Journal of Economic Behavior and Organization 229 (2025) 106816

Contents lists available at ScienceDirect

Journal of Economic Behavior and Organization

journal homepage: www.elsevier.com/locate/jebo

Opinion dynamics meet agent-based climate economics: An integrated analysis of carbon taxation

Teresa Lackner [a,*], Luca E. Fierro [b,c], Patrick Mellacher [a]

[a] University of Graz, Graz Schumpeter Centre, Graz, Austria
[b] International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria
[c] Scuola Superiore Sant'Anna, Institute of Economics, Pisa, Italy

ARTICLE INFO

Dataset link: https://github.com/teresa-lackner

JEL classification:
C63
H31
Q43
Q50

Keywords:
Climate change
Mitigation policy
Opinion dynamics
Agent-based models
Transition risks

ABSTRACT

We introduce an integrated approach, blending Opinion Dynamics with a Macroeconomic Agent-Based Model (OD-MABM) to explore the co-evolution of climate change mitigation policy and public support. The OD-MABM links a novel opinion dynamics model that is calibrated for European countries using survey data to the Dystopian Schumpeter meeting Keynes model (DSK). Opinion dynamics regarding climate policy arise from complex interactions among social, political, economic and climate systems where a household's opinion is affected by individual economic conditions, perception of climate change, industry-led (dis-)information and social influence. We examine 133 policy pathways in the EU, integrating various carbon tax schemes and revenue recycling mechanisms. Our findings reveal that effective carbon tax policies initially lead to a decline in public support due to substantial macroeconomic transition costs, threatening political feasibility. However, they also pave the way for a positive social tipping point in the future. This shift stems from the evolving economic and political influence associated with the fossil fuel-based industry, which gradually diminishes as the transition unfolds. Second, hybrid revenue recycling strategies that combine green subsidies with climate dividends successfully address this intertemporal trade-off in our model by accelerating the transition and mitigating its economic fallout, thus broadening public support.

1. Introduction

The unfolding climate crisis has put climate change at the top of the global policy agenda. Governments around the world have started to implement carbon pricing policies to mitigate climate change, either via carbon taxes or cap and trade systems (Blanchard et al., 2023; Black et al., 2023). While current policies fall short of what would be necessary to give us a fighting chance of climate stabilization at between 1.5 and 2 degrees of global warming (IPCC, 2023), carbon pricing remains the benchmark of decarbonization policies in mainstream economics (Tooze, 2023). The climate team of the International Monetary Fund (IMF) recently issued a stocktake of climate change mitigation efforts, arguing that a carbon price of \$75 per ton of CO_2 would bring most countries close to their Nationally Determined Contributions (NDCs) (Black et al., 2023).

Despite the compelling nature of carbon pricing, public reactions around the world warrant caution regarding its political feasibility. The Gilet Jaunes protests in France in 2018 serve as a case in point, warning against excessively ambitious carbon taxes. A portfolio of economic policies, including green incentives and fiscal stabilizers, may be better suited to fight climate change, especially when taking into consideration the political feasibility of transition pathways.

* Corresponding author.
E-mail address: teresa.lackner@uni-graz.at (T. Lackner).

https://doi.org/10.1016/j.jebo.2024.106816
Received 15 February 2024; Received in revised form 13 August 2024; Accepted 7 November 2024

Available online 6 December 2024
0167-2681/

In this paper, we investigate public opinion about climate change policies by linking a novel empirically calibrated opinion dynamics (OD) model with a macroeconomic agent-based integrated-assessment model (MABM), the Dystopian Schumpeter meeting Keynes (DSK) model (Lamperti et al., 2018, 2019a). Although opinion dynamics surrounding climate change arise from complex interactions among social, political, economic and climate systems, these elements are hardly analysed in this particular context. The model we propose here represents a significant methodological advancement as it is among the first to integrate a macroeconomic ABM with opinion dynamics, grounded in a complexity economics framework and careful empirical calibration. Compared to reduced-form models, our framework allows for a more nuanced investigation of system interactions and feedback mechanisms that may impede or accelerate shifts in public opinion about climate policy.

Specifically, our opinion dynamics model considers four channels through which opinion about climate policies is affected: (i) economic conditions, (ii) perception of climate change, (iii) industry lobbying and (iv) social influence, where the importance of each channel has been carefully calibrated using survey and complementary empirical data. The DSK model is an out-of-equilibrium evolutionary simulation laboratory that accounts for continuous interactions between the economy and the climate. It offers an advantageous alternative to the standard cost-benefit assessment of climate policies which is grounded on general equilibrium models (Mercure et al., 2018; Balint et al., 2017; Lamperti et al., 2019b; Hafner et al., 2020) and frequently fails to adequately account for transition risks (Mercure et al., 2021; Lamperti et al., 2019c; Lamperti and Roventini, 2022; Lamperti et al., 2022). By encompassing both short and long-run dynamics within a single framework, the DSK model enables the study of climate change mitigation policies at business cycle frequencies and with respect to long-term growth effects. Combining both models, we introduce an integrated Opinion Dynamics-Macroeconomic Agent-Based model (OD-MABM) framework which provides a useful simulation laboratory to study the co-evolution of the coupled climate-macro systems that interact with the social and political spheres giving rise to complex, potentially non-linear opinion dynamics.

On the other hand, our framework does not consider how political support influences the design and long-term commitment to transition policies. Although this issue is fundamentally relevant (e.g., see Meng and Rode, 2019; Peng et al., 2021; Konc et al., 2022; Sordi and Dávila-Fernández, 2023; Di Benedetto et al., 2024), we chose to abstract from it to clarify the channels connecting the macroeconomic effects of green policies to public support. Moreover, we can reasonably assume that introducing opinion-to-policy feedback would affect the policy trajectory, but not how opinions respond to a given policy, which is the main focus of this paper.

In our analysis, we focus on the European Union (EU), where carbon pricing is the cornerstone of climate policy. Operating under the cap and trade principle, the European Emissions Trading System (EU-ETS) constitutes the largest carbon market in the world. It covers greenhouse gas emissions from the power sector, energy-intensive industries and aviation which together account for around 40% of the EU's total greenhouse gas emissions (Känzig, 2023). Additionally, many countries have implemented national carbon taxes to cover emissions from sectors that are not (yet) regulated by the EU-ETS (i.e., so-called Effort Sharing sectors including transport, buildings, agriculture, waste and small industry) or even impose double taxation on emissions from EU-ETS sectors (e.g. Finland, Ireland, the Netherlands) (World Bank, 2023). Auctioning revenues generated under the EU-ETS and national carbon tax revenues provide additional public revenues for member states which may serve as a means to increase public support for stringent climate policy. This makes the EU an interesting case study to explore the co-dynamics of carbon pricing policies and public support and investigate the role of revenue recycling in enhancing political support for climate policy.

We shall add to the discussion that although interesting, the European case can only be generalized to a certain extent, specifically, to advanced economies, relatively poor in fossil fuel resources. For example, our results would only partially apply to countries whose economies heavily rely on fossil fuel extraction and trade, as the economic costs of decarbonization in these regions are more severe and far-fetched than in Europe (Semieniuk et al., 2021; Magacho et al., 2023; Moreno et al., 2024). Moreover, countries more exposed to climate events than Europe — typically due to geography, lack of climate change-adaptation capacity, or productive structure (e.g., a large share of agriculture in GDP) (Dell et al., 2012; Kalkuhl and Wenz, 2020; Palagi et al., 2022) - are likely to respond differently to the introduction of climate policies than our opinion-dynamics model in its current calibration predicts.

Our key finding reveals a crucial intertemporal trade-off inherent in effective carbon tax schemes. Ambitious carbon taxes, while initially imposing a significant macroeconomic burden on households, can diminish public support for green policies upon their introduction. Conversely, our model illustrates that over the long term, carbon taxes hold the potential to trigger a positive social tipping point as the economic influence of the fossil industry, and consequently their lobbying power, diminishes. The question of whether these carbon taxes might undermine their own public support before the positive tipping point occurs remains unanswered in our model. This complex issue is challenging to address with a high degree of certainty, hence, policymaking strategies relying on the assumption that public opinion will favourably shift at the opportune moment appear to be excessively risky. We indeed find that comprehensive policy packages, which use carbon tax revenues to finance policies aimed at alleviating macroeconomic costs and further hampering the lobbying power of the fossil fuel-based industries, are much more preferable. After studying a battery of 133 different policy scenarios and conducting numerous sensitivity analyses, we conclude that a strategy which combines a stringent carbon tax with a full redistribution of the tax revenues in the form of a high subsidy for investment in renewable energy and a lump sum transfer to workers fares best in terms of public support, as well as in terms of transition effectiveness.

This is an important result for real-world policy design, as a carbon tax refund scheme has been enacted in some countries (e.g. Switzerland, Austria), but not in others at the time of writing this paper. Most prominently, the German government's plans regarding the utilization of carbon tax revenues recently[1] faced reconsideration due to financial constraints imposed by

[1] i.e., towards the end of 2023

a constitutional court ruling, leading to increased debates about the role of revenue earmarking to align economic, social and environmental objectives (Wettengel, 2024; Benjamin Wehrmann, 2024).

The remainder of the paper is organized as follows. In the next Section 2, we discuss how this paper contributes to the existing literature. Section 3 describes the integrated OD-MABM approach, the calibration method and the simulated policy experiments. In Section 4, we present the results on the co-dynamics of climate policy and opinion dynamics. Section 5 demonstrates the robustness of our results by means of a comprehensive sensitivity analysis and with respect to extensions of the opinion dynamics model. Section 6 concludes.

2. Contribution to the literature

The contribution of this paper is twofold. First, it contributes to a nascent literature aiming at the integration of dynamic representation of human behaviour and social systems into integrated assessment models (IAMs). Combining insights from climate science and economics, IAMs constitute key tools for assessing long term climate change mitigation scenarios (Weyant, 2017; Fisher-Vanden and Weyant, 2020) and are attributed a central role in the assessments of the Intergovernmental Panel on Climate Change (IPCC). Yet, they are increasingly criticized for being abstract and their inability to capture the complex trade-offs policy makers face in light of their commitment to respond to constituencies and corporate leaders with vested interests (Peng et al., 2021). For a thorough review of recently emerging critiques, we refer the reader to Keppo et al. (2021) and suggest the more condensed Beckage et al. (2020, 2022) and Peng et al. (2021) focusing on the integration of social and political systems into the domain of IAMs. This literature stresses the relevance of integrating opinion formation about climate change, yet only few attempts exist towards this end. Lipari et al. (2024) explore the interplay between social and political dynamics and how it affects climate policy support based on a multiplex network. Their study highlights the positive effect of (even minimal) peer pressure, warns against the assumption of uniform self-efficacy across society to avoid overestimation of public support and demonstrates the relevance of accounting for regional heterogeneity. van den Bergh et al. (2019) study opinion dynamics in the growth-vs-environment debate based on an extended replicator dynamics approach which accounts for social influence, opinion segregation within like-minded communities, exposure to empirical information about environmental change and psychological resistance to opinion change. The authors find that local interactions sustain multiple opinions, global interactions make consensus more likely and uniform information across opinion groups does not necessarily translate in their joint survival. Most notably, they show that opinions shift from green growth to agrowth and degrowth if environmental conditions worsen under continuing economic growth. These studies integrate the social and political systems by studying opinion dynamics within the electorate but do not consider endogenous feedback within the macroeconomic system. Moore et al. (2022) aim at endogenizing the socio-politico-technical processes that determine climate policy and emission pathways. They build a stylized model of the climate-social system, accounting for a variety of feedback processes, which exhibits non-linearities and tipping points that arise from interactions across spatial scales (i.e., individual, community, national and global level). Based on extensive simulations, the authors identify 5 clusters with global warming until 2100 ranging from 1.8 °C to 3.6 °C compared to pre-industrial. They identify public perception of climate change, the future cost and effectiveness of mitigation technologies, and the responsiveness of political institutions as the constraints of global warming, explaining the bulk of variation in simulated emission trajectories. Konc et al. (2022) connect a policy-design module, a policy-impact module which is based on a simple general-equilibrium model, and a policy-support module to study co-dynamics of climate policy stringency and public support. Their policy-support module accounts for three well-known determinants of public acceptance of a carbon tax, which comprise environmental effectiveness concerns, inequality concerns and self-interest (see Dechezleprêtre et al., 2022). The authors highlight the importance of social influence, opinion stability and income inequality for public support of climate policies. Comparing carbon taxation and performance standards, their analysis finds highest public support for a gradually increasing carbon tax pathway with progressive revenue recycling to households. Isley et al. (2015) propose an agent-based, game theoretic model to study how near-term policy choices can affect long-term emission pathways within IAMs. The authors extend the Keynes+Schumpeter model by a game theoretic component describing the competition among firms trying to influence climate policy. Integrating the co-dynamics of an industry, its technology and shifting political coalitions that lobby to align future policy stringency with their interests, they show that recycling carbon tax revenues to firms in proportion to their market share can positively affect decarbonization by creating a political constituency for continuing the carbon pricing policy. Sordi and Dávila-Fernández (2023) extend the Marx–Keynes–Schumpeter model[2] to study the social dimension of climate change in an integrated model framework. They introduce environmental attitudes of households that link energy efficiency and the labour market to climate change. In their model, the population consists of supporters and opponents of a carbon tax. The composition of the population affects the tax rate and evolves over time depending on social interaction, unemployment and energy efficiency in the economy which is modelled based on a continuous-time version of the discrete-choice approach. The carbon tax negatively affects capital accumulation but promotes the development of energy-saving production techniques. The net effect on economic activity depends on the relative strength of these two effects and resulting unemployment and emission reductions feedback on environmental attitudes. The authors show that a sufficiently strong sensitivity of attitudes to emission reductions may dissipate the equilibrium in which most agents oppose regulation, hinting at a novel source of growth-cycle dynamics.[3] Di Benedetto et al. (2024) add a social layer to the DSK by linking it to a simple two-party election model. Climate policies are implemented by a green

[2] originally developed by Flaschel (2015).

[3] Note that Dávila-Fernández et al. (2023) suggest a similar approach to model the social dimension.

party which is re-elected with a probability depending on the state of the economy and climate. If policies cause unemployment, the party is less likely to be re-elected. Their analysis suggests that a sufficiently high carbon tax is unfeasible, because the resulting high unemployment will make it difficult for the green party to stay in power.

The present paper also studies the co-dynamics of climate change mitigation policy and public support by integrating dynamic representation of the socio-political spheres into an agent-based IAM. We contribute to the literature by extending the conceptualization of opinion dynamics within the electorate by an important political economy constraint which remains unaddressed by existing studies: the influence of industry-led (dis-)information campaigns.[4] Moreover, we employ an elaborate estimation procedure to calibrate the opinion dynamics model to Eurobarometer survey data over 2011–2019 and illustrate descriptive output validation of the model for the 26 countries that have been part of the EU throughout the whole period between 2011 and 2023. In contrast, past studies do not bring their model to data or rely on simplified calibration approaches based on cross-sectional and often only single-country surveys which make an empirical identification of the parameters very difficult. Thus, our methodology offers a novel examination of co-evolving climate change mitigation policy and public support which proves fruitful to inform policy pathways in order to remove politico-economic barriers and broaden public support for mitigation policy.

Second, our paper contributes to the literature on policy design to maximize public support while remaining environmentally effective (Meckling et al., 2015, 2017; Pahle et al., 2018; Kallbekken, 2023; Montfort et al., 2023). Studying climate change mitigation policies in the economy as complex evolving system points to the potential of significant macroeconomic transition risks (Mercure et al., 2018; Semieniuk et al., 2021; Känzig, 2023) that need to be addressed by an adequate policy mix. As outlined by Kallbekken (2023), few studies consider public support for policy packages, i.e., the combination of multiple instruments, which resemble policy implementation in the real world. Broadening the scope for research on public support raises methodological challenges as the effect of policy packages is analytically less tractable, requiring increased methodological diversity. Conjoint analyses based on simulations (e.g., combining policy impact, policy support and policy design modules in an integrated model framework as exemplified by the studies above) are acknowledged as particularly useful to explore temporal dynamics (Kallbekken, 2023). In this tradition, our paper expands the literature on the optimal design of carbon taxes (Klenert et al., 2018; Carattini et al., 2018; Muth, 2023). Studying a battery of different configurations of hybrid carbon tax recycling, we provide novel insights how the combination of green energy subsidies and climate dividends can lead to a desirable tipping point in public support for climate policy by effectively alleviating politico-economic barriers.

3. An integrated opinion dynamics-MABM approach

To study public support for climate policy over time, we employ two Agent-Based Models (ABMs): an opinion dynamics model and a climate-macroeconomic model. We implement various green policies in our climate-macroeconomic model and evaluate their effects on key variables like the share of green production capacity in the energy sector, employment levels, and global surface temperature. These variables are subsequently used as inputs for the opinion dynamics model to assess public support for green policies.

The dynamics in the economic and climate system affect public support which is modelled by an empirically calibrated opinion dynamics model developed in this paper. To this end, we use an agent-based approach that considers heterogeneous households who are differently affected by macroeconomic transition risks, climate change dynamics and the influence of industry lobbying which directly affects individual policy opinion. Through interactions in a social network, individual households exchange their opinions allowing direct effects experienced by some households to propagate further in society via social influence. Our opinion dynamics model advances beyond the state-of-the-art by offering a more disaggregated approach, which is grounded in empirical data and accounts for mutual interactions among heterogeneous households with cognitive attributes (see the discussion by van den Bergh et al., 2019). To evaluate a set of climate change mitigation policy pathways with respect to macroeconomic effects, emission reduction and related dynamics of the earth's mean surface temperature, we use the most recent vintage of the Dystopian Schumpeter meeting Keynes (DSK) model, originally developed by Lamperti et al. (2018). Together, the integrated OD-MABM approach offers a novel framework to examine the co-dynamics of climate policy and public opinion and identify leverage points to accelerate and maintain public support during the transition (see Fig. 1).

3.1. The opinion dynamics model

To capture heterogeneous, dynamic and interactive opinions about climate policy in the EU countries over the transition period 2020–2050, we develop and empirically calibrate an opinion-dynamics agent-based model. By describing a population of heterogeneous agents with a diverse array of possible behaviours and interactions, ABMs constitute a powerful tool to depart from traditional assumptions about representative and socially isolated agents and enrich the study of opinion dynamics (Castro et al., 2020). We calibrate the opinion dynamics model based on country-specific time series data over the 2011–2019 period, specifically, we use Eurobarometer survey waves and other indicators concerning climate and economic dynamics (see Section 3.2). Comparing the empirical and simulated time series for 26 EU countries, we demonstrate that it is possible to calibrate the four free parameters of the model to fit empirical survey data very well and suggest a new benchmark in the field by providing insights on opinion dynamics over a duration hitherto unexplored in similar studies.

[4] While Mellacher (2021) analyses the impact of such disinformation campaigns, his framework is purely theoretical and does not explicitly model a climate sphere.

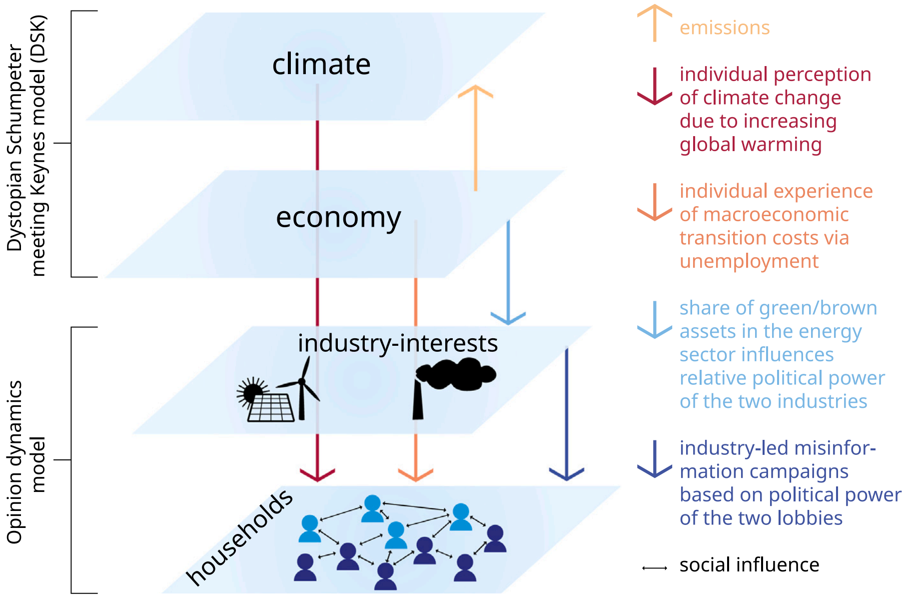


Fig. 1. Overview of the integrated Opinion Dynamics — Macroeconomic Agent-Based Model approach (OD-MABM).

The model goes beyond modelling public support for climate change as a simple reaction to economic impacts alone. In particular, we include four relevant dimensions which are illustrated in Fig. 1: (i) individual economic conditions (i.e., unemployment); (ii) individual perception of climate change; (iii) top-down interaction with heterogeneous interest groups (i.e., industry lobbying); and (iv) horizontal interactions within the social network (i.e., social conformity). There is ample evidence for the effect of each dimension on policy support but only few attempts exist to examine the implications of this complex interaction structure for emission pathways in general and opinion dynamics in particular (Moore et al., 2022).

In the model, a household's opinion depends on the individual economic conditions which are affected by macroeconomic transition costs of climate policy. Increasing unemployment may reduce climate change concern and policy support of the unemployed which tend to overweight recent events and shift their beliefs to reduce cognitive dissonance about short-term needs and long-term problems (Hurst et al., 2013; Kahn and Kotchen, 2011; Brulle et al., 2012; Scruggs and Benegal, 2012; Kachi et al., 2015; Benegal, 2018; Meