been officially translated in different languages). It proved particularly useful for languages with rich nominal inflection. Second, for most languages, native speakers were asked to validate the translations. The authors wish to thank for their precious contribution Adrian Rinscheid, Jessica Gagete Miranda, Marcela Rubio, Marina Petrova, Martina Barjaková, Zornitsa Todorova, Bo Jellesmark Thorsen, Mikko Poutanen, Theofanis Katsanevakis, Blanka Imre, Vytenis Juozas Deimantas, Maria Arejola, Marcin Swierkosz, Dan Vîlcu, and Kennet Uggeldahl.

The index of climate change keywords in all European languages we developed for this study is on its own a resource potentially valuable to future studies and we report it in Table A.1.

Keywords

Language	**Countries**	**Climate Change**	**Global Warming**
Bulgarian	BG	промян* на климата	глобалн* затопляне
		Промяна* на климата	
		климат* изменен*	
		климат* промени	

		климат* промяна	
		изменени* на климата	
Croatian	HR	klimatsk* promjen*	globaln* zatopljenj*
		promjen* klim*	globaln* zagrijavanj*
		promjen* klim*	globaln* zagrevanj*
Czech	CZ	klimatick* změn*	globáln* oteplován*
		změn* klimatu	
Danish	DK	klima forandrin*	globa* opvarmnin*
		klimaforandrin*	
		klimaændrin*	
Dutch	NL & BE	klimaatveranderin*	opwarmin* van de aarde
		klimaatsveranderin*	global warming
		climate change	wereldwijd* opwarmin*
English	GB & IE & MT	climate change	global warming
		climatic change	
Estonian	EE	kliimamuut*	globaal* soojenem*
Finnish	FI	ilmastonmuut*	ilmast* lämpenemin*
		ilmastomuut*	ilmast* lämpen*
		ilmast* muut*	globaal* lämpenemin*
		maailmanlaaj* ilmastonmuut*	maapall* lämpenemin*
French	FR & BE & LU	changement climatique	réchauffement climatique
		changements climatiques	réchauffement global
		changement du climat	réchauffement mondial
		changements du climat	réchauffement de la planète
		modification climatique	réchauffement planétaire
		modifications climatiques	réchauffement de la terre
		modification du climat	réchauffement du globe
		modifications du climat	
		variation climatique	
		variations climatiques	
		variation du climat	

		variations du climat	
		évolution climatique	
		évolutions climatiques	
		évolution du climat	
		évolutions du climat	
German	DE & AT & LU	Klimawandel	globale Erwärmung
		Klimawandels	globaler Erwärmung
		Klimaveränderung	globalen Erwärmung
		Klimaveränderungen	globale Erderwärmung
		Klimaänderung	globalen Erderwärmung
		Klimaänderungen	globaler Erderwärmung
		Klimaentwicklung	Erderwärmung
		Klimaentwicklungen	
		klimatische Änderung	
		klimatischen Änderung	
		klimatischer Änderung	
		klimatische Änderungen	
		klimatischen Änderungen	
		klimatischer Änderungen	
Greek	GR & CY	αλλαγ* του κλίματος	παγκόσμ* θέρμανσ*
		κλιματικ* αλλαγ*	παγκόσμ* υπερθέρμανσ*
		κλιματικ* μεταβολ*	θέρμανσ* του πλανήτη
		κλιματολογικ* αλλαγ*	υπερθέρμ* του πλανήτη
			παγκόσμ* άνοδ* της θερμοκρασίας
Hungarian	HU	klímaváltoz*	globál* felmeleged*
		éghajlatváltoz*	
		éghajlat-változ*	
Italian	IT & MT	cambiamento climatico	riscaldamento globale
		cambiamenti climatici	surriscaldamento globale
Latvian	LV	klimata izmaiņas	globāl* sasilšan*

		klimata pārmaiņ*	
		klimata maiņa	
Lithuanian	LT	klimato kait*	pasaulin* atšilim*
			visuotin* atšilim*
			globalin* atšilim*
			klimato atšilim*
Polish	PL	zmia* klimat*	global* ocieplen*
			ocieplen* global*
Portuguese	PT	mudança climática	aquecimento global
		mudanças climáticas	aquecimento do planeta
		mudança do clima	
		mudança de clima	
		mudanças do clima	
		mudanças de clima	
		alteração climática	
		alterações climáticas	
		alteração do clima	
		alterações do clima	
		alteração de clima	
		alterações de clima	
		variação climática	
		variações climáticas	
		variação do clima	
		variações do clima	
		variação de clima	
		variações de clima	
Romenian	RO	schimbăr* climatic*	încălzir* global*
		schimbar* climatic*	
		modificăr* climatic*	
Slovak	SK	zmen* podneb*	globáln* otepľovan*
		zmien* podneb*	

		zmen* klím* zmie* klím* klimat* zmen* klimat* zmie*	
Slovenian	SI	podnebn* sprememb* sprememb* podnebj* klimatsk* spremem* klimátsk* sprémémb*	globaln* segrevanj* segrevanj* ozračj*
Spanish	ES	cambio climático cambios climáticos cambios del clima cambio del clima	calentamiento global calentamiento del planeta recalentamiento global recalentamiento del planeta calentamiento de la tierra calentamiento de la atmósfera calentamiento atmosférico recalentamiento de la tierra recalentamiento de la atmósfera recalentamiento atmosférico
Swedish	SE	klimatförändr* klimatisk förändr*	globa* uppvärmn* jordens uppvärmn* uppvärmn* av jorden

Table A.1: Translations of "climate change" and "global warming" in the 22 most spoken languages in the EU

Scraping procedure

We downloaded article records from the Europe Media Monitor (EMM) using an RSS-feed consumption script developed for this project using the statistical software R. The EMM allows public searches of its database of news records through a web browser (https://emm.newsbrief.eu/NewsBrief/search/en/advanced.html) or RSS request. For each article, The EMM provides the title, a short summary, the URL of the article, and the date and time of publication. We iteratively ran this script to download all article records available given our keywords and countries of interest.

The script we developed to download articles through the EMM RSS feed involved a dynamic time window to ensure efficiency of our RSS calls. The script would start with a 180 day window and decrease the window as needed to maximize the number of article records returned per request without going over the per-request limit of 100 articles. In order to ensure we downloaded a comprehensive set of article records given our keywords without missing records due to processing failures, we ran the procedure two full times and consolidated the results. Our media data is winsorized at 400, as we queried 4 times per day (4x100 per query=400). This upper threshold was reached only 88 times out of 150,000 day x country x phrase opportunities. As this represents only 6/1000 of our queries, we are convinced that this upper threshold on article downloads does not impact our results, and rather prevents outliers from over-influencing them.

Variables and descriptive statistics

To carry out our analyses at the daily, weekly and monthly level, we create three datasets with temperature and media data collapsed at the daily, weekly and monthly level.

Temperature

We obtain temperature data from the E-OBS dataset, which provides high-resolution daily gridded observational temperature data in Europe since 1950. We obtain data for Malta from the Global Historical Climatology Network (GHCN). The unit of measurement is degrees Celsius. Table A.2 presents a brief description and basic descriptive statistics of the measures of temperature and temperature abnormality. We use the following measures:

Short-term temperature abnormalities are computed as the difference between average temperature in each country in each time period (day, week and month of the year) and average temperature in the same country and time period in the previous n years, with N:=$\{1,2,3, \ldots, 20\}$. Our main measure of short-term temperature abnormality is the deviation from average temperature over the previous 5 years. Figure A.1 displays the country-specific trends of daily short-term temperature abnormalities measured as deviations from average temperatures on the same day over the previous 5 years.

Long-term temperature abnormalities mirror what climate scientists define as changes in climate. Our main long-term abnormality measure is defined as the difference between average temperature in each country in each time period (day, week and month of the year) and average temperature in the same country and time period in the period 1951-1980.

We develop a second measure of long-term abnormality to use in robustness checks employing the period 1961-1990 as baseline. Figure A.2 displays the country-specific trends of daily long-term temperature abnormalities measured as deviations from averages on the same day in the baseline period 1951-1980.

Temperature level is computed as the daily, weekly or monthly average temperature at the country level.

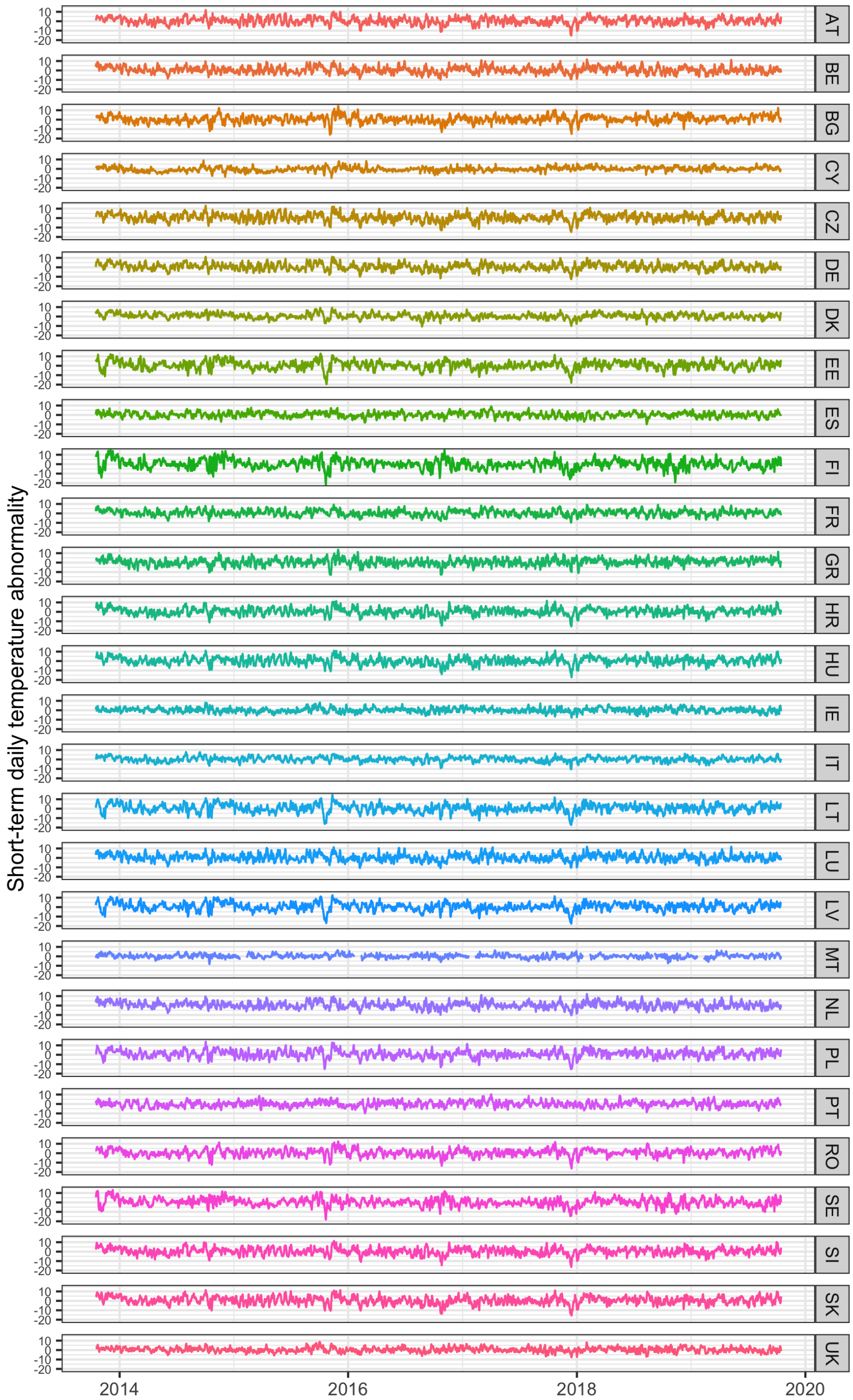


Figure A.1: Short-term Abnormalities

Daily temperature abnormalities measured as the deviation of daily temperature (in degrees Celsius) with respect to average temperatures (in degrees Celsius) on the same day over the previous 5 years.

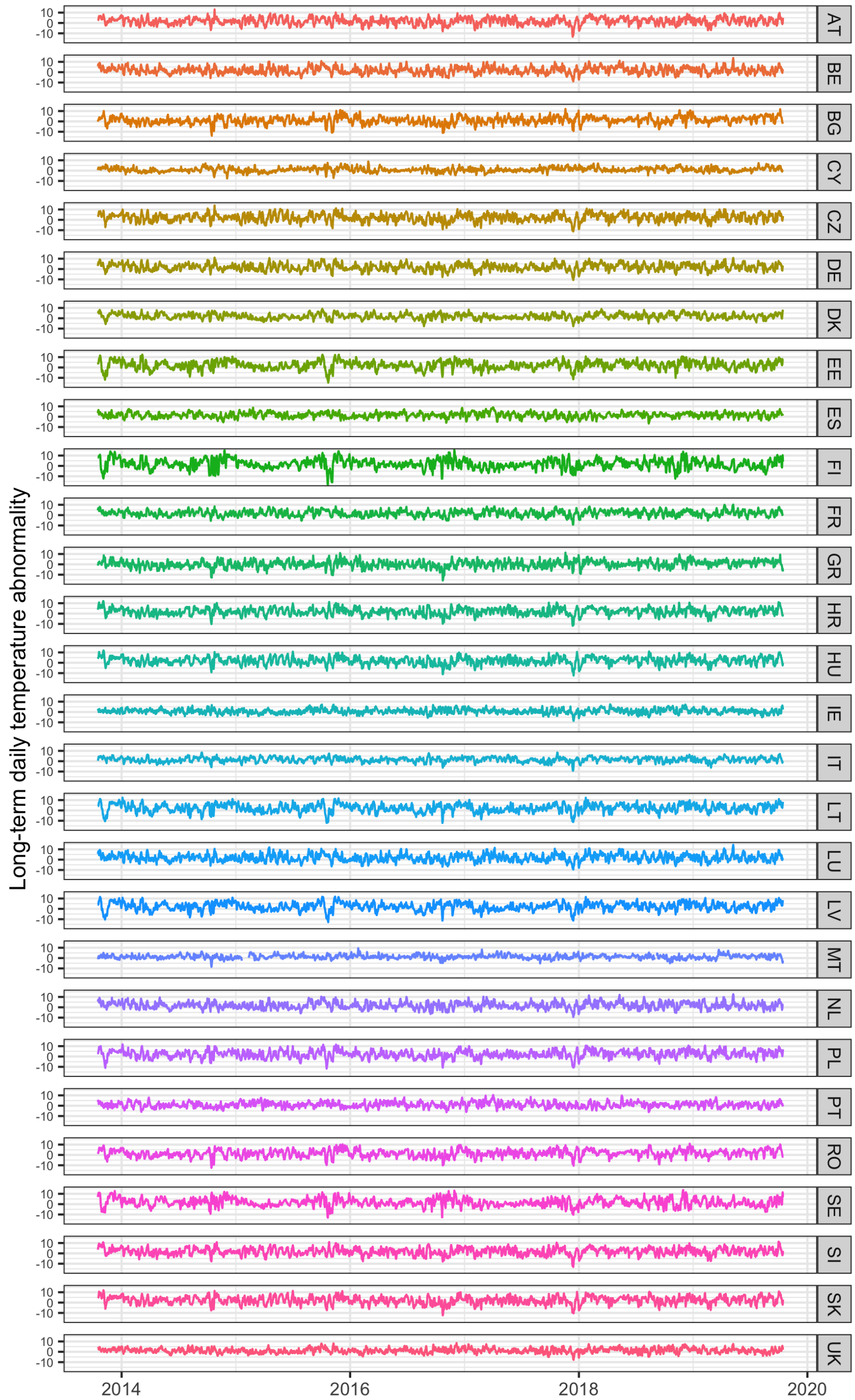


Figure A.2: Long-term Abnormalities

Daily temperature abnormalities measured as the deviation of daily temperature (in degrees Celsius) with respect to average temperatures (in degrees Celsius) on the same day in the baseline period 1951-1980.

Construct	Measure	Mean	Std.Dev.
Daily			
Short-Term Abnormality	Deviation from previous 5 years' average by country & day	0.41	3.43
Long-Term Abnormality	Deviation from 1951-1980 average by country & day	1.67	3.21
Temperature level	Daily average temperature by country	10.79	8.06
Weekly			
Short-Term Abnormality	Deviation from previous 5 years' average by country & week	0.41	2.70
Long-Term Abnormality	Deviation from 1951-1980 average by country & week	1.67	2.53
Temperature level	Weekly average temperature by country	10.80	7.82
Monthly			
Short-Term Abnormality	Deviation from previous 5 years' average by country & month	0.41	1.77
Long-Term Abnormality	Deviation from 1951-1980 average by country & month	1.67	1.67
Temperature level	Monthly average temperature by country	10.80	7.54

Correlations

	Daily Short-Term Abn.	Daily Long-Term Abn.	Daily Temperature
Daily Short-Term Abn.	1.0000	-	-
Daily Long-Term Abn.	0.8905	1.0000	-
Daily Temperature	0.2845	0.2766	1.0000
	Weekly Short-Term Abn.	Weekly Long-Term Abn.	Weekly Temperature
Weekly Short-Term Abn.	1.0000	-	-
Weekly Long-Term Abn.	0.8868	1.0000	-
Weekly Temperature	0.1958	0.1728	1.0000
	Monthly Short-Term Abn.	Monthly Long-Term Abn.	Monthly Temperature
Monthly Short-Term Abn.	1.0000	-	-
Monthly Long-Term Abn.	0.8732	1.0000	-
Monthly Temperature	0.0578	-0.0015	1.0000

Table A.2: Definition and Descriptive Statistics of the Temperature Variables

Media coverage

Table A.3 presents basic descriptive statistics of our measure of media coverage of climate change, showing the mean and standard deviation of the daily, weekly and monthly number of articles mentioning 'climate change' or 'global warming' in each country. To assign equal weight to relative variations in different countries, we use as main outcome variable the weekly number of articles divided by the country-specific standard deviation. To compute the magnitude of the impact of short-term temperature abnormalities in each country, the coefficients in Table 1.2 can be multiplied by the country-specific standard deviation of the weekly number of climate articles, presented in Column (5) of Table A.3.

Figure A.3 presents a visual representation of the evolution of media coverage of climate change over time in different countries. It plots the average daily number of articles mentioning climate change in each country for each year in the period 2014-2019.

Table A.3: Daily, Weekly and Monthly Number Climate Articles: Descriptive Statistics by Country

Country	D.Mean	D.Std.Dev	W.Mean	W.Std.Dev	M.Mean	M.Std.Dev
AT	17.690	16.520	17.730	12.630	17.580	10.580
BE	26.400	24.220	26.470	17.440	26.280	12.990
BG	32.550	33.010	32.590	23.490	32.360	18.040
CY	6.260	8.260	6.250	5.800	6.270	4.640
CZ	17	16.610	17	12.100	16.910	10.360
DE	104.130	107.140	104.040	85.680	104.650	74.100
DK	19.780	23.790	19.770	15.460	19.880	11.440
EE	2.030	2.790	2.030	1.930	2.030	1.580
ES	86.660	64.430	86.830	51.530	87.230	44.880
FI	23.100	24.310	23.160	18.910	22.960	16.230
FR	57.910	57.530	57.920	43.610	58.260	33.390
GR	47.030	46.280	46.950	36.590	46.910	30.940
HR	11.210	10.660	11.250	6.700	11.220	4.550
HU	18.160	24.560	18.260	21.380	18.030	20.470
IE	16.010	13.970	16.080	10.020	15.970	8.100
IT	80.150	71.960	80.080	59.170	80.620	52.800
LT	3.640	4.080	3.650	2.800	3.640	2.220
LU	3	3.970	3.010	2.530	3.020	1.900
LV	1.970	2.850	1.990	1.720	1.960	1.410
MT	1.710	2.160	1.710	1.510	1.720	1.080
NL	24.600	22.780	24.630	15.320	24.530	11.440
PL	13.550	17.140	13.540	13.880	13.460	11.460
PT	18.530	22.250	18.490	17.260	18.650	13.850
RO	23.240	22.680	23.240	15.470	23.160	9.970
SE	26.390	30.270	26.450	23.260	26.200	20.020
SI	5.430	5.810	5.440	3.840	5.440	2.800
SK	9.640	10.800	9.620	7.930	9.580	6.550
UK	143.440	109.020	143.440	89.480	144.120	83.620

Notes: Descriptive statistics of variables measuring the daily, weekly and monthly number of climate articles in each country. Columns (2) and (3) display the mean and standard deviation of the daily number of climate articles; Columns (4) and (5) display the mean and standard deviation of the weekly number of climate articles; Columns (6) and (7) display the mean and standard deviation of the monthly number of climate articles.

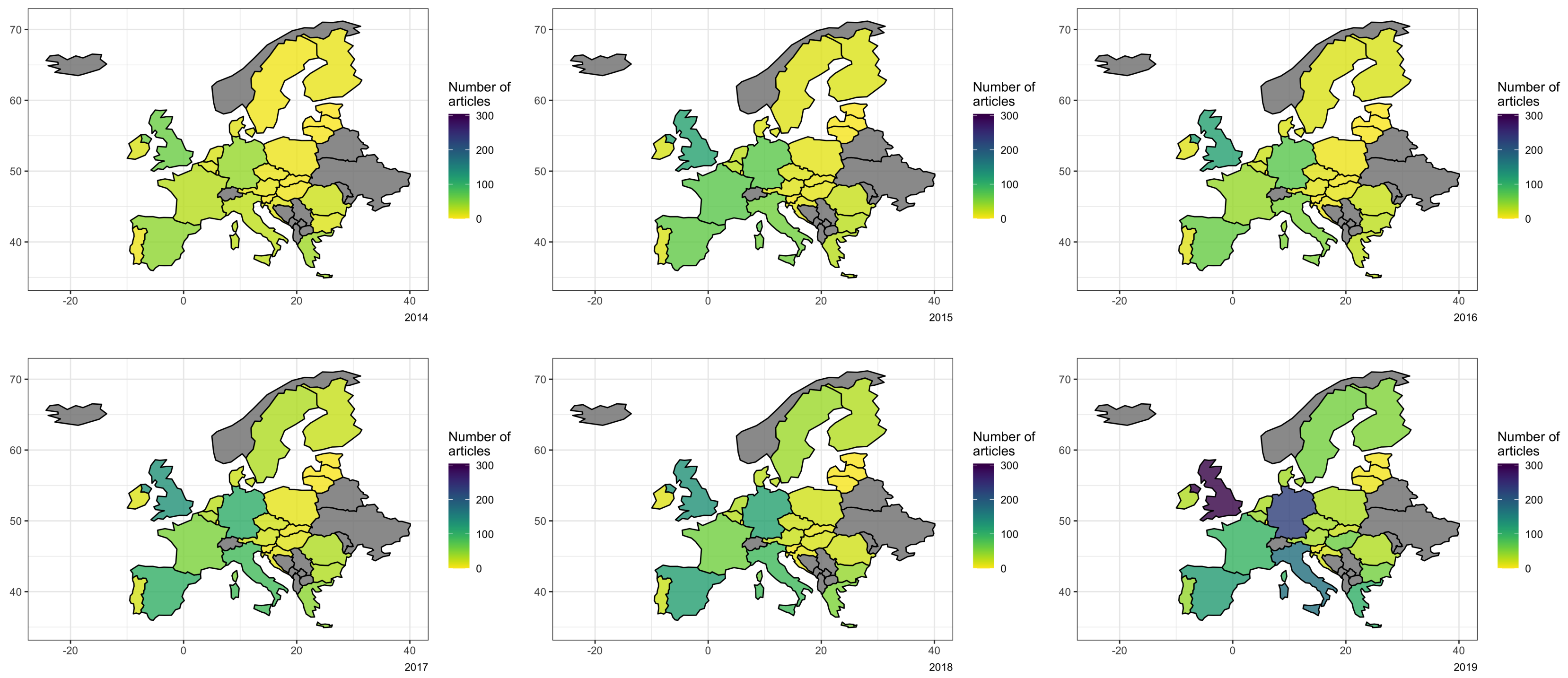


Figure A.3: Media coverage of climate change in the 28 EU countries. Total number of articles mentioning climate change in the 28 EU countries every year for the period 2014-2019

Robustness checks

Robustness checks with different sets of control variables

Table A.4 presents models testing, like Model (1) of Table 1.2, the impact of short-term temperature abnormality - computed as the difference between present average weekly temperature and average temperature in the same week of the year over the previous five years - with different sets of control variables. Model (1) in Table A.4 does not include any controls; Model (2) includes country fixed effects - which allow to control for country-specific time-invarying unobserved factors; Model (3) includes country fixed effects and a time trend - which allow to control time-invarying unobserved factors; Model (4) includes country fixed effects and a time trend, and a dummy for each calendar month - which allow to control for seasonality; Model (5) corresponds to Model (1) in Table 1.2, and includes - besides country fixed effects, a time trend, a dummy for each calendar month - an interaction between country fixed effects and the time trend, which allows to control also for country-specific time-varying unobserved factors. As evident from the table, our results are robust to these different model specifications.

Table A.4: The Impact of Short-term Temperature Abnormality: Robustness Checks With Different Sets of Control Variables

VARIABLES	(1) Coverage	(2) Coverage	(3) Coverage	(4) Coverage	(5) Coverage
Short-Term Abnormality	0.018**	0.016**	0.016**	0.017***	0.018***
	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
Constant	1.307***	1.400***	0.522***	0.252***	0.026
	(0.041)	(0.002)	(0.054)	(0.063)	(0.021)
Observations	8,065	8,065	8,065	8,065	8,065
Adjusted R-squared	0.002	0.043	0.283	0.333	0.355
Country FE	-	✓	✓	✓	✓
Time trend	-	-	✓	✓	✓
Country FE × Time trend	-	-	-	-	✓
Month FE	-	-	-	✓	✓

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Notes: Standard errors are clustered at the country level. Media coverage is measured as the country weekly number of climate articles divided by the country-specific standard deviation. Temperature abnormalities are computed as the difference between average temperature in each country in each week and average temperature in the same country and week over the previous 5 years.

Analyses with an alternative measure of long-term temperature abnormality (baseline 1961-1990)

Table A.5 presents the same models present in Table 1.3, but using a different baseline period (1961-1990 instead of 1951-1980) to compute long-term temperature abnormality in Column (2) (Hulme et al., 1999; Mitchell Jones, 2005). Results are almost identical, with the coefficient of long-term abnormality = 0.009 compared to 0.010 when using 1951-1980 as baseline period (as in Table 1.3).

Table A.5: Comparing the Impact of Short-term and Long-term Temperature Abnormalities and Present Temperature on Media Coverage of Climate Change

VARIABLES	(1) Coverage	(2) Coverage	(3) Coverage
Short.Term.Abnormality	0.018***		
	(0.004)		
Long.Term.Abnormality		0.009*	
		(0.004)	
Present Temperature			0.009*
			(0.004)
Constant	0.026	0.018	0.046*
	(0.021)	(0.022)	(0.020)
Observations	8,065	8,073	8,073
Adjusted R-squared	0.355	0.353	0.353
Country FE × Time trend	✓	✓	✓
Month FE	✓	✓	✓

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Notes: Standard errors are clustered at the country level. Media coverage is measured as the country weekly number of climate articles divided by the country-specific standard deviation. In Model (1) short-term temperature abnormality is computed as the difference between average temperature in each country in each week and average temperature in the same country and week in the previous 5 years. In Model (2) long-term temperature abnormality is computed as the difference between average temperature in each country in each week and average temperature in the same country and week in the baseline period 1961-1990. In Model (3) the temperature level is measures as the weekly average temperature in degrees Celsius.

The impact of temperature when controlling for short term abnormality

Table A.6 shows that the impact of of temperature becomes non-significant when short-term abnormality is controlled for. While these results have to be interpreted with caution due to the collinearity between the variables, they suggest that the impact of short-term abnormality is stronger and more robust.

Table A.6

VARIABLES	(1) Coverage	(2) Coverage
Temperature level	0.009*	-0.007
	(0.004)	(0.007)
Short-Term Abnormality		0.024***
		(0.007)
Constant	0.046*	0.011
	(0.020)	(0.022)
Observations	8,073	8,065
Adjusted R-squared	0.353	0.355
Country FE × Time trend	✓	✓
Month FE	✓	✓

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Notes: Standard errors are clustered at the country level. Media coverage is measured as the country weekly number of climate articles divided by the country-specific standard deviation. Short-term temperature abnormality is computed as the difference between average temperature in each country in each week and average temperature in the same country and week of the year in the previous 5 years. The temperature level is measured as the weekly average temperature in degrees Celsius.

Analyses at the daily level

In Table A.7 and Table A.8 we replicate the analyses presented in Tables 1.2 and 1.3 in the main text, using data at the daily (instead of weekly) level. Results are qualitatively equivalent. Coefficients are smaller in size, and the impacts of long-term abnormality and present temperature are not significant.

Table A.7: Replicating Table 1.2 with Daily Data
Short-term Temperature Abnormality and Media Coverage of Climate Change

VARIABLES	(1) Coverage	(2) Coverage
Temp.Abnormality	0.007***	
	(0.002)	
Neg.Temp.Abnormality		-0.007**
		(0.002)
Pos.Temp.Abnormality		0.020***
		(0.003)
Constant	0.015	-0.036
	(0.015)	(0.019)
Observations	56,584	56,584
Adjusted R-squared	0.206	0.206
Country FE × Time trend	✓	✓
Month FE	✓	✓

Robust standard errors in parentheses
*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Notes: Standard errors are clustered at the country level. Media coverage is measured as the country daily number of climate articles divided by the country-specific standard deviation. Model (1): Temperature abnormalities are computed as the difference between average temperature in each country in each day and average temperature in the same country and day of the year over the previous 5 years. In Model (2), negative and positive short-term temperature abnormalities are computed employing a spline of the variable employed in Model (1): *Neg.Temp.Abnormality = Temp.Abnormality if Temp.Abnormality < 0 ; Pos.Temp.Abnormality = Temp.Abnormality if Temp.Abnormality > 0*

Table A.8: Replicating Table 1.3 with Daily Data
Comparing the Impact of Short-term and Long-term Temperature Abnormalities and Present Temperature on Media Coverage of Climate Change

VARIABLES	(1) Coverage	(2) Coverage	(3) Coverage
Short.Term.Abnormality	0.007***		
	(0.002)		
Long.Term.Abnormality		0.003	
		(0.002)	
Present Temperature			0.003
			(0.002)
Constant	0.015	0.013	0.022
	(0.015)	(0.016)	(0.015)
Observations	56,584	56,670	56,670
Adjusted R-squared	0.206	0.205	0.205
Country FE $\times$ Time trend	✓	✓	✓
Month FE	✓	✓	✓

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Notes: Standard errors are clustered at the country level. Media coverage is measured as the country daily number of climate articles divided by the country-specific standard deviation. We compare here the impact of short-term temperature abnormalities, long-term temperature abnormalities, and present temperature on media coverage of climate change. In Model (1) short-term temperature abnormality is computed as the difference between average temperature in each country in each day and average temperature in the same country and day of the year in the previous 5 years. In Model (2) long-term temperature abnormality is computed as the difference between average temperature in each country in each day and average temperature in the same country and day of the year over the baseline period 1951-1980. In Model (3) the temperature level is measured as the daily average temperature in degrees Celsius.

Analyses at the monthly level

In Table A.9 and Table A.10 we replicate the analyses presented in Tables 1.2 and 1.3 in the main text, using data aggregated at the monthly (instead of weekly) level. Results are qualitatively equivalent. Coefficients are bigger in size, and the impacts of long-term abnormality and present temperature have a higher significance level. The impact of short-term abnormality is stronger than the impact of long-term abnormality and of present temperature.

Table A.9: Replicating Table 1.2 with Monthly Data
Short-term Temperature Abnormality and Media Coverage of Climate Change

VARIABLES	(1) Coverage	(2) Coverage
Temp.Abnormality	0.048***	
	(0.009)	
Neg.Temp.Abnormality		0.004
		(0.016)
Pos.Temp.Abnormality		0.084***
		(0.020)
Constant	0.065*	-0.007
	(0.025)	(0.044)
Observations	1,862	1,862
Adjusted R-squared	0.532	0.534
Country FE × Time trend	✓	✓
Month FE	✓	✓

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Notes: Standard errors are clustered at the country level. Media coverage is measured as the country daily number of climate articles divided by the country-specific standard deviation. Model (1): Temperature abnormalities are computed as the difference between average temperature in each country in each month and average temperature in the same country and month over the previous 5 years. In Model (2), negative and positive short-term temperature abnormalities are computed employing a spline of the variable employed in Model (1): *Neg.Temp.Abnormality = Temp.Abnormality if Temp.Abnormality < 0 ; Pos.Temp.Abnormality = Temp.Abnormality if Temp.Abnormality > 0*

Table A.10: Replicating Table 1.3 with Monthly Data
Comparing the Impact of Short-term and Long-term Temperature Abnormalities and Present Temperature on Media Coverage of Climate Change: Monthly Analyses

VARIABLES	(1) Coverage	(2) Coverage	(3) Coverage
Short.Term.Abnormality	0.048***		
	(0.009)		
Long.Term.Abnormality		0.044***	
		(0.011)	
Present Temperature			0.032**
			(0.011)
Constant	0.065*	0.019	0.135***
	(0.025)	(0.029)	(0.032)
Observations	1,862	1,862	1,862
Adjusted R-squared	0.532	0.531	0.530
Country FE × Time trend	✓	✓	✓
Month FE	✓	✓	✓

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Notes: Standard errors are clustered at the country level. Media coverage is measured as the country daily number of climate articles divided by the country-specific standard deviation. We compare here the impact of short-term temperature abnormalities, long-term temperature abnormalities, and present temperature on media coverage of climate change. In Model (1) short-term temperature abnormality is computed as the difference between average temperature in each country in each month and average temperature in the same country and month in the previous 5 years. In Model (2) long-term temperature abnormality is computed as the difference between average temperature in each country in each month and average temperature in the same country and month over the baseline period 1951-1980. In Model (3) the temperature level is measured as the monthly average temperature in degrees Celsius.

Quadratic Models

We also test a quadratic model to see if there is a non-linear relationship between short-term temperature abnormalities and media coverage of climate change. In Table A.11, for daily, weekly, and monthly data, we test models that include both a linear and a quadratic term of short-term temperature abnormality. Columns (1) and (2) present results of monthly analyses, Column (3) and (4) present results of weekly analyses, and Column (5) and (6) presents results of daily analyses. While quadratic terms are significant, their impact is small compared to linear terms and their inclusion in our models do not significantly increase model fit.

For monthly analyses, including a quadratic trend increases the adjusted R-squared from 0.532 - Column (1) to 0.534 - Column (2). For weekly analyses, including a quadratic trend increases the adjusted R-squared from 0.355 - Column (3) - to 0.534 - Column (4). For daily analyses, the adjusted R-squared is identical (0.206) for the model with a simple linear term - Column (5) - and for the model with both a linear and a quadratic term - Column (6).

Table A.11: Testing quadratic relationships

VARIABLES	(1) Std.M.coverage	(2) Std.M.coverage	(3) Std.W.coverage	(4) Std.W.coverage	(5) Std.D.coverage	(6) Std.D.coverage
M. Short-term Abn	0.048***	0.045***				
	(0.009)	(0.008)				
M. Short-term Abn^2		0.010*				
		(0.004)				
W. Short-term Abn			0.018***	0.018***		
			(0.004)	(0.003)		
W. Short-term Abn^2				0.003***		
				(0.001)		
D. Short-term Abn					0.007***	0.007***
					(0.002)	(0.002)
D. Short-term Abn^2						0.001***
						(0.000)
Constant	0.065*	0.011	0.026	-0.019	0.015	-0.012
	(0.025)	(0.038)	(0.021)	(0.026)	(0.015)	(0.017)
Observations	1,862	1,862	8,065	8,065	56,584	56,584
Adjusted R-squared	0.532	0.534	0.355	0.356	0.206	0.206
Country FE × Time trend	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓

Robust standard errors in parentheses
*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Notes: Standard errors are clustered at the country level. Media coverage is measured as the country daily number of climate articles divided by the country-specific standard deviation. Short-term temperature abnormality is computed as the difference between average temperature in each country in each period and average temperature in the same country and period in the previous 5 years.

Analyses with a non-standardized measure of media coverage of climate change

In our main analyses, we use a standardized measure of media coverage of climate change, obtained dividing the variable measuring the number of climate articles in each country and each time period by its country-specific standard deviation. This choice was made in order to assign equal weight to relative variations in different countries.

In Table A.12 and Table A.13 we replicate the analyses presented in Tables 1.2 and 1.3 in the main text, using a simple measure of media coverage, which is a count of the number of climate articles in each country and each week. We run these analyses using a negative binomial regression, which is the most appropriate tool to analyse overdispersed count data. Our media coverage variable is overdispersed, with a variance (2174) which is around 70 times its mean (30.04). This has been confirmed by goodness of fit analyses of poisson regressions, which display a large chi-square value and a significant (0= 0.000) test statistic.

Comparing Table A.12 with Table 1.2 and Table A.13 with Table 1.3, we can see that the impact of short-term abnormality is robust to the use of different measures of media coverage. The main difference in results when using the non-standardized measure of media coverage is that the impact of long-term abnormality has a higher significance level (see Column (2) in Table A.13). However, its impact is still smaller in size than the impact of short-term abnormality.

Using a non-standardized measure of media coverage assigns more weight to countries with levels of media coverage that are on average higher. We are therefore convinced that using a measure of coverage standardized by country-specific standard deviations is more appropriate.

Table A.12: Replicating Table 1.2: Temperature Abnormality and Media Coverage of Climate Change: Results of Negative Binomial Regressions with a Non-standardized Measure of Media Coverage

	(1)	(2)
VARIABLES	W.Coverage	W.Coverage
Temp.Abnormality	0.017***	
	(0.002)	
Neg.Temp.Abnormality		-0.007
		(0.004)
Pos.Temp.Abnormality		0.037***
		(0.005)
Constant	1.770***	1.704***
	(0.020)	(0.025)
Observations	8,065	8,065
Country FE × Time trend	✓	✓
Month FE	✓	✓

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Notes: Standard errors are clustered at the country level. Media coverage is measured as the weekly number of climate articles per country. In Model (1) temperature abnormalities are computed as the difference between average temperature in each country in each week and average temperature in the same country and week over the previous 5 years. In Model (2), negative and positive short-term temperature abnormalities are computed employing a spline of the variable employed in Model (1): *Neg.Temp.Abnormality = Temp.Abnormality if Temp.Abnormality < 0 ; Pos.Temp.Abnormality = Temp.Abnormality if Temp.Abnormality > 0*

Table A.13: Replicating Table 1.3: Comparing the Impact of Short-term and Long-term Temperature Abnormalities and Present Temperature on Media Coverage of Climate Change: Results of Negative Binomial Regressions with a Non-standardized Measure of Media Coverage

VARIABLES	(1) W.Coverage	(2) W.Coverage	(3) W.Coverage
Short.Term.Abnormality	0.017***		
	(0.002)		
Long.Term.Abnormality		0.011***	
		(0.002)	
Present Temperature			0.008*
			(0.003)
Constant	1.770***	1.759***	1.788***
	(0.020)	(0.021)	(0.018)
Observations	8,065	8,073	8,073
Country FE × Time trend	✓	✓	✓
Month FE	✓	✓	✓

Robust standard errors in parentheses
*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Notes: Standard errors are clustered at the country level. Media coverage is measured as the weekly number of climate articles per country. We compare here the impact of short-term temperature abnormalities, long-term temperature abnormalities, and present temperature on media coverage of climate change. In Model (1) short-term temperature abnormality is computed as the difference between average temperature in each country in each week and average temperature in the same country and week in the previous 5 years. In Model (2) long-term temperature abnormality is computed as the difference between average temperature in each country in each week and average temperature in the same country and week over the baseline period 1951-1980. In Model (3) the temperature level is measured as the weekly average temperature in degrees Celsius.

Short-term Temperature Abnormalities and Media Coverage of Climate Change - Results with Measures Based on Different Baselines

Table A.14 displays the impact on media coverage of climate change of different measures of short-term temperature abnormalities, computed with respect to different recent baselines that range from the previous year to the previous 20 years. Figure 3.3 in the main text is based on these results. Table A.14 presents coefficients of twenty separate regression analyses where our measure of media coverage of climate change - standardized on country-specific standard deviations - is regressed on different measures of short-term abnormalities. The latter are computed as the difference between average temperature in each country in each week and average temperature in the same country and week in the previous n years, with N:=$\{1,2,3, \ldots, 20\}$. All regressions follow the same specification described in the main text and employed in our main analyses in column (1) of Table 1.2. We control for country fixed effects, a general time trend, country-specific time trends, and calendar month fixed effect. Together, the latter terms allow us to control for general time-variant unobserved factors, time-invariant and time-variant country-level unobserved factors, and for seasonality.

As shown in Figure 3.3, deviations from temperatures in baseline periods ranging from the previous 2 to 20 years all significantly predict media coverage of climate change. The model that best fits the data and presents the strongest effect is the model with temperature abnormalities computed with respect to the previous 5 years. Effect sizes decrease for somewhat shorter and longer baselines, and are halved for baselines based on the previous 15 to 20 years. Deviations from temperatures in the same time period in the previous year have no statistically significant impact on media coverage of climate change.

Table A.14: Different Measures of Short-term Abnormalities and Media Coverage of Climate Change

	Coefficient	St.Err(Coefficient)	Constant	St.Err(Constant)	Observations	Adj. R-squared
Abn. wrt. previous year	-0.001	(0.003)	0.013	(0.020)	8,088	0.360
Abn. wrt. previous 2 years	0.008*	(0.003)	0.013	(0.020)	8,086	0.360
Abn. wrt. previous 3 years	0.013**	(0.004)	0.012	(0.020)	8,084	0.361
Abn. wrt. previous 4 years	0.013**	(0.004)	0.011	(0.020)	8,082	0.361
Abn. wrt. previous 5 years	0.018***	(0.004)	0.007	(0.021)	8,082	0.362
Abn. wrt. previous 6 years	0.018***	(0.004)	0.005	(0.021)	8,082	0.362
Abn. wrt. previous 7 years	0.015***	(0.004)	0.005	(0.021)	8,082	0.361
Abn. wrt. previous 8 years	0.012**	(0.004)	0.009	(0.021)	8,082	0.361
Abn. wrt. previous 9 years	0.010*	(0.004)	0.009	(0.021)	8,082	0.361
Abn. wrt. previous 10 years	0.011**	(0.004)	0.009	(0.021)	8,082	0.361
Abn. wrt. previous 11 years	0.012**	(0.004)	0.009	(0.021)	8,082	0.361
Abn. wrt. previous 12 years	0.010**	(0.004)	0.010	(0.021)	8,082	0.361
Abn. wrt. previous 13 years	0.010*	(0.004)	0.010	(0.021)	8,082	0.361
Abn. wrt. previous 14 years	0.010**	(0.004)	0.010	(0.021)	8,082	0.360
Abn. wrt. previous 15 years	0.009*	(0.004)	0.011	(0.021)	8,082	0.360
Abn. wrt. previous 16 years	0.008*	(0.004)	0.011	(0.020)	8,082	0.360
Abn. wrt. previous 17 years	0.010*	(0.004)	0.011	(0.020)	8,082	0.360
Abn. wrt. previous 18 years	0.009*	(0.004)	0.011	(0.020)	8,082	0.360
Abn. wrt. previous 19 years	0.009*	(0.004)	0.011	(0.020)	8,082	0.360
Abn. wrt. previous 20 years	0.009*	(0.004)	0.011	(0.020)	8,082	0.360
Country FE	✓					
Time trend	✓					
Country FE × Time trend	✓					
Month FE	✓					

*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Placebo tests

As a robustness check, we performed a placebo test to check whether when shifting the time series of the dependent variable backward our analyses produce, as should be the case, insignificant results. In other words, we are checking whether it is the case that future temperature abnormalities have no significant relationship with past media coverage of climate change. We performed two placebo tests. We shifted the time series of the dependent variable (media coverage) 6 months backward (see Table A.15) and 12 months backward (see Table A.16). We ran these analyses using different measures of short-term abnormality, computed with respect to the previous 5 (Column 1), 10 (Column 2),15 (Column 3), and 20 years (Column 4). All coefficients are insignificant, supporting our conclusion that there is only a significant effect of present temperature on present media coverage of climate change.

Table A.15: Weekly-level analyses with a shift of the dependent variable 6 months backward

	(1)	(2)	(3)	(4)
VARIABLES	Lag_6m W.Coverage	Lag_6m W.Coverage	Lag_6m W.Coverage	Lag_6m W.Coverage
W.Temp.Abn_5	0.005			
	(0.004)			
W.Temp.Abn_10		0.006		
		(0.004)		
W.Temp.Abn_15			0.004	
			(0.004)	
W.Temp.Abn_20				0.004
				(0.004)
Constant	0.011	0.011	0.012	0.012
	(0.018)	(0.018)	(0.018)	(0.018)
Observations	7,578	7,578	7,578	7,578
R-squared	0.346	0.346	0.346	0.346
Controls	C*Wdate+Mth	C*Wdate+Mth	C*Wdate+Mth	C*Wdate+Mth

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Notes: Standard errors are clustered at the country level. Media coverage is measured as the weekly number of climate articles per country divided by the country-specific standard deviation, *lagged by six months*. In Model (1) temperature abnormalities are computed as the difference between average temperature in each country in each week and average temperature in the same country and week over the previous 5 years. In Model (2), temperature abnormalities are computed as the difference between average temperature in each country in each week and average temperature in the same country and week over the previous 10 years. In Model (3), temperature abnormalities are computed as the difference between average temperature in each country in each week and average temperature in the same country and week over the previous 15 years. In Model (4), temperature abnormalities are computed as the difference between average temperature in each country in each week and average temperature in the same country and week over the previous 20 years.

Table A.16: Weekly-level analyses with a shift of the dependent variable 12 months backward

	(1)	(2)	(3)	(4)
VARIABLES	Lag_12m W.Coverage	Lag_12m W.Coverage	Lag_12m W.Coverage	Lag_12m W.Coverage
W.Temp.Abn_5	0.001			
	(0.002)			
W.Temp.Abn_10		-0.001		
		(0.003)		
W.Temp.Abn_15			-0.001	
			(0.003)	
W.Temp.Abn_20				-0.003
				(0.003)
Constant	0.120***	0.120***	0.120***	0.120***
	(0.019)	(0.019)	(0.019)	(0.019)
Observations	6,851	6,851	6,851	6,851
R-squared	0.310	0.310	0.310	0.310
Controls	C*Wdate+Mth	C*Wdate+Mth	C*Wdate+Mth	C*Wdate+Mth

Robust standard errors in parentheses
*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Notes: Standard errors are clustered at the country level. Media coverage is measured as the weekly number of climate articles per country divided by the country-specific standard deviation, *lagged by twelve months*. In Model (1) temperature abnormalities are computed as the difference between average temperature in each country in each week and average temperature in the same country and week over the previous 5 years. In Model (2), temperature abnormalities are computed as the difference between average temperature in each country in each week and average temperature in the same country and week over the previous 10 years. In Model (3), temperature abnormalities are computed as the difference between average temperature in each country in each week and average temperature in the same country and week over the previous 15 years. In Model (4), temperature abnormalities are computed as the difference between average temperature in each country in each week and average temperature in the same country and week over the previous 20 years.

Hot vs. cold countries

To test whether the impact of temperature abnormalities is different in countries with higher or lower average temperatures, we replicate the models in Tables 1.2 and 1.3 in the main text for the two subsamples of countries with average temperatures higher or lower than 10 degrees Celsius. Table A.17 shows results for the subsample of colder countries, with average temperatures lower than or equal to 10 degrees Celsius (Austria, Czech Republic, Denmark, Estonia, Finlanda, Ireland, Lithuania, Latvia, Poland, Sweden, Slovakia and the United Kingdom). Table A.18 shows results for the subsample of hotter countries, with average temperatures higher than 10 degrees Celsius (Belgium, Bulgaria, Cyprus, Germany, Apain, France, Greece, Hungary, Croatia, Italy, Luxembourg, Malta, the Netherlandsm Portugal, Romania and Slovenia). Short-term abnormality has a significant impact on media coverage of climate change in both subsamples, though its impact is twice in size in hotter than in colder countries (See Model (1) in Table A.17 and Table A.18). Negative abnormalities - temperatures colder than recent baselines - have a significant impact on media coverage in cold countries (half in size with respect to the impact of positive abnormalities), while they have a non-significant impact in hotter countries, where the impact of positive abnormalities is stronger. Long-term abnormalities and present temperature have in both subsamples a non-significant (or marginally significant) impact on media coverage of climate change.

These results suggest that media coverage is more sensitive to positive abnormalities - temperatures warmer than recent baselines - in countries with higher average temperatures and relatively more sensitive to negative abnormalities in countries with lower average temperatures.

Table A.17: Cold countries

VARIABLES	(1) Coverage	(2) Coverage	(3) Coverage	(4) Coverage
Short-term Temp.Abnormality	0.012**			
	(0.003)			
Negative Short-term Abn.		-0.022**		
		(0.006)		
Positive Short-term Abn.		0.043***		
		(0.006)		
Long.Term.Abnormality			0.009	
			(0.004)	
Present Temperature				0.004
				(0.004)
Constant	0.022	-0.087	0.015	0.035
	(0.039)	(0.044)	(0.038)	(0.039)
Observations	3,463	3,463	3,463	3,463
Adjusted R-squared	0.398	0.401	0.398	0.397
Country FE × Time trend	✓	✓	✓	✓
Month FE	✓	✓	✓	✓

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Notes: Standard errors are clustered at the country level. Media coverage is measured as the weekly number of climate articles per country divided by the country-specific standard deviation. In Model (1) temperature abnormalities are computed as the difference between average temperature in each country in each week and average temperature in the same country and week over the previous 5 years. —-

Table A.18: Hot countries

VARIABLES	(1) Coverage	(2) Coverage	(3) Coverage	(4) Coverage
Short-term Temp.Abnormality	0.025**			
	(0.006)			
Negative Short-term Abn.		-0.016		
		(0.008)		
Positive Short-term Abn.		0.058***		
		(0.014)		
Long.Term.Abnormality			0.014*	
			(0.006)	
Present Temperature				0.013
				(0.007)
Constant	0.517***	0.425***	0.502***	0.500***
	(0.025)	(0.039)	(0.028)	(0.033)
Observations	4,602	4,602	4,610	4,610
Adjusted R-squared	0.327	0.329	0.324	0.325
Country FE × Time trend	✓	✓	✓	✓
Month FE	✓	✓	✓	✓

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Notes: Standard errors are clustered at the country level. Media coverage is measured as the weekly number of climate articles per country divided by the country-specific standard deviation. In Model (1) temperature abnormalities are computed as the difference between average temperature in each country in each week and average temperature in the same country and week over the previous 5 years. —-

The role of education

To test the potential role of education levels as a predictor of media coverage as well as as a mediator of the impact of temperature abnormalities on media coverage, we took country-level data on educational attainment from the Wittgenstein Centre Dataset. As EU countries have on average very high education levels, we tested a model where we include a variable measuring the proportion of the population with upper education both as a predictor of media coverage and as a mediator (interacting the temperature abnormality variable with the education variable). Table A.19 shows that while higher levels of education at the country level significantly predict higher media coverage of climate change, education is not a significant moderator of the impact of temperature abnormality on media coverage of climate change. A higher average education level therefore does not strengthen the impact of temperature abnormalities on media coverage of climate change.

Table A.19: Temperature abnormality and education

VARIABLES	(1) Coverage
Short-term Abnormality	0.028
	(0.014)
Prop. upper education	0.324***
	(0.053)
Short-term Abnormality*Proport.upper education	-0.025
	(0.030)
Constant	-0.110***
	(0.028)
Observations	8,065
Adjusted R-squared	0.355
Country FE $\times$ Time trend	✓
Month FE	✓

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Notes: Standard errors are clustered at the country level. Media coverage is measured as the weekly number of climate articles per country divided by the country-specific standard deviation. Temperature abnormalities are computed as the difference between average temperature in each country in each week and average temperature in the same country and week over the previous 5 years. Upper education is measured as the proportion of the population with upper education in each country.

Appendix B

Supplementary Material: Chapter 2

Study procedure and sample distribution of socio-demographic variables

The data employed for Chapters 2 and 3 were collected through the same survey. To field the survey, we contracted with the survey company Lightspeed. Respondents were incentivized based on Lightspeed's standards[1]. Median survey completion time was 19 minutes and 43 seconds. To ensure high-quality data, several respondents were excluded based on a number of criteria. First, 560 inattentive respondents did not pass an attention check implemented a third of the way into the survey and were immediately excluded. Second, 34 speedsters with short completion time ($<$ 40% of median time) were excluded. Also excluded were 111 respondents who gave no consent and 17 respondents who did not match our restrictions in terms of age (minimum 18 years). The data of all these 722 individuals never show up in our analyses, as they are not included in our sample of 1,520 American residents.

[1]Respondents recruited by lightspeed receive „LifePoints" (lightspeed's internal currency) for their participation in surveys. For our study, respondents received 100 LifePoints. Respondents can pay out their LifePoints via PayPal, exchange them for vouchers (e.g., amazon), or donate the money to UNICEF.

Table B.1: Sample distribution of socio-demographic variables and comparison with US population

Variable	**Sample**	**US population**
Age		
18-29	18.3 %	21.3 %
30-39	19.0 %	17.0 %
40-49	16.3 %	16.5 %
50-59	19.3 %	17.9 %
60-69	17.0 %	14.6 %
70+	10.2 %	12.7 %
Gender		
Male	44.7 %	49 %
Female	55.3 %	51 %
Region		
Northeast	18.8 %	17.3 %
Midwest	22.8 %	20.9 %
South	39.5 %	38.0 %
West	18.9 %	23.8 %
Annual Family Income		
Less than $20,000$	14.7 %	16 %
$20,000-39{,}999$	20.2 %	19 %
$40,000-59{,}999$	17.0 %	16 %
$60,000-74{,}999$	13.4 %	9 %
$75,000-99{,}999$	10.1 %	12 %
$100,000-149{,}999$	15.3 %	14 %
More than $150,000$	8.6 %	14 %
(Don´t know/Prefer not to say)	0.6 %	
Party Affiliation		
Democrat	35.8 %	33 %
Independent	32.6 %	37 %
Republican	31.5 %	26 %

Notes: Information on socio-demographic characteristics of the US population was obtained from the U.S. Census Bureau (for age and sex composition (2016) see `https://www.census.gov/data/tables/2016/demo/age-and-sex/2016-age-sex-composition.html;forregions(2016)seehttps://www.census.gov/popclock/data_tables.php?component=growth`, for income (2017) see `https://www2.census.gov/programs-surveys/cps/tables/hinc-06/2017/hinc06.xls`). Information on party affiliation is based on Pew Research Center surveys conducted in 2017 (`http://www.people-press.org/wp-content/uploads/sites/4/2018/03/03-20-18-Party-Identification.pdf`). The total percentage for Pew data does not add up to 100 as the remaining share belongs to the category "other."

Relative to US census figures, our sample slightly over-represents individuals between 30 and 69, and slightly under-represents individuals in the segments between 18 and 29 and over 70, but the differences are overall quite small. Our sample contains 44.7% males and under- represents the West, while the other three census regions are slightly over-represented. Income distributions are overall well matched, but our sample contains a lower share of high-income individuals. In terms of party identification, a comparison with the US population is not straightforward, but the distribution in our sample (roughly one third Democrats, Independents and Republicans, respectively) matches the numbers of recent Pew surveys, which can serve as a benchmark.

Survey flow

The data employed for Chapters 2 and 3 were collected through the same survey. Respondents first answered to several items measuring relevant covariates. Next, they were randomly assigned to either the choice experiment about fossil fuel cars phase-out policies or the experiment on CCS deployment policies, and received basic information about the respective policy debate and relevant policy design attributes. After reading information on the policy, participants completed the conjoint experiment. Next, respondents who had first been assigned to the phase-out experiment were assigned to the CCS experiment, and vice versa. Again, the provision of policy information preceded the choice experiment. After this second round, respondents answered some final questions and received a short debriefing.

Conjoint experiment: Procedure and information provided to participants

At the beginning of the conjoint experiment, participants were provided with the following introduction to the topic:

Please read the following lines carefully.

The transportation sector is a major contributor to greenhouse gas emissions, which are being held responsible for climate change. As you might have heard, climate scientists agree that phasing out all fossil fuels is necessary to avert dangerous climate change. With the aim of reducing emissions in the transportation sector, a number of countries have announced a ban on the sale of new fossil fuels cars. For instance, France, the United Kingdom, India, Norway and China all plan to phase out cars with internal combustion engines between 2025 and 2040.

Meanwhile, the topic of phasing out fossil fuel cars is also being discussed in several US American states. In order to learn more about your point of view with regard to this important topic, the next part of the questionnaire will be devoted to some scenarios about a possible phase-out of fossil fuel cars.

You may or may not agree with phasing out fossil fuel cars, but if a phase-out were to be implemented in your state, you may still have different preferences as to specific phase-out scenarios. In the following, we will sketch out some scenarios for a phase-out. Please take a look at these scenarios and evaluate them.

For each respondent, the words "your state" were replaced by the state of residence chosen by each individual at the beginning of the survey.

Next, respondents were given information about the five policy attributes used in the conjoint experiment and the attribute levels:

Don't worry: it is not necessary that you remember every detail, but in going through the following aspects, you should get a feeling of what matters in a potential phase-out of fossil fuel cars.

You will not be allowed to proceed before having read the following lines on this page.

The below-mentioned fossil fuel cars phase-out scenarios each consist of 5 aspects:

1. ***Policy type**: Which policies should be implemented to ultimately phase out fossil fuel cars?*

    a) *A **ban** on new fossil fuel car sales: A state law could prohibit the sale of cars that run on gasoline or diesel.*

    b) *Government **subsidies** for low-emission transportation alternatives: Alternatives to fossil fuel cars could be strongly supported through state subsidies for the purchase of non-fossil fuel cars and/or subsidies for the use of public transportation.*

    c) *Increase in fossil fuel **taxes** at the state level: Such a policy would lead to higher fuel prices, which would make it more expensive for Americans to use fossil fuel cars.*

2. ***Policy cost**: Costs of the phase-out of fossil fuel cars will depend on many factors, such as the concrete policy calibration, economic conditions, etc. Estimates for a phase-out policy currently range between monthly costs of US$ 2 and 14 per household.*

3. ***Beginning of policy implementation***: *When should the policy be implemented? Various scenarios include implementation in 2020, 2030, 2040 or 2050.*

4. ***Pollution reduction***: *A phase-out policy would lead to reductions in the concentration of particulate matters and other pollutants with adverse health impacts. These effects could be noticeable very quickly (within 1 year after policy enactment). The average concentration of such pollutants could be reduced by 10 to 30 percent.*

5. ***Policy endorsement:*** *Various stakeholders (e.g., Greenpeace or the U.S. Alliance of Automobile Manufacturers) and political parties (Democrats, Republicans) have their own opinions on policy proposals to phase out fossil fuel cars.*

Example of a choice task

	Scenario 1	**Scenario 2**
Policy types	Ban on new fossil fuel car sales	Government subsidies for low-emission transportation alternatives
Immediate pollution reduction	10% immediate reduction of air pollution	10% immediate reduction of air pollution
Beginning of policy implementation	2020	2030
Policy cost (per household, per month)	\$6	\$10
Policy endorsement by	Democratic Party	U.S. Alliance of Automobile Manufacturers
Select one	○	○

If you had the possibility to vote for Scenario 1 in a direct democratic vote, how likely would you vote for it? (0 is "would definitely NOT vote for" and 10 is "would definitely vote for")

Scenario 1	0	1	2	3	4	5	6	7	8	9	10

If you had the possibility to vote for Scenario 2 in a direct democratic vote, how likely would you vote for it? (0 is "would definitely NOT vote for" and 10 is "would definitely vote for")

Scenario 2	0	1	2	3	4	5	6	7	8	9	10

Figure B.1: Example of a choice task

Survey items and descriptive statistics

Table B.2: Survey items and descriptive statistics: Moderators

Variable	Questions and Distribution	Aggregation
Party identification	*Generally speaking, do you consider yourself a(n):* 1 = Strong Democrat (17.6%); 2 = Weak Democrat (8.9%); 3 = Lean Democrat (9.3%); 4 = Independent (32.6%); 5 = Lean Republican (11.2%); 6 = Weak Republican (6.2%); 7 = Strong Republican (14.2%)	n.a.
Psychological distance of climate change	Factor variable, based on 6 items (one omitted): *My local area is likely to be affected by climate change.* (psy1) 1 = strongly disagree (7.0%); 2 (7.6%); 3 (16.3%); 4 (25.0%); 5 (20.9%); 6 = strongly agree (23.2%) *Climate change most likely affects areas that are far away from here.* (psy2) 1 = strongly disagree (27.6%); 2 (18.5%); 3 (21.3%); 4 (14.7%); 5 (9.1%); 6 = strongly agree (8.7%) *Climate change is likely to have a big impact on people like me.* (psy3) 1 = strongly disagree (8.0%); 2 (8.2%); 3 (15.3%); 4 (22.4%); 5 (19.9%); 6 = strongly agree (26.3%) *I am certain that climate change is really happening.* (psy4) 1 = strongly disagree (6.5%); 2 (6.1%); 3 (11.3%); 4 (17.2%); 5 (18.6%); 6 = strongly agree (40.3%) *Most scientists agree that human activities are causing climate change.* (psy5) 1 = strongly disagree (5.3%); 2 (4.2%); 3 (12.2%); 4 (21.2%); 5 (22.4%); 6 = strongly agree (34.8%) *When, if at all, do you think America will start feeling the effects of human-caused climate change?* (psy6) 1 = We are already feeling the effects (58.8%); 2 = within the next 10 years (12.2%); 3 = within the next 25 years (9.5%); 4 = within the next 50 years (3.6%); 5 = within the next 100 years (3.2%); 6 = beyond the next 100 years (3.7%); 7 = never (9.0%)	First, an initial correlation analysis shows that *psy2* does not correlate with the other 5 items: psy1 psy2 psy3 psy4 psy5 psy6 psy1 psy2 -.02 psy3 .77 .01 psy4 .73 .01 .77 psy5 .65 .03 .68 .71 psy6 -.61 .05 -.63 -.68 -.60 Next, we reverse-scored *psy6* and used confirmatory factor analysis to check whether the remaining five items are valid representations of the underlying latent construct. All factor loadings are above .75, which supports the validity of the factor model: psy1 = .81 / psy3 = .85 / psy4 = .90 / psy5 = .80 / psy6 = .75 (all significant at $p < .001$). According to various fit indices, the model fits our data well (CFI=1.000; RMSEA=0.000; SRMR=0.003). Scale reliability coefficient (Cronbach's alpha): .909
Trust in stakeholders	*To what extent do you mistrust or trust the following actors and organizations?* Greenpeace: 1 = Strongly mistrust: 8.7%; 2 = Mistrust: 11.7%; 3 = Neither mistrust nor trust: 41.4%; 4 = Trust: 30.7%; 5 = Strongly trust: 7.5% U.S. Alliance of Automobile Manufacturers: 1 = 5.4%; 2 = 19.5%; 3 = 58.1%; 4 = 14.7%; 5 = 2.2% Democratic Party: 1 = 21.1%; 2 = 22.0%; 3 = 28.6%; 4 = 20.3%; 5 = 8.0% Republican Party: 1 = 24.1%; 2 = 23.8%; 3 = 27.8%; 4 = 17.5%; 5 = 6.7%	n.a.

Table B.3: Survey items and descriptive statistics: Other variables

Variable	Questions and Distribution
Age	*Please indicate your year of birth.*
	Transformed to respondents' age.
Gender	*Please indicate your gender.*
	Male 44.7%, Female 55.3%
Income	*Please indicate an estimate of your annual family income (before taxes):*
	1 = Less than $20,000 (14.7%) / 2 = $20,000 - $39,999 (20.2%) / 3 = $40,000 - $59,999 (17.0%) / 4 = $60,000 - $79,999 (13.4%) / 5 = $80,000 - $99,999 (10.1%) / 6 = $100,000 - $149,999 (15.3%) / 7 = More than $150,000 (8.6%) / 8 = Don't know / Prefer not to answer (0.6%)
Urban-rural	*Which of the following best describes the area you live in?*
	1 = Urban (24.6%); 2 = Suburban (52.4%); 3 = Rural (23.0%)
Car ownership	Ratio of cars per household, computed based on:
	1) How many cars does your household own?
	1 (7.0%); 2 (44.7%); 3 (35.9%); 4 (9.1%); 5 or more (3.3%)
	2) How many people live in your household (yourself included)?
	1 (23.6%); 2 (40.0%); 3 (17.4%) 4 (11.8%); 5 (5.3%); 6 or more (2.0%)
Energy knowledge	Additive index, based on 3 items:
	Know how many nuclear reactors are currently in operation in the US (10.7% correct)
	Know renewable energy sources (65.5% correct)
	Heard of carbon capture and storage technologies before (18.9% yes; 24.0% not sure; 57.2% no)
Environmental behavior	Additive index, based on a summated rating scale (3 items):
	How often do you recycle?
	1 = never (6.3%); 2 (5.0%); 3 (5.0%); 4 (11.4%); 5 (13.6%); 6 (16.2%); 7 = very often (42.6%)
	How often do you buy organic products?
	1 = never (18.2%); 2 (17.2%); 3 (14.3%); 4 (19.1%); 5 (15.2%); 6 (7.7%); 7 = very often (8.2%)
	How often do you try to limit your meat consumption?
	1 = never (21.1%); 2 (12.1%); 3 (12.8%); 4 (20.1%); 5 (12.6%); 6 (9.5%); 7 = very often (11.8%)

Conjoint analysis results

Average effects of policy attributes on respondents' policy support

Table B.4: Average marginal effects from conjoint experiment

	Policy support (binary indicator)
Beginning of policy implementation	
Baseline: 2020	
2030	0.0260** (0.00833)
2040	-0.0203* (0.00877)
2050	-0.0385*** (0.00919)
Policy type	
Baseline: ban on new fossil fuel car sales	
Government subsidies for low-emission alternatives	0.0516*** (0.00846)
Increase in fossil fuel taxes	0.000226 (0.00875)
Policy cost (per household & month)	
Baseline: $2	
$6	-0.0192* (0.00880)
$10	-0.0458*** (0.00909)
$14	-0.0894*** (0.00958)
Pollution reduction within one year of policy enactment	
Baseline: 10%	
20%	-0.00315 (0.00770)
30%	0.0337*** (0.00790)
Policy endorsement	
Baseline: U.S. Alliance of Automobile Manufacturers	
Greenpeace	0.0258** (0.00931)
Democratic Party	0.00173 (0.00936)
Republican Party	-0.00176 (0.00988)
Constant	0.450*** (0.0145)
N	24,320

*Notes: Coefficients from OLS regressions; robust standard errors (clustered by respondent) in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001. The dependent variable is the dichotomized rating outcome described in section 4.2 in the paper. The results shown here refer to Figure 1 in the paper.*

Average effects of policy attributes on policy support, conditional on psychological distance and party identification

Table B.5: Average marginal effects, conditional on psychological distance

	Policy support if psych. distance = HIGH	Policy support if psych. distance = LOW
Beginning of policy implementation		
Baseline: 2020		
2030	0.0268* (0.0108)	0.0145 (0.0119)
2040	-0.0095 (0.0111)	-0.0384** (0.0127)
2050	-0.0026 (0.0112)	-0.0810*** (0.0137)
Policy type		
Baseline: ban on new fossil fuel car sales		
Government subsidies for low-emission alternatives	0.0539*** (0.0115)	0.0459*** (0.0122)
Increase in fossil fuel taxes	0.0099 (0.0115)	-0.0073 (0.0125)
Policy cost (per household & month)		
Baseline: $2		
$6	-0.0170 (0.0120)	-0.0181 (0.0118)
$10	-0.0567*** (0.0120)	-0.0369** (0.0124)
$14	-0.0688*** (0.0129)	-0.107*** (0.0131)
Pollution reduction within one year of policy enactment		
Baseline: 10%		
20%	-0.0013 (0.0101)	0.0003 (0.0108)
30%	0.0102 (0.0104)	0.0634*** (0.0112)
Policy endorsement		
Baseline: U.S. Alliance of Automobile Manufacturers		
Greenpeace	0.0187 (0.0124)	0.0312* (0.0127)
Democratic Party	-0.0158 (0.0122)	0.0193 (0.0128)
Republican Party	0.0264* (0.0128)	-0.0246 (0.0137)
Constant	0.3033*** (0.0194)	0.598*** (0.0189)
N	12,128	12,192

*Notes: Coefficients from OLS regressions; robust standard errors (clustered by respondent) in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001. The dependent variable is the dichotomized rating outcome described in section 4.2 in the paper. The results for the attribute "beginning of policy implementation" refer to Figure 2 (left panel) in the paper.*

Table B.6: Average marginal effects, conditional on party identification

	Policy support if party ID = DEMOCRAT	Policy support if party ID = INDEPENDENT	Policy support if party ID = REPUBLICAN
Beginning of policy implementation			
Baseline: 2020			
2030	0.00667 (0.0137)	0.0153 (0.0146)	0.0505*** (0.0140)
2040	-0.0280 (0.0151)	-0.0363* (0.0150)	0.00336 (0.0139)
2050	-0.0601*** (0.0160)	-0.0567*** (0.0158)	-0.00142 (0.0143)
Policy type			
Baseline: ban on new fossil fuel car sales			
Government subsidies for low-emission alternatives	0.0436** (0.0134)	0.0348* (0.0155)	0.0718*** (0.0146)
Increase in fossil fuel taxes	0.00296 (0.0145)	-0.0252 (0.0153)	0.0152 (0.0143)
Policy cost (per household & month)			
Baseline: $2			
$6	0.00781 (0.0143)	-0.0362* (0.0153)	-0.0358* (0.0151)
$10	-0.0278 (0.0149)	-0.0602*** (0.0153)	-0.0576*** (0.0162)
$14	-0.0722*** (0.0159)	-0.0994*** (0.0169)	-0.0951*** (0.0161)
Pollution reduction within one year of policy enactment			
Baseline: 10%			
20%	0.000109 (0.0125)	-0.00933 (0.0138)	0.000350 (0.0129)
30%	0.0473*** (0.0131)	0.0453** (0.0142)	0.00802 (0.0129)
Policy endorsement			
Baseline: U.S. Alliance of Automobile Manufacturers			
Greenpeace	0.0545*** (0.0148)	0.00679 (0.0163)	0.00217 (0.0165)
Democratic Party	0.0691*** (0.0151)	-0.0239 (0.0167)	-0.0422** (0.0158)
Republican Party	-0.0482** (0.0160)	-0.0266 (0.0173)	0.0784*** (0.0171)
Constant	0.561*** (0.0230)	0.444*** (0.0255)	0.342*** (0.0250)
N	8,720	7,920	7,680

*Notes: Coefficients from OLS regressions; robust standard errors (clustered by respondent) in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependent variable is the dichotomized rating outcome described in section 4.2 in the paper. The results for the attribute "beginning of policy implementation" refer to Figure 2 (right panel) in the paper.*

Policy support: predicted values for implementation time horizons, contingent on party identification

Here, we explore absolute levels of policy support for the three partisan groups investigated in section 4.3 of the paper. To do so, we rescale the policy ratings and map them onto the set [0, 100]. This allows us to predict levels of support for policies implemented in different years by (first) estimating the effect of all policy attributes on the rescaled rating variable, and (second) computing predicted values for specific policy proposals. These predicted values can be interpreted as the share of support a policy gets on the level of the respective population subgroup; i.e., Democrats, Independents, or Republicans.[2] In the following, we show predicted values for policies implemented in 2020, 2030, 2040 and 2050. We average over all other policy attributes, which is why there could still be considerable variation for specific policy proposals implemented in the respective years (e.g., costlier policies getting less support).

Table B.7: Predicted level of policy support for different implementation time horizons, conditional on party identification

	Beginning of policy implementation			
	2020	2030	2040	2050
Democrats	68.4 [65.8, 70.9]	69.1 [66.3, 71.9]	67.6 [65.0, 70.2]	65.5 [62.9, 68.0]
Independents	47.1 [43.5, 50.7]	47.9 [44.6, 51.1]	46.0 [42.6, 49.5]	43.6 [40.3, 47.0]
Republicans	51.0 [47.2, 54.7]	54.6 [50.7, 58.6]	51.2 [47.6, 54.9]	51.3 [47.6, 54.9]

Notes: The table shows predicted levels of support for policy implementation in 2020, 2030, 2040 and 2050, conditional on party identification and averaging over all other policy attributes. 95% confidence intervals are shown in brackets.

[2]See Bechtel, M. M., Scheve, K. F. (2013). Mass support for global climate agreements depends on institutional design. Proceedings of the National Academy of Sciences of the United States of America, 110(34), 13763–13768.

Average effects of policy attributes on policy support: interacting the 'policy type' attribute with other policy attribute

Table B.8: Average marginal effects of policy attributes, conditional on policy instrument

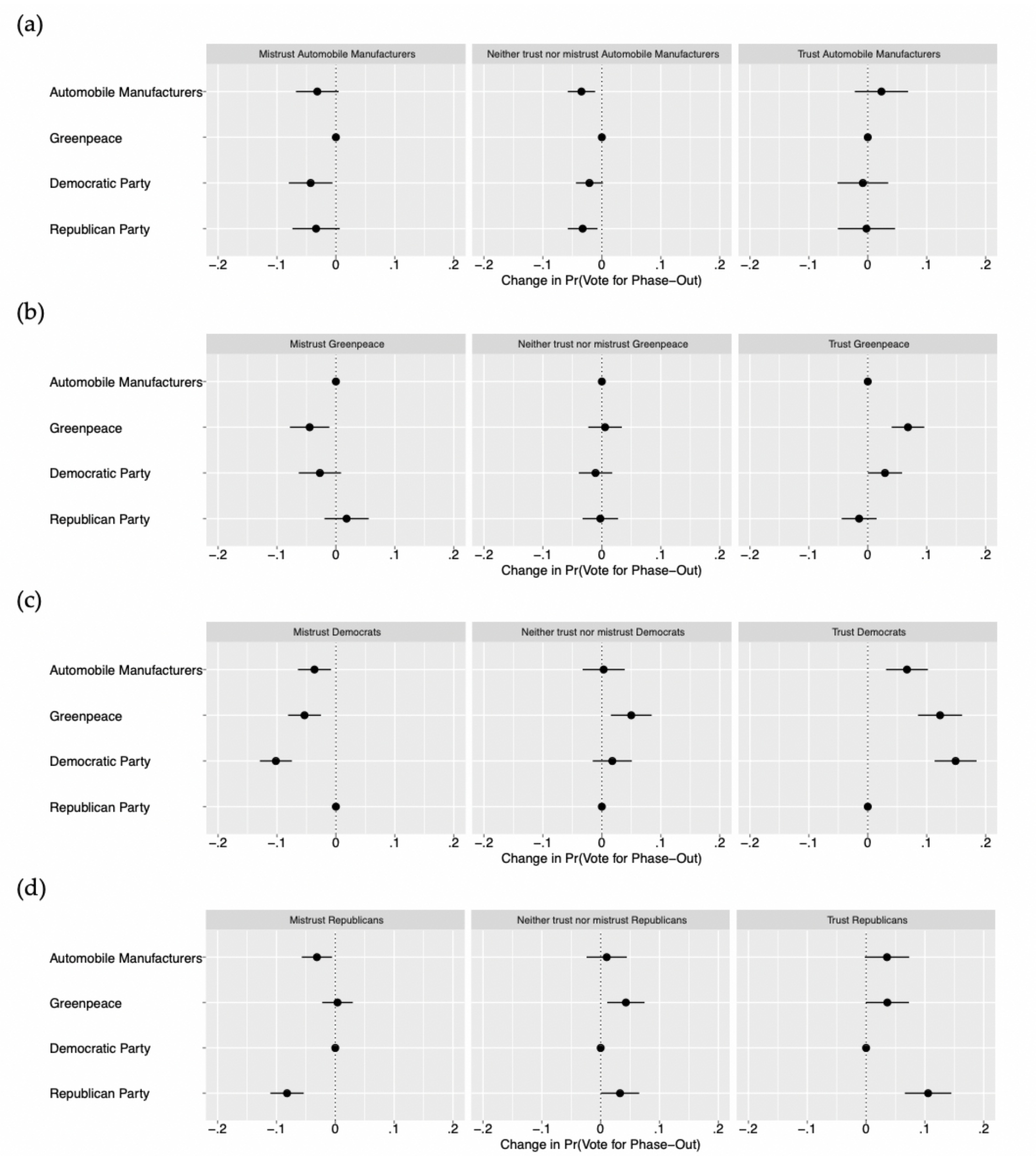
	Policy support if interacted with BAN	Policy support if interacted with SUBSIDIES	Policy support if interacted with TAXES
Beginning of policy implementation			
2020	0.0316* (0.0157)	0.0441** (0.0155)	0.0398* (0.0161)
2030	0.0686*** (0.0155)	0.0738*** (0.0170)	0.0512** (0.0162)
2040	0.0212 (0.0152)	0.0141 (0.0153)	0.0193 (0.0147)
Baseline: 2050			
Policy cost (per household & month)			
Baseline: $2			
$6	-0.0132 (0.0152)	-0.0447** (0.0154)	0.000525 (0.0159)
$10	-0.0406** (0.0152)	-0.0469** (0.0162)	-0.0499*** (0.0147)
$14	-0.0924*** (0.0154)	-0.0993*** (0.0160)	-0.0765*** (0.0157)
Pollution reduction within one year of policy enactment			
Baseline: 10%			
20%	0.00150 (0.0143)	-0.00301 (0.0135)	-0.00787 (0.0142)
30%	0.0262 (0.0139)	0.0356* (0.0142)	0.0394** (0.0137)
Policy endorsement			
Baseline: U.S. Alliance of Automobile Manufacturers			
Greenpeace	0.00425 (0.0154)	0.0368* (0.0151)	0.0364* (0.0164)
Democratic Party	0.00318 (0.0147)	-0.0124 (0.0166)	0.0145 (0.0160)
Republican Party	-0.000776 (0.0163)	-0.000655 (0.0161)	-0.00377 (0.0170)
Constant	0.416*** (0.0203)	0.470*** (0.0213)	0.402*** (0.0225)
N	8,107	8,103	8,110

*Notes: Coefficients from OLS regressions; robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependent variable is the dichotomized rating outcome described in section 4.2 in the paper. The results for the attribute "beginning of policy implementation" refer to Figure 3 in the paper.*

Trust in stakeholders as a moderator of endorsement effects

The following graphs show average marginal effects of stakeholder endorsements on the probability to vote for a policy proposal in a referendum, conditional on trust in stakeholders. The calculations are based on regression analyses with dichotomized rating outcomes (N = 24,320 policy proposals), the full set of attribute values as predictors, and clustered standard errors. The analysis is reiterated four times so as to visualize the effects conditional on trust in each stakeholder separately. E.g., panel (a) shows the effects of endorsement by the U.S. Alliance of Automobile Manufacturers (taking Greenpeace as baseline), conditional on different trust levels. We transformed the original 5-point scale of the trust variable (see Table B.2) into three categories: "mistrust" (left column), "neither trust nor mistrust" (middle column), and "trust" (right column).

Figure B.2: Effect of stakeholder endorsements on policy support, by trust in stakeholders.



Notes: (a) AMEs of stakeholder endorsement by trust in the U.S. Alliance of Automobile Manufacturers (baseline Greenpeace). (b) AMEs of stakeholder endorsement by trust in Greenpeace (baseline U.S. Alliance of Automobile Manufacturers). (c) AMEs of stakeholder endorsement by trust in Democrats (baseline Republicans). (d) AMEs of stakeholder endorsement by trust in Republicans (baseline Democrats).

Robustness checks

Analysis of conjoint experiment using logistic regression

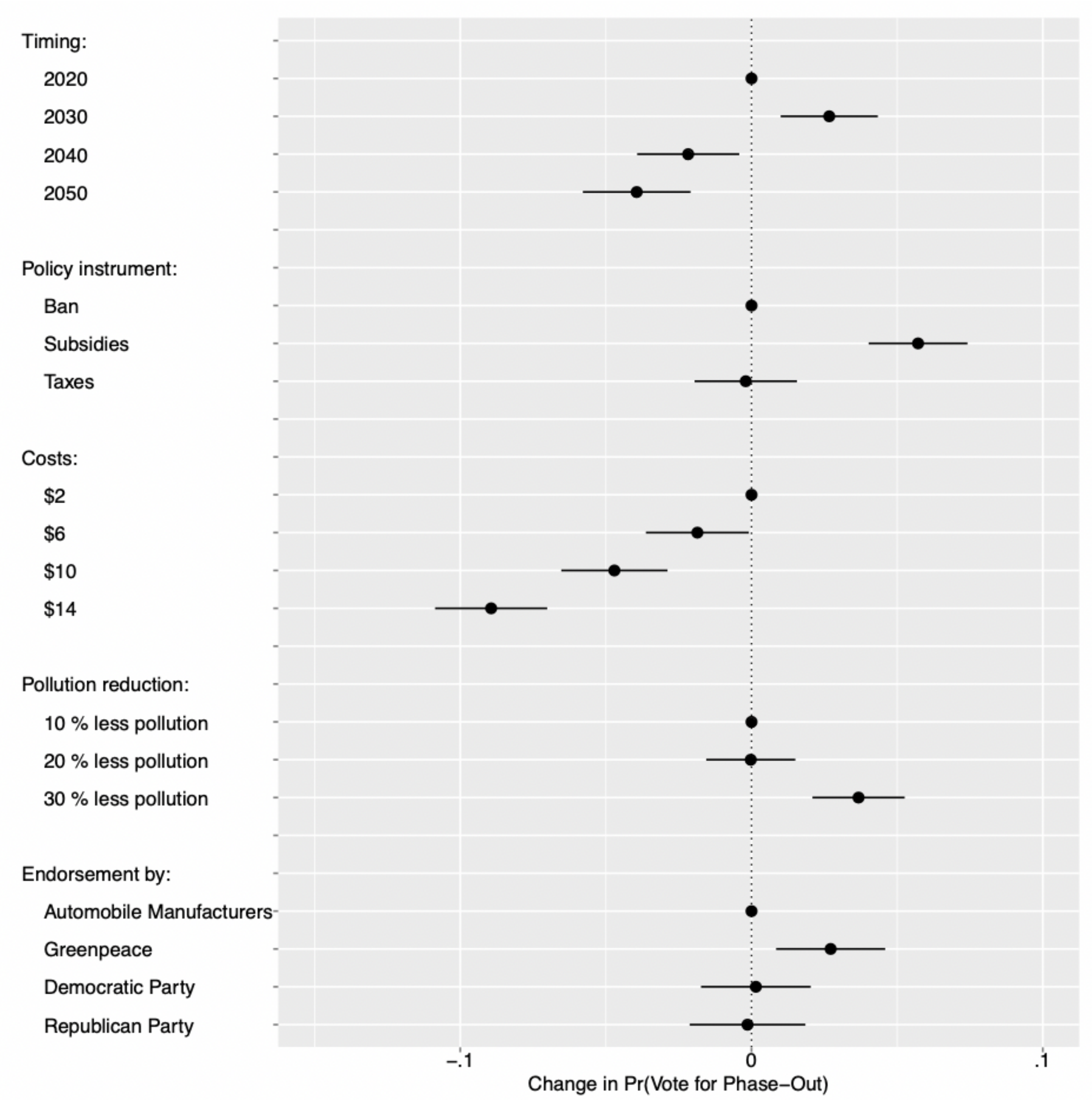
Table B.9: Average marginal effects from conjoint experiment, using logistic regression

	Policy support	
	(logit coefficients)	(marginal effects)
Beginning of policy implementation		
Baseline: 2020		
2030	0.106** (0.0339)	0.0260** (0.00833)
2040	-0.0833* (0.0360)	-0.0203* (0.00877)
2050	-0.159*** (0.0379)	-0.0385*** (0.00919)
Policy type		
Baseline: ban on new fossil fuel car sales		
Government subsidies for low-emission alternatives	0.211*** (0.0346)	0.0516*** (0.00846)
Increase in fossil fuel taxes	0.000936 (0.0362)	0.000226 (0.00875)
Policy cost (per household & month)		
Baseline: $2		
$6	-0.0775* (0.0356)	-0.0192* (0.00880)
$10	-0.186*** (0.0370)	-0.0458*** (0.00909)
$14	-0.368*** (0.0397)	-0.0894*** (0.00958)
Pollution reduction within one year of policy enactment		
Baseline: 10%		
20%	-0.0130 (0.0318)	-0.00315 (0.00770)
30%	0.138*** (0.0323)	0.0337*** (0.00790)
Policy endorsement		
Baseline: U.S. Alliance of Automobile Manufacturers		
Greenpeace	0.106** (0.0381)	0.0258** (0.00931)
Democratic Party	0.00711 (0.0385)	0.00173 (0.00936)
Republican Party	-0.00724 (0.0407)	-0.00176 (0.00988)
Constant	-0.201*** (0.0592)	
N	24,320	24,320

*Notes: Coefficients from logit regressions and transformed into average marginal effects; robust standard errors (clustered by respondent) in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependent variable is the dichotomized rating outcome described in section 4.2 in the paper. The results shown here complement Table S4.*

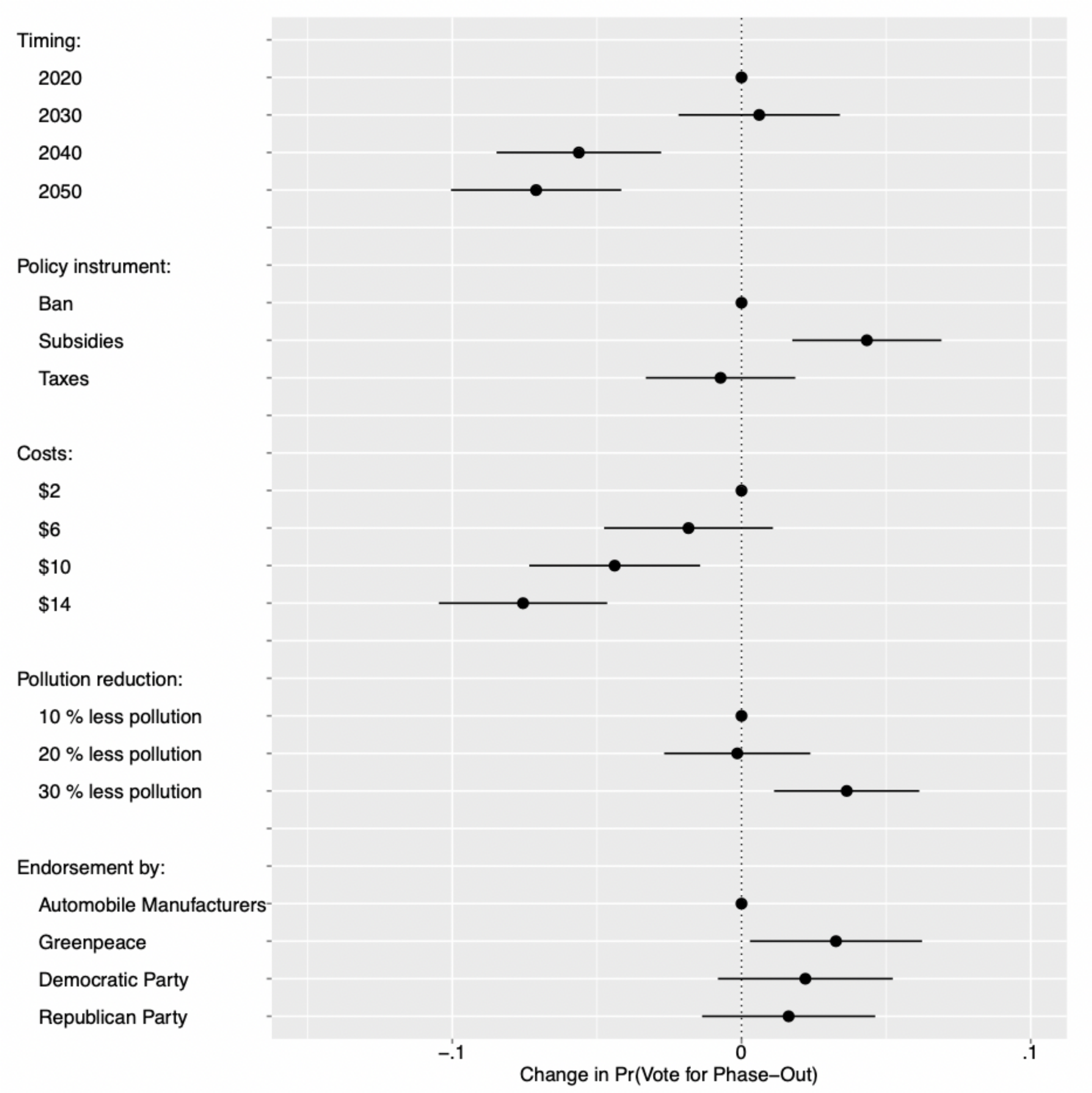
Analysis of conjoint experiment excluding speeders

Figure B.3: Robustness check II: Replication of analysis of conjoint experiment data, excluding speeders.



Notes: This is essentially a replication of Figure 2.1 in the paper, but excluding 59 respondents that took the conjoint in less than 33.4% of median completion time. Calculations are based on regression analyses with dichotomized rating outcomes and standard errors grouped at the level of the individual (clustered standard errors). N = 23,376 policy proposals. Using different thresholds to define speeders yields substantively the same results.

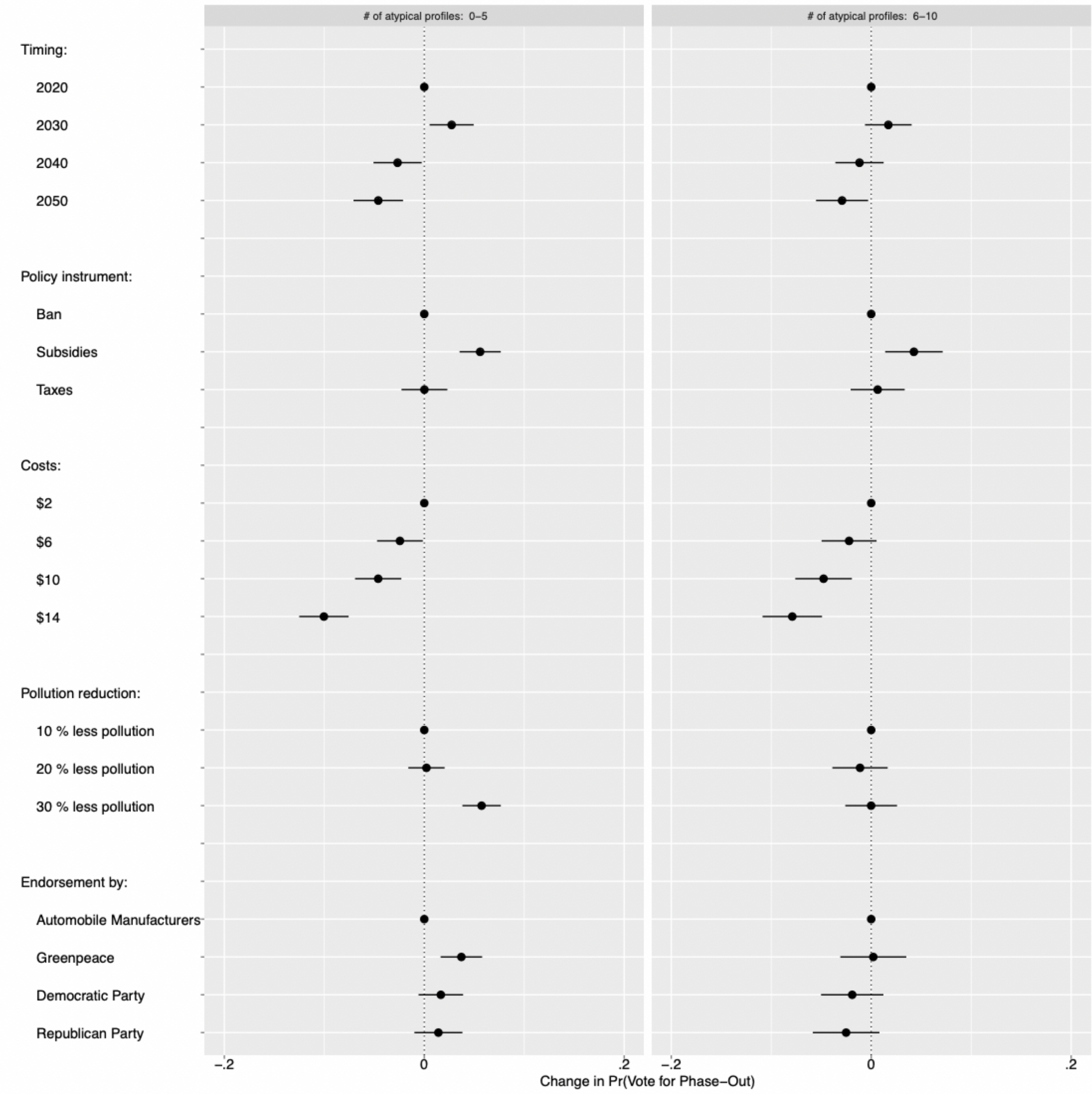
Figure B.4: Robustness check III: Replication of analysis of conjoint experiment data, excluding choice tasks no. 4 to 8 for each respondent.



Notes: This is essentially a replication of Figure 2.1 in the paper, but excluding choice tasks no. 4 to 8 for every respondent. The rationale is to check whether respondents' preferences in the first 3 choice sets are different from their preferences across all 8 choice sets. Calculations are based on regression analyses with dichotomized rating outcomes and standard errors grouped at the level of the individual (clustered standard errors). N = 9,120 policy proposals.

Analysis of conjoint experiment: influence of atypical profiles

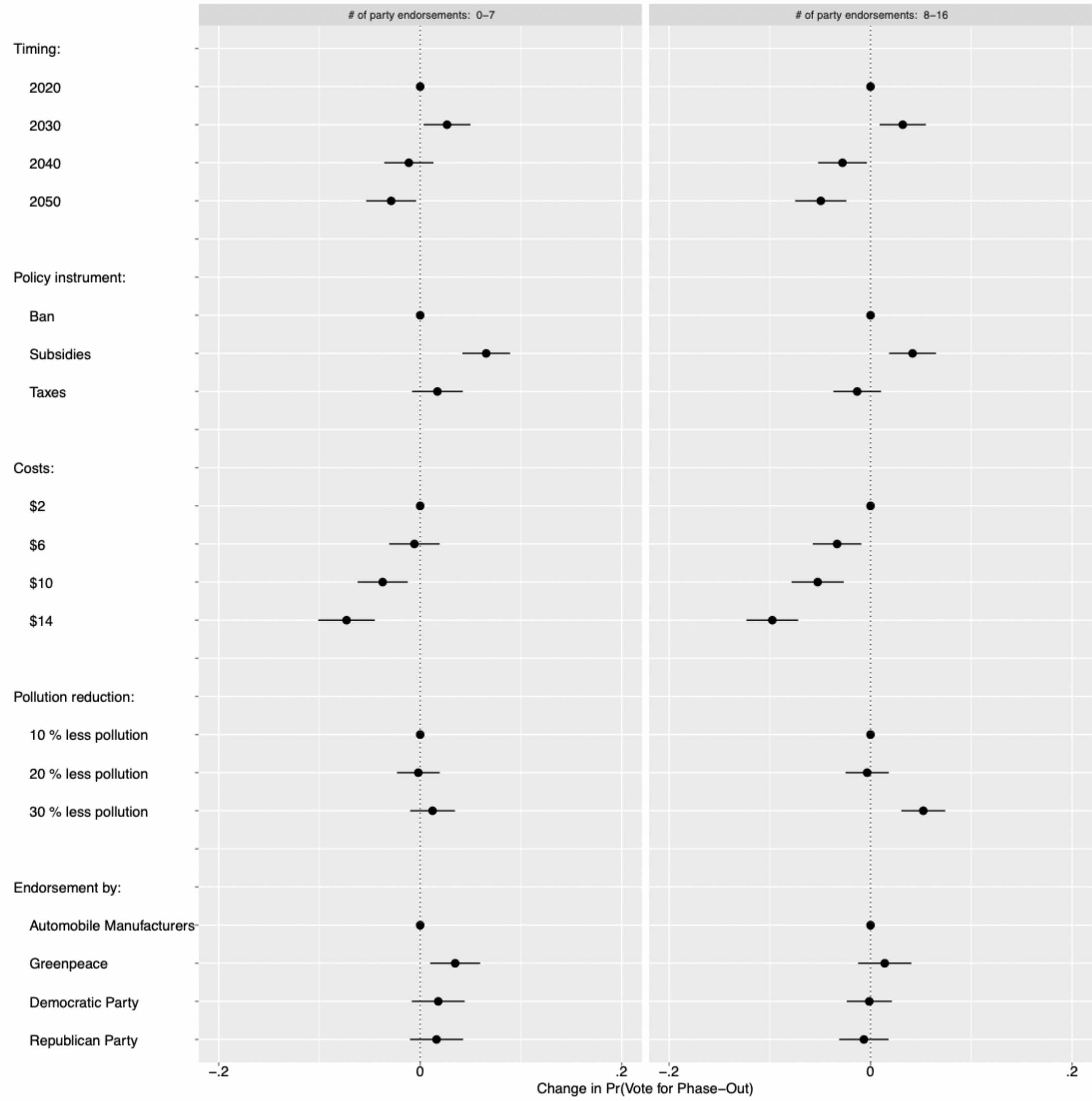
Figure B.5: Robustness check IV: Replication of analysis of conjoint experiment data, differentiating between respondents with low (n = 928) versus high (n = 592) numbers of atypical profiles.



Notes: This figure compares AMEs of the group of respondents that received a low number (up to 5) of atypical policy scenarios and the group of respondents that received a higher number (6 or more) of atypical policy scenarios. Atypical policy scenarios include all scenarios in which either the Republican Party or the Alliance of Automobile Manufacturers advocate for a ban on new fossil fuel car sales or tax increases. Calculations are based on regression analyses with dichotomized rating outcomes and standard errors grouped at the level of the individual (clustered standard errors). N = 24,320 policy proposals.

Analysis of conjoint experiment: frequency of partisan endorsements

Figure B.6: Robustness check V: Replication of analysis of conjoint experiment data, differentiating between respondents with low (n = 802) versus high (n = 718) numbers of policy proposals endorsed by political parties.

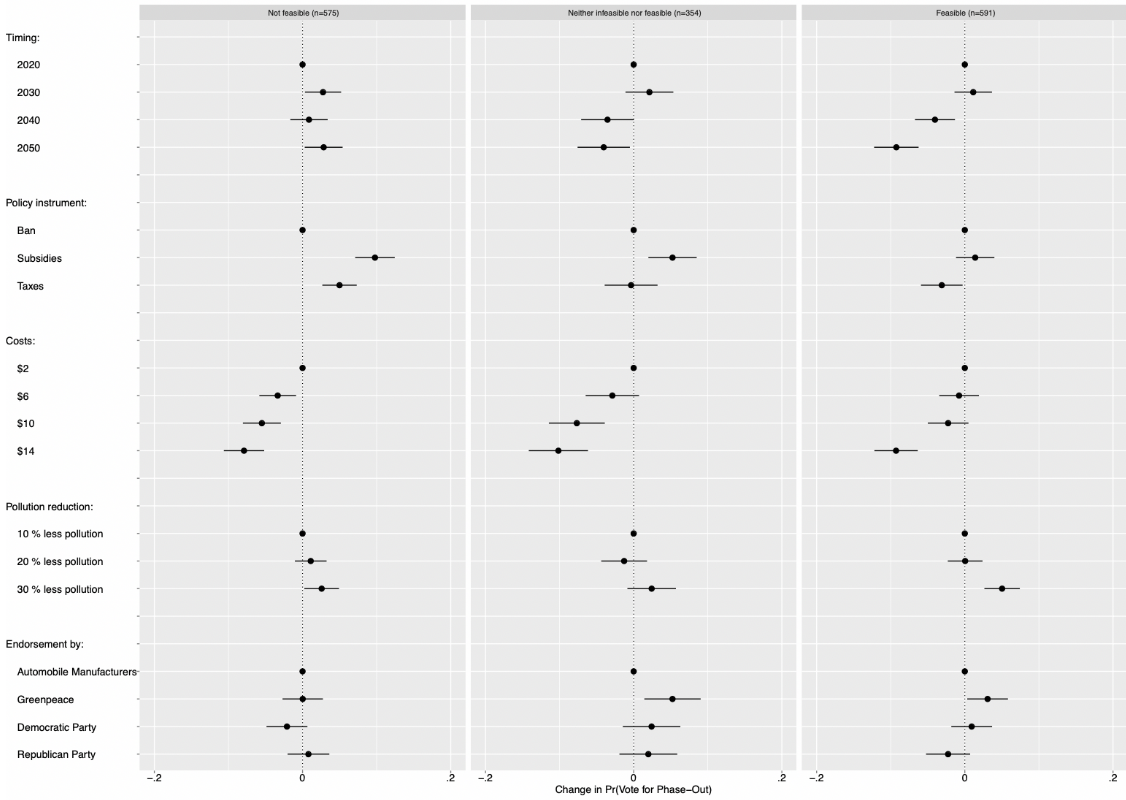


Notes: This figure compares AMEs of the group of respondents that received a low number (up to 7) of policy scenarios including endorsement by one of the political parties and the group of respondents that received a high number (8 or more) of such policy scenarios. Calculations are based on regression analyses with dichotomized rating outcomes and standard errors grouped at the level of the individual (clustered standard errors). N = 24,320 policy proposals.

Additional exploratory analyses

Average effects of policy attributes on policy support, conditional on perceived feasibility of phasing out fossil fuel cars

Figure B.7: Average effects of policy attributes on respondents' policy preference by perceived feasibility.



Notes: This figure compares AMEs of respondents who assign different degrees of feasibility to a phase-out of fossil fuel cars. Subgroups are based on respondents' answers to the question "To what extent do you think phasing out fossil fuel cars is feasible at all?", which was measured right before the conjoint experiment on a 7-point Likert scale from 1 ("Not at all feasible") to 7 ("Extremely feasible"). Left panel: n = 575 (values 1 to 3), middle panel: n = 354 (4), right panel: n = 591 (5 to 7). Calculations are based on regression analyses with dichotomized rating outcomes and standard errors grouped at the level of the individual (clustered standard errors). N = 24,320 policy proposals.

Willingness to pay for faster implementation of climate action

The results of our conjoint experiment allow us to calculate US residents' willingness to pay (WTP) for earlier policy action on climate change, in this case phase out of fossil fuel cars. To calculate the WTP, we regress the dichotomized rating outcome on a parametrized – that is, continuous – variable of the cost attribute and all other variables used in the conjoint experiment. This parameterization is based on the assumption of a linear relationship between cost and policy support, which is supported by the marginal effects for the different cost levels (see Figure 1.1). The resulting coefficient of the cost variable measures the extent to which increasing the policy cost by one US dollar influences the probability of the corresponding policy proposal being chosen. The WTP for all attributes can be determined by multiplying their coefficients by -1 and dividing each result by the coefficients of the cost variable. [3]

[3]See Bechtel, M. M., Genovese, F., Scheve, K. F. (2017). Interests, Norms and Support for the Provision of Global Public Goods: The Case of Climate Co-operation. British Journal of Political Science, 1–23.

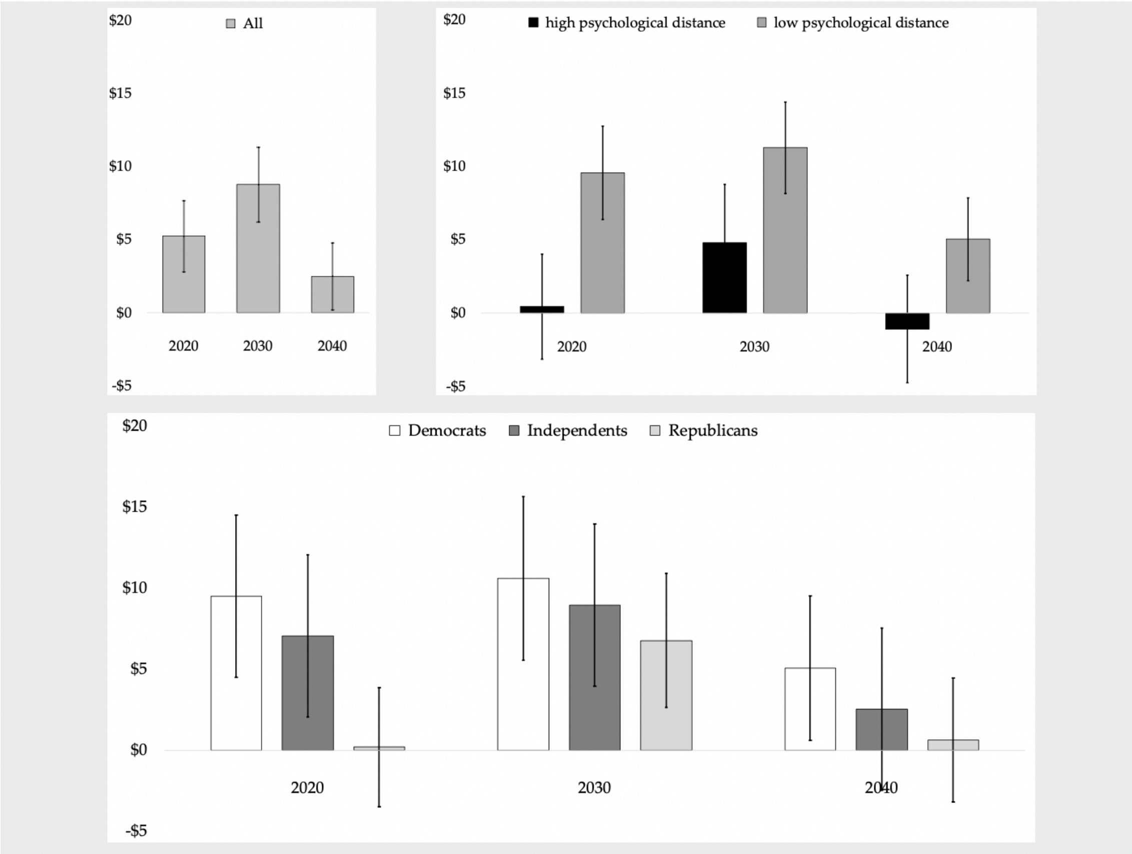
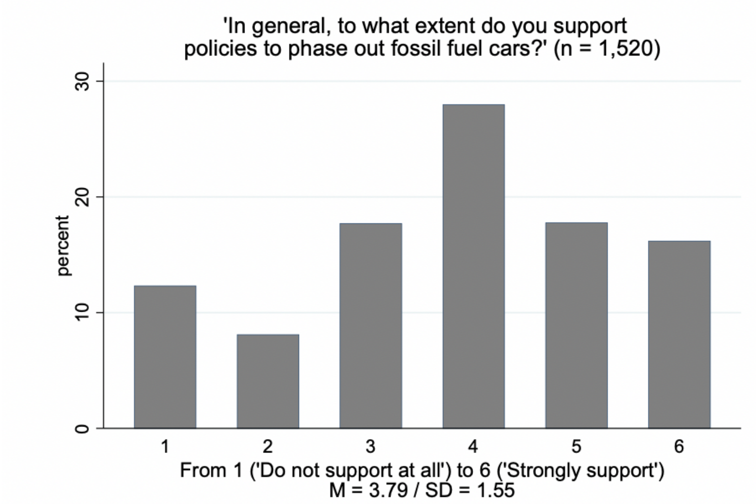


Figure B.8: Implicit WTP (per month household) for implementing policies to phase out fossil fuel cars until 20xy (reference year: 2050). The bars show 95% confidence intervals.

Based on the conjoint experiment data, Figure B.8 shows citizens' average implicit WTP for the implementation of phase-out policies by 2020, 2030 and 2040, compared to policy action by 2050. Citizens are on average willing to pay for an earlier phase-out of fossil fuel cars. In line with the results shown before, citizens' average WTP for policy action by 2030 instead of 2050 is $8.70 per month and household, while their WTP for policy action by 2020 is $5.20. Even though these two estimates have overlapping confidence intervals, these analyses again suggest that on average American citizens are not willing to procrastinate much longer when it comes to taking ambitious decarbonization measures and prefer policy action in 2020 or 2030 to later action. Figure B.8 also shows that this positive WTP is conditional on citizens' perceived psychological distance and party identification. It is worth noting, however, that WTP even for Republican respondents and for respondents with high psychological distance to climate change is not significantly different from zero, i.e., not negative.

Pre-experimental support for policies to phase out fossil fuel cars

Figure B.9: Initial support for policies to phase out fossil fuel cars.



Overview on current announcements to phase-out cars with internal combustion engines

Table B.10: Jurisdictions with a political commitment to ban new gasoline and diesel vehicle sales, and planned year of policy enactment (as of early 2019).

Jurisdiction	Proposed year of policy enactment
Austria	2020
Costa Rica	2021
Norway	2025
Denmark	2030
India	2030
Ireland	2030
Israel	2030
Netherlands	2030
Slovenia	2030
Sweden	2030
Scotland	2032
China	2040
France	2040
Sri Lanka	2040
Taiwan	2040
United Kingdom	2040

Notes: Own compilation, based on data from the International Energy Agency (IEA 2018) and the Center for Climate Protection (Burch and Gilchrist 2018). Denmark and Sweden were added as they announced their bans only recently (see https://www.reuters.com/article/us-denmark-autos/denmark-embraces-electric-car-revolution-with-petrol-and-diesel-ban-plan-idUSKCN1MC121 and https://www.regeringen.se/tal/20192/01/regeringsforklaringen-den-21-januari-2019/).

Sources:

Burch, I., Gilchrist, J. (2018). Survey of Global Activity to Phase Out Internal Combustion Engine Vehicles. Santa Rosa, CA: Center for Climate Protection. Retrieved from https://climateprotection.org/wp-content/uploads/2018/10/Survey-on-Global-Activities-to-Phase-Out-ICE-Vehicles-FINAL-Oct-3-2018.pdf

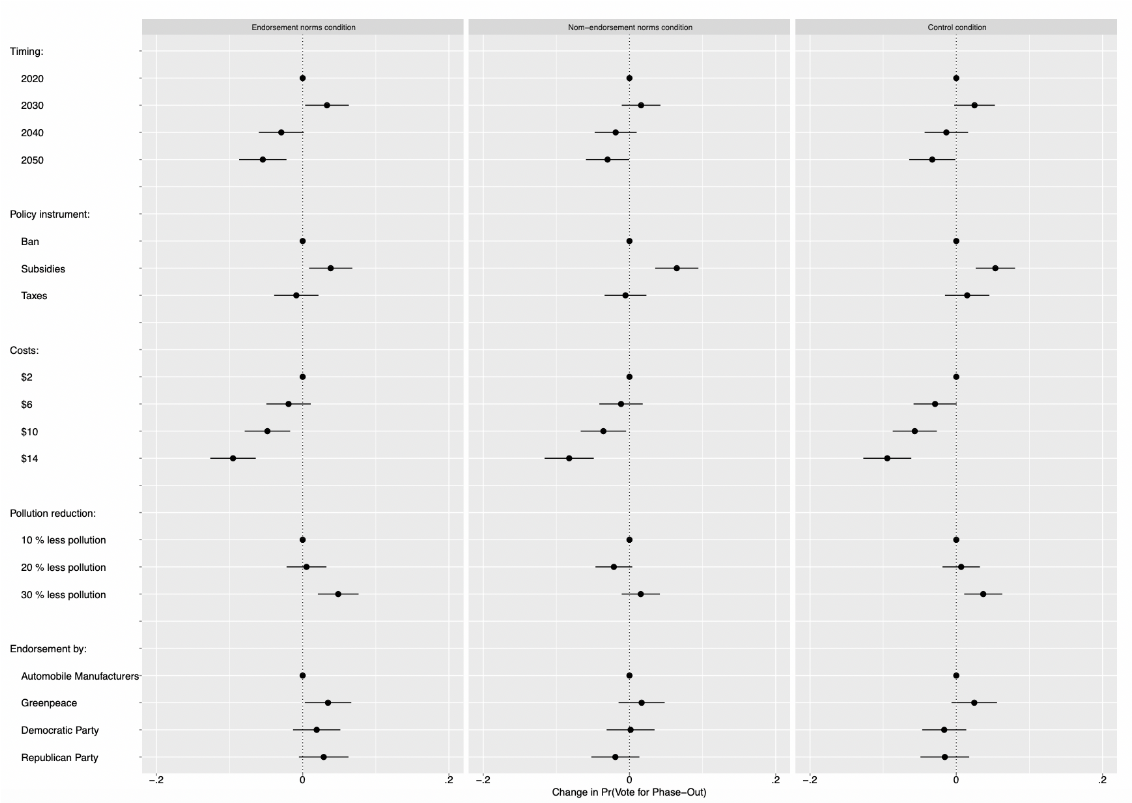
International Energy Agency (2018). Global EV Outlook 2018 – Towards cross-modal electrification. Paris: OECD/IEA. Retrieved from https://www.connaissancedesenergies.org/sites/default/files/pdf-actualites/globalevoutlook2018.pdf

Independence of attribute effects from social norms interventions

The conjoint experiment was embedded in a broader survey on climate policy preferences which, in addition to the conjoint experiment, involved a randomized controlled experiment. Before completing the conjoint tasks, respondents were randomly assigned to an endorsement norms condition, a non-endorsement norms condition, or a control condition. In the two experimental conditions, respondents read a short text highlighting policy-relevant attitudes and behaviors of other people living in their state. In the endorsement norms condition, this included a statement about the increased diffusion of sustainable mobility behaviors in the state population (highlighting a relative increase in sustainable behaviors), while in the non-endorsement norms condition, it included a statement about the limited diffusion of sustainable mobility behaviors (highlighting low absolute levels of sustainable behaviors). For more detailed information, see the materials deposited on the Open Science Framework platform:https://osf.io/6w4h3/?view_only=b59087110dad4733b1dbc218c22a9eeb.

Here we document that the social norms manipulations did not have a systematic influence on respondents' policy preferences. As Figure B.10 illustrates, the information about descriptive social norms provided to study participants did not interact in statistically significant ways with any attribute used in the conjoint experiments. Even if some differences with regard to the size of effects can be detected in some cases (e.g., subsidies lead to a higher increase in policy support for the non-endorsement condition compared to the endorsement condition), the associated confidence intervals overlap in all these cases. As the effects of attribute levels on preferences do not depend on the experimental manipulations, the analyses shown in the paper are based on the pooled data obtained from the conjoint experiment.

Figure B.10: The non-existing contingency of policy attribute effects on descriptive social norms.



Notes: This is essentially a replication of Figure2.1 in the paper, but instead of pooling the three experimental conditions.

Appendix C

Supplementary Material: Chapter 3

Survey procedure

The data employed for Chapters 2 and 3 were collected through the same survey. The survey developed for this study was composed by three main sections: (1) a first set of survey questions, including questions on demographic characteristics, environmental attitudes, and perceptions of CCS technologies; (2) the conjoint experiments; (3) a second small set of survey questions, including questions on attitudes toward government, on trust in elite cues, partisan orientation and education. In the conjoint experiment section, respondents were randomly assigned to either the conjoint experiment about fossil fuel cars phase-out policies or the experiment on CCS deployment policies. Next, respondents who had first been assigned to the phase-out experiment were assigned to the CCS experiment, and vice versa.

Conjoint experiment

Respondents first read a short text with basic information on policy proposals regarding CCS. Second, all policy attributes were briefly explained and information on attribute levels was provided. Third, respondents were shown eight pairs of policy scenarios that differ randomly on five attributes (see the full list of attributes and their levels in Table 3.1 and an example of a choice screen in Figure C.1). Respondents had to decide, for each pair of scenarios, which one they preferred (forced choice outcome), and indicate on an 11- point scale for each scenario their likelihood of supporting it if it were put to a referendum (rating outcome, in 10 % increments from 0 to 100 %).

Information on CCS provided to participants

At the beginning of the conjoint experiment, participants were provided with the following introduction to the topic:

Carbon capture and storage (CCS) is a set of technologies aimed at capturing, transporting, and storing carbon dioxide (CO_2) emitted from industrial facilities and power plants that use fossil fuels like coal and natural gas. CO_2 emissions are one of the major contributors to climate change. The goal of CCS is to prevent CO_2 from reaching the atmosphere by injecting it in suitable underground geological formations - depleted oil and gas fields and deep saline formations - for permanent storage.

Some scientific studies promote CCS as a prospective solution to climate change, as it could significantly contribute to the reduction of CO_2 emissions, while other studies emphasize that CCS is a very costly technology and there is a need to investigate its potential risks in order to ensure that its deployment would not have an adverse impact on people and the environment. Political discussions currently focus on how to regulate and implement the use of CCS.

You may or may not agree with scaling up CCS, but if a scale-up were to be implemented *in your state, you may still have different preferences as to specific scenarios. In the following, we will sketch out some scenarios for a scale-up of CCS. Please take a look at these scenarios and evaluate them.*

Description of policy attributes and their levels

Participants were then provided with the following description of policy attributes and their levels:

Please read the following lines carefully! Don't worry: it is not necessary that you remember every detail, but in going through the following aspects, you should get a feel for what matters in a potential scale-up of CCS technologies.

You will not be allowed to proceed before having read the following lines on this page.

The below mentioned policy scenarios each consist of 5 aspects:

1. ***Policy type**: Which policies should be implemented to promote CCS?*

    a) *A **ban** on the construction of **new fossil fuel power plants without CCS** in your state: According to this policy, no new coal- or gas-fired power stations can be built in your state without including CCS.*

    b) *Government **subsidies** for CCS in your state: Your state government could subsidize CCS projects. This would make deployment of the technology more economically attractive.*

    c) *Increase in **taxes on fossil fuel power generation without CCS** in your state: Such a policy would make fossil fuel power generation with no CCS more expensive.*

2. ***Policy cost***: *All policies to scale up CCS would produce some costs for American consumers. However, the exact amount depends on many factors, such as the concrete policy calibration, economic conditions, etc. Estimates for a scale-up policy currently range between costs of US$ 4 and 19 per household (per month).*

3. ***Beginning of policy implementation***: *When should the policy be implemented? Various scenarios include implementation in 2020, 2030, 2040 or 2050.*

4. ***Distance from residential areas***: *CCS facilities are currently planned in many American states. Some people fear that they could negatively affect buildings and the safety of communities. Different rules regarding the required distance of CCS facilities from residential areas are currently been discussed: 2 miles / 5 miles / 10 miles / 50 miles.*

5. ***Policy endorsement***: *Various* **stakeholders** *(e.g., Greenpeace or the U.S.-based Carbon Capture Coalition) and political* **parties** *(Democrats, Republicans) have their own opinions on policy proposals to scale up CCS.*

Figure C.1 presents an example of a choice screen displayed to participants to the conjoint experiment.

Figure C.1: An example of a choice screen

	Scenario 1	**Scenario 2**
Policy types	Ban on new fossil fuel plants without CCS	Government subsidies for CCS
Beginning of policy implementation	2020	2030
Policy cost (per household, per month)	$4	$12
Distance from residential areas	2 miles	50 miles
Policy endorsement by	Democratic Party	Republican Party
Select one	○	○

If you had the possibility to vote for Scenario 1 in a direct democratic vote, how likely would you vote for it? (0 is "would definitely NOT vote for" and 10 is "would definitely vote for")

Scenario 1	0	1	2	3	4	5	6	7	8	9	10

If you had the possibility to vote for Scenario 2 in a direct democratic vote, how likely would you vote for it? (0 is "would definitely NOT vote for" and 10 is "would definitely vote for")

Scenario 2	0	1	2	3	4	5	6	7	8	9	10

Sample of survey respondents

To field the survey, we contracted with the survey company Lightspeed. Respondents were incentivized based on Lightspeed's standards[1]. Median survey completion time was 19 minutes and 43 seconds. To ensure high-quality data, several respondents were excluded based on a number of criteria. First, 560 inattentive respondents did not pass an attention check implemented a third of the way into the survey and were immediately excluded. Second, 34 speedsters with short completion time ($<$ 40% of median time) were excluded. Also excluded were 111 respondents who gave no consent and 17 respondents who did not match our restrictions in terms of age (minimum 18 years). The data of all these 722

[1]Respondents recruited by lightspeed receive „LifePoints" (lightspeed's internal currency) for their participation in surveys. For our study, respondents received 100 LifePoints. Respondents can pay out their LifePoints via PayPal, exchange them for vouchers (e.g., amazon), or donate the money to UNICEF.

individuals never show up in our analyses, as they are not included in our sample of 1,520 American residents.

Table C.1: Sample distribution of socio-demographic variables and comparison with US population

Variable	**Sample**	**US population**
Age		
18-29	18.3 %	21.3 %
30-39	19.0 %	17.0 %
40-49	16.3 %	16.5 %
50-59	19.3 %	17.9 %
60-69	17.0 %	14.6 %
70+	10.2 %	12.7 %
Gender		
Male	44.7 %	49 %
Female	55.3 %	51 %
Region		
Northeast	18.8 %	17.3 %
Midwest	22.8 %	20.9 %
South	39.5 %	38.0 %
West	18.9 %	23.8 %
Annual Family Income		
Less than 20,000	14.7 %	16 %
20,000–39,999	20.2 %	19 %
40,000–59,999	17.0 %	16 %
60,000–74,999	13.4 %	9 %
75,000–99,999	10.1 %	12 %
100,000–149,999	15.3 %	14 %
More than 150,000	8.6 %	14 %
(Don´t know/Prefer not to say)	0.6 %	
Party Affiliation		
Democrat	35.8 %	33 %
Independent	32.6 %	37 %
Republican	31.5 %	26 %

Notes: Information on socio-demographic characteristics of the US population was obtained from the U.S. Census Bureau (for age and sex composition (2016) see `https://www.census.gov/data/tables/2016/demo/age-and-sex/2016-age-sex-composition.html;forregions(2016)seehttps://www.census.gov/popclock/data_tables.php?component=growth`, for income (2017) see `https://www2.census.gov/programs-surveys/cps/tables/hinc-06/2017/hinc06.xls`). Information on party affiliation is based on Pew Research Center surveys conducted in 2017 (`http://www.people-press.org/wp-content/uploads/sites/4/2018/03/03-20-18-Party-Identification.pdf`). The total percentage for Pew data does not add up to 100 as the remaining share belongs to the category “other.”

Relative to US census figures, our sample slightly over-represents individuals between 30 and 69, and slightly under-represents individuals in the segments between 18 and 29 and over 70, but the differences are overall quite small. Our sample contains 44.7% males and under-represents the West, while the other three census regions are slightly over-represented. Income distributions are overall well matched, but our sample contains a lower share of high-income individuals. In terms of party identification, a comparison with the US population is not straightforward, but the distribution in our sample (roughly one third Democrats, Independents and Republicans, respectively) matches the numbers of recent Pew surveys, which can serve as a benchmark.

Survey items and descriptive statistics

Variable	Questions and Distribution	Aggregation
Age	*Please indicate your year of birth.* Transformed to respondents' age.	n.a.
Gender	*Please indicate your gender.* Male 44.7%, Female 55.3%	n.a.
Education	*What is the highest level of education you have completed?* 1 = Less than high school degree (1.78%); 2 = Graduated from high school (18.62%); 3 = Some college (30.92%); 4 = Four-year college degree (33.29%); 5 = Advanced degree (15.39%)	n.a.
Income	*Please indicate an estimate of your annual family income (before taxes):* 1 = Less than $20,000 (14.7%) / 2 = $20,000 - $39,999 (20.2%) / 3 = $40,000 - $59,999 (17.0%) / 4 = $60,000 - $79,999 (13.4%) / 5 = $80,000 - $99,999 (10.1%) / 6 = $100,000 - $149,999 (15.3%) / 7 = More than $150,000 (8.6%) / 8 = Don't know / Prefer not to answer (0.6%)	n.a.
Urban-rural	*Which of the following best describes the area you live in?* 1 = Urban (24.6%); 2 = Suburban (52.4%); 3 = Rural (23.0%)	n.a.
Partisan orientation	*Generally speaking, do you consider yourself a(n):* 1 = Strong Democrat (17.6%); 2 = Weak Democrat (8.9%); 3 = Lean Democrat (9.3%); 4 = Independent (32.6%); 5 = Lean Republican (11.2%); 6 = Weak Republican (6.2%); 7 = Strong Republican (14.2%)	n.a.
Previous CCS awareness	*Have you ever heard of carbon capture and storage technologies (often abbreviated as "CCS")?* 1 = Yes (18.88%); 2 = I am not sure (23.95%); 3 = No (57.17%).	n.a.

Psychological distance of climate change

Factor variable, based on 6 items (one omitted):

My local area is likely to be affected by climate change. (psy1)
1 = strongly disagree (7.0%); 2 (7.6%); 3 (16.3%); 4 (25.0%); 5 (20.9%); 6 = strongly agree (23.2%)

Climate change most likely affects areas that are far away from here. (psy2)
1 = strongly disagree (27.6%); 2 (18.5%); 3 (21.3%); 4 (14.7%); 5 (9.1%); 6 = strongly agree (8.7%)

Climate change is likely to have a big impact on people like me. (psy3)
1 = strongly disagree (8.0%); 2 (8.2%); 3 (15.3%); 4 (22.4%); 5 (19.9%); 6 = strongly agree (26.3%)

I am certain that climate change is really happening. (psy4)
1 = strongly disagree (6.5%); 2 (6.1%); 3 (11.3%); 4 (17.2%); 5 (18.6%); 6 = strongly agree (40.3%)

Most scientists agree that human activities are causing climate change. (psy5)
1 = strongly disagree (5.3%); 2 (4.2%); 3 (12.2%); 4 (21.2%); 5 (22.4%); 6 = strongly agree (34.8%)

When, if at all, do you think America will start feeling the effects of human-caused climate change? (psy6)
1 = We are already feeling the effects (58.8%); 2 = within the next 10 years (12.2%); 3 = within the next 25 years (9.5%); 4 = within the next 50 years (3.6%); 5 = within the next 100 years (3.2%); 6 = beyond the next 100 years (3.7%); 7 = never (9.0%)

First, an initial correlation analysis shows that psy2 does not correlate with the other 5 items:

	psy1	psy2	psy3	psy4	psy5	psy6
psy1						
psy2	-.02					
psy3	.77	.01				
psy4	.73	.01	.77			
psy5	.65	.03	.68	.71		
psy6	-.61	.05	-.63	-.68	-.60	

Next, we reverse-scored psy6 and used confirmatory factor analysis to check whether the remaining five items are valid representations of the underlying latent construct. All factor loadings are above .75, which supports the validity of the factor model: psy1 = .81 / psy3 = .85 / psy4 = .90 / psy5 = .80 / psy6 = .75 (all significant at $p < .001$).

According to various fit indices, the model fits our data well (CFI=1.000; RMSEA=0.000; SRMR=0.003).

Scale reliability coefficient (Cronbach's alpha): .909

To simplify the interpretation of results, in the regression analysis we employ a binary variable, which is simply a dichotomized version of the original Psychological Distance Index. Regression results are equivalent when employing the original index instead of its dychomotized version.

Table C.2: Survey items and descriptive statistics

Conjoint analysis results: Regression Table

Table C.3: Average marginal effects from conjoint experiment

	Policy Support
Policy type	
Baseline: Bans	
Subsidies	-0.0182**
	(0.00576)
Taxes	-0.0262***
	(0.00544)
Timing	
Baseline: 2020	
2030	0.000805
	(0.00519)
2040	-0.0139*
	(0.00542)
2050	-0.0211***
	(0.00570)
Costs	
Baseline: $ 4	
$ 9	-0.0139**
	(0.00539)
$ 14	-0.0420***
	(0.00608)
$ 19	-0.0519***
	(0.00653)
Distance	
Baseline: 2 miles	
5 miles	0.0240***
	(0.00603)
10 miles	0.0379***
	(0.00580)
50 miles	0.0564***
	(0.00663)
Endorsement	
Baseline: CC Coalition	
Greenpeace	-0.00895
	(0.00513)
Democratic Party	-0.0192***
	(0.00575)
Republican Party	-0.00860
	(0.00570)
Constant	0.490***
	(0.00913)
N	24320

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Notes: Coefficients from OLS regressions; robust standard errors (clustered by respondent) in parentheses. The results shown here correspond to Figure 3.2 in the paper.

Robustness check: Logistic Regression

Table C.4: Analysis of conjoint experiment results using logistic regression and the forced choice outcome variable

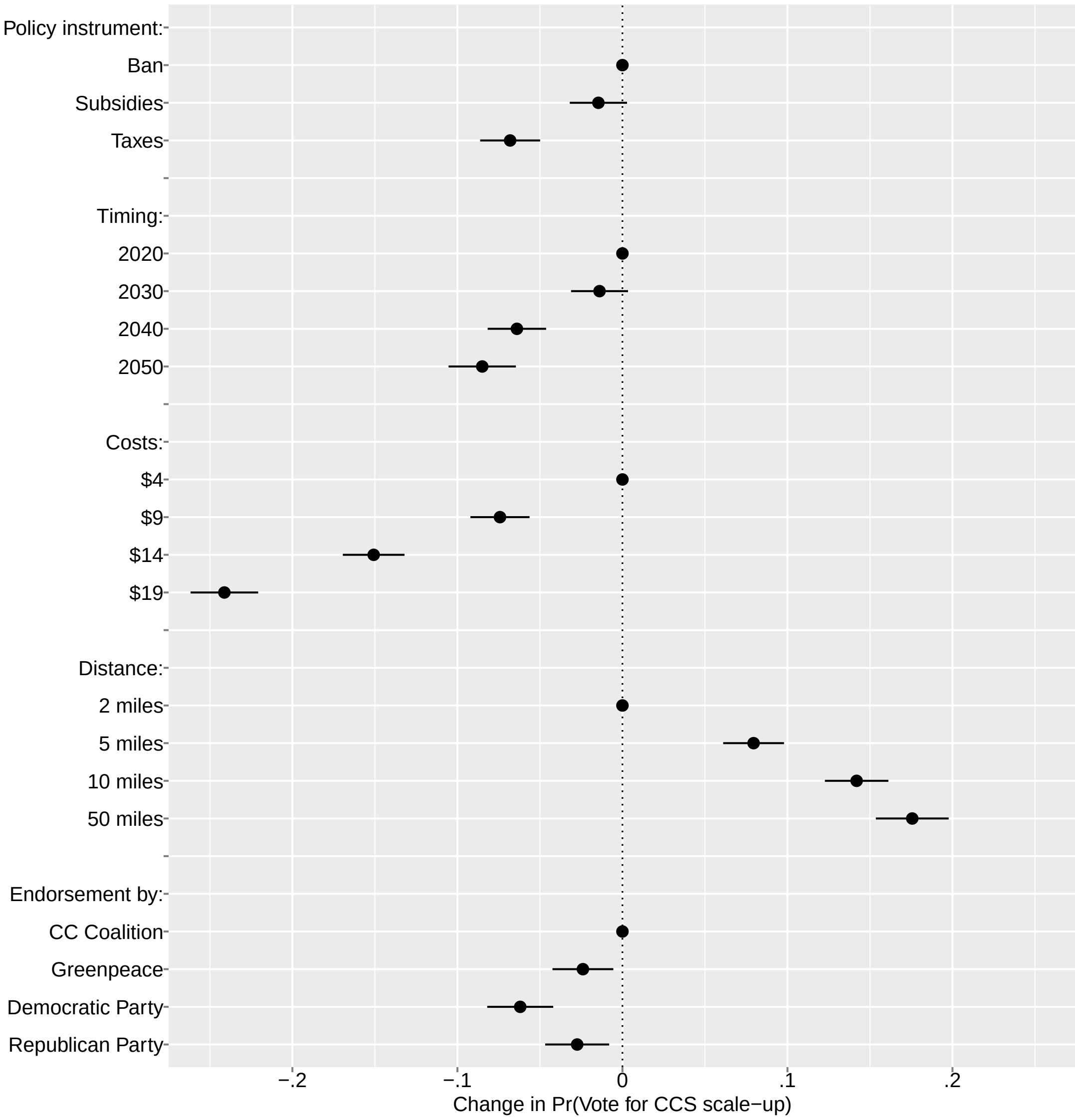
	(1) Policy Support (Logit Coefficients)	(2) Policy Support (Marginal Effects)
Policy type		
Baseline: Bans		
Subsidies	-0.0619	-0.0146
	(0.0376)	(0.00885)
Taxes	-0.289***	-0.0681***
	(0.0395)	(0.00927)
Timing		
Baseline: 2020		
2030	-0.0591	-0.0139
	(0.0375)	(0.00880)
2040	-0.271***	-0.0640***
	(0.0385)	(0.00903)
2050	-0.361***	-0.0850***
	(0.0444)	(0.0104)
Costs		
Baseline: $ 4		
$ 9	-0.314***	-0.0742***
	(0.0389)	(0.00913)
$ 14	-0.631***	-0.151***
	(0.0405)	(0.00954)
$ 19	-1.014***	-0.241***
	(0.0458)	(0.0104)
Distance		
Baseline: 2 miles		
5 miles	0.338***	(0.00941)
	(0.0403)	
10 miles	0.599***	0.142***
	(0.0421)	(0.00981)
50 miles	0.742***	0.176***
	(0.0487)	(0.0113)
Endorsement		
Baseline: CC Coalition		
Greenpeace	-0.102*	-0.0240*
	(0.0401)	(0.00941)
Democratic Party	-0.264***	-0.0620***
	(0.0435)	(0.0102)
Republican Party	-0.117**	-0.0274**
	(0.0420)	(0.00989)
Constant	0.479***	
	(0.0565)	
N	24,32	24,32

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Notes: Coefficients from logistic regressions (Model 1) and transformed into average marginal effects (Model 2) ; robust standard errors (clustered by respondent) in parentheses. Forced outcome policy support variable used as outcome variable. Results are equivalent to results of linear regression analysis.

Conjoint plot based on forced choice outcome variable

Figure C.2: Conjoint plot based on the forced choice outcome



Notes: Average effects of CCS policy attributes on policy support. Each dot represents an average marginal effect of an attribute level on the probability of voting for a policy proposal in relation to a proposal with the reference level for the same attribute. The horizontal bars represent the associated 95% confidence intervals. Dots without bars represent the reference level for each policy attribute. Calculations are based on logistic regression analyses with the binary forced choice outcome variable and standard errors grouped at the level of the individual. N = 24,320 policy proposals.

Comparing the results of the conjoint experiment on the full sample and on a sample excluding speeders

Table C.5: Comparing results of the conjoint experiment on the full sample and on the sample excluding speeders

	(1) Policy Support (Full sample)	(2) Policy Support (No speeders)
Policy type		
Baseline: Bans		
Subsidies	-0.0182**	-0.0184**
	(0.00576)	(0.00589)
Taxes	-0.0262***	-0.0279***
	(0.00544)	(0.00559)
Timing		
Baseline: 2020		
2030	0.000805	0.000202
	(0.00519)	(0.00529)
2040	-0.0139*	-0.0146**
	(0.00542)	(0.00548)
2050	-0.0211***	-0.0209***
	(0.00570)	(0.00585)
Costs		
Baseline: $ 4		
$ 9	-0.0139**	-0.0151**
	(0.00539)	(0.00550)
$ 14	-0.0420***	-0.0466***
	(0.00608)	(0.00623)
$ 19	-0.0519***	-0.0552***
	(0.00653)	(0.00669)
Distance		
Baseline: 2 miles		
5 miles	0.0240***	0.0244***
	(0.00603)	(0.00613)
10 miles	0.0379***	0.0380***
	(0.00580)	(0.00593)
50 miles	0.0564***	0.0573***
	(0.00663)	(0.00678)
Endorsement		
Baseline: CC Coalition		
Greenpeace	-0.00895	-0.00775
	(0.00513)	(0.00526)
Democratic Party	-0.0192***	-0.0184**
	(0.00575)	(0.00586)
Republican Party	-0.00860	-0.00833
	(0.00570)	(0.00587)
Constant	0.490***	0.488***
	(0.00913)	(0.00928)
N	24320	23296

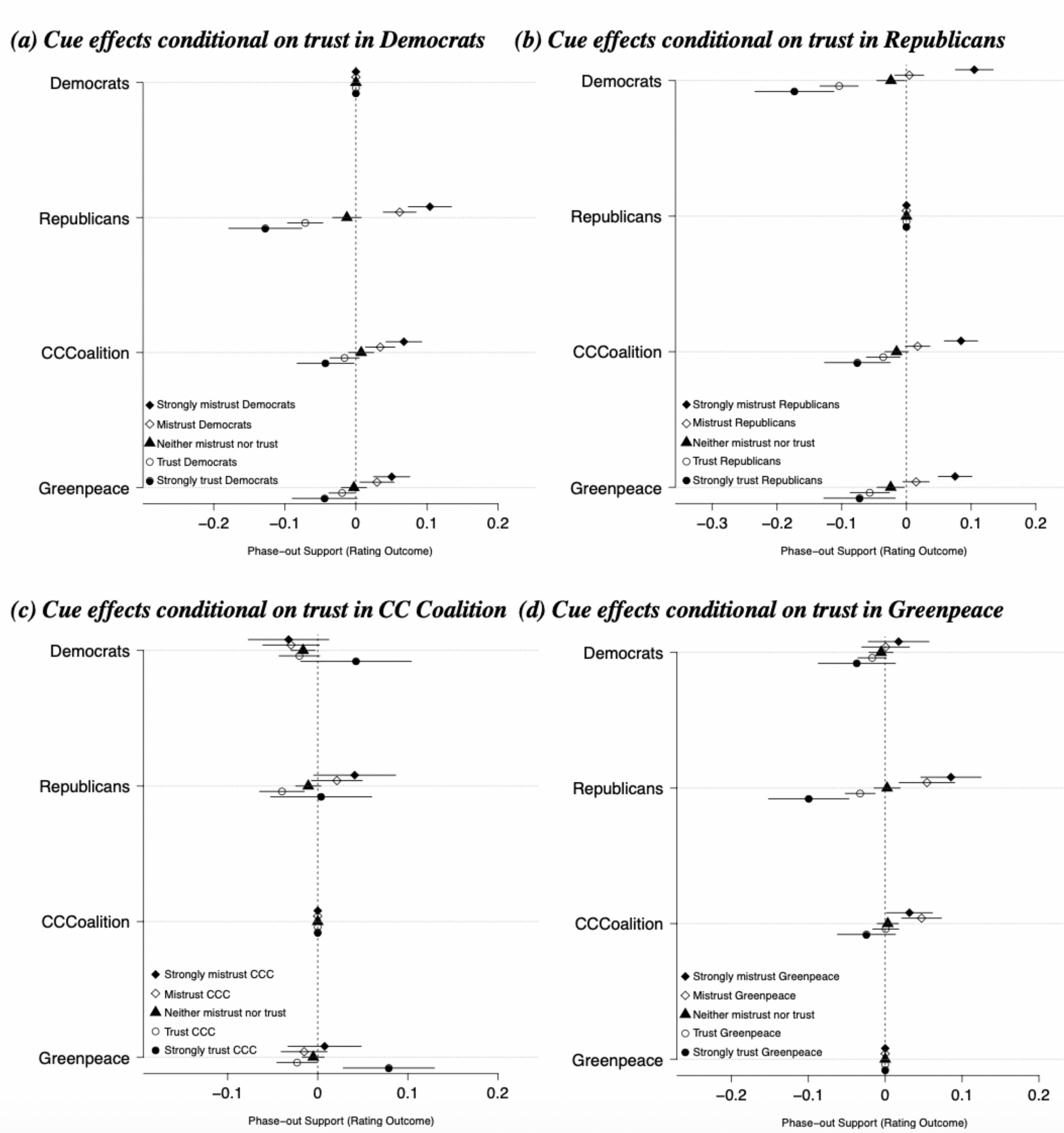
Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Notes: We report average marginal effects from the conjoint experiment - coefficients from OLS regressions - with robust standard errors (clustered by respondent) in parentheses. The results for the full sample shown in Model (1) here refer to Figure 3.2. We show in Model (2) that the results of the same regression run on a sample excluding respondents who took the conjoint experiment in less than 33.4% of median completion time (N = 23,376 policy proposals) are equivalent.

Trust in stakeholders as a moderator of endorsement effects

The following graphs show average marginal effects of stakeholder endorsements on the probability to vote for a policy proposal in a referendum, conditional on trust in stakeholders. The calculations are based on regression analyses with rating outcomes (N = 24,320 policy proposals), the full set of attribute values as predictors, and standard errors clustered per respondent. The analysis is reiterated four times so as to visualize the effects conditional on trust in each stakeholder separately. E.g., panel (a) shows the effects of endorsement by different stakeholders (taking Democrats as baseline), conditional on different trust levels for Democrats.

Figure C.3: Effects of stakeholder endorsements on CCS policy support, conditional on respondents' level of trust in these actors.



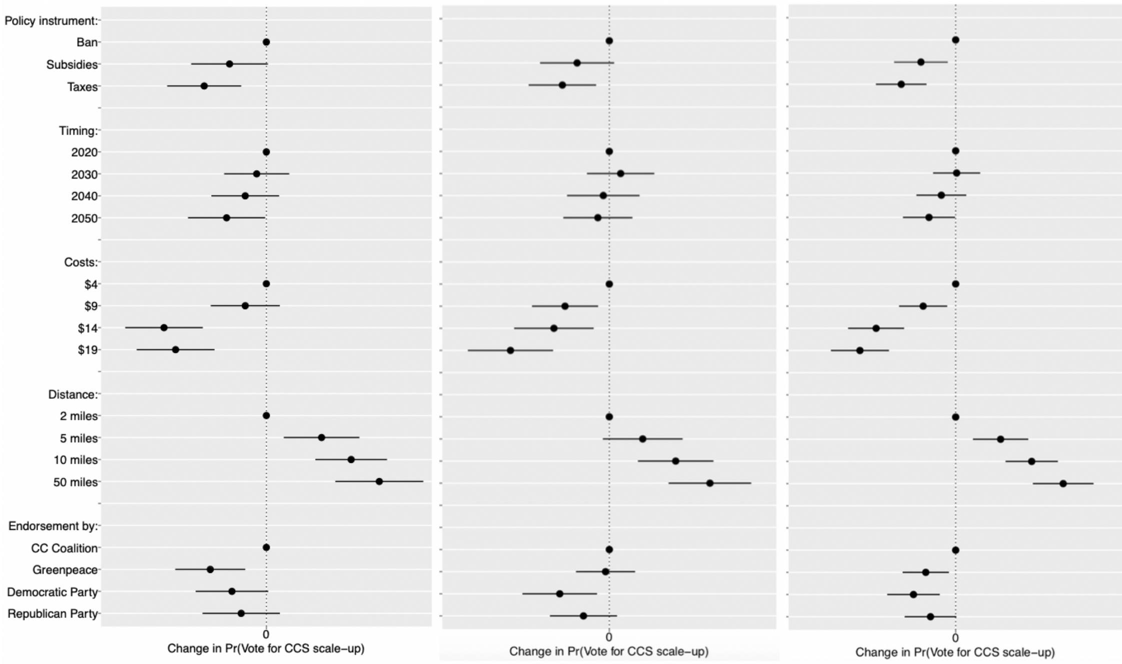
Notes: Each dot represents an average marginal component effect (AMCE) of an individual attribute level (i.e., endorsement by stakeholders) on respondents' probability to choose a policy proposal in relation to a proposal with the reference level. Horizontal bars represent associated 95% confidence intervals. The calculations are based on regression analyses with rating outcomes, the full set of attribute levels included, and standard errors grouped at the level of the individual (clustered standard errors). n = 1,520.

Independence of attribute effects from social norms interventions

The conjoint experiment was embedded in a broader survey on climate policy preferences which, in addition to the conjoint experiment, involved a randomized controlled experiment. Before completing the conjoint tasks, respondents were randomly assigned to an endorsement norms condition, a non-endorsement norms condition, or a control condition. In the two experimental conditions, respondents read a short text highlighting policy-relevant attitudes and behaviors of other people living in their state. In the endorsement norms condition, this included a statement about the increasing support for policies to scale up CCS among state citizens (highlighting a relative increase in support, in order not to make use of deception), while in the non-endorsement norms condition, it included a statement about the limited support for policies to scale up CCS (highlighting low absolute levels of support). For more detailed information, see the materials deposited on the OSF platform: https://osf.io/6w4h3/?view$_{o}nly = b59087110dad4733b1dbc218c22a9eeb$).

Here we document that the social norms manipulations did not have a systematic influence on respondents' policy preferences. As Figure C.4 illustrates, information about descriptive social norms provided to study participants did not interact in statistically significant ways with any attribute used in the conjoint experiments. Even if some differences with regard to the size of effects can be detected in some cases (e.g., in particular, the cost attribute for respondents assigned to the endorsement norm condition had slightly different effect sizes with respect to the other treatment groups), the associated confidence intervals overlap in all these cases. As the effects of attribute levels on preferences do not depend on the experimental manipulations, the analyses shown in the paper are based on the pooled data obtained from the conjoint experiment.

Figure C.4: The non-existing contingency of policy attribute effects on descriptive social norms.



Notes: This is essentially a replication of Figure 3.2, but it shows the AMEs of individual attribute levels for the three norms treatment conditions separately. Calculations are based on regression analyses with rating outcomes and standard errors grouped at the level of the individual (clustered standard errors). N = 24,320 policy proposals.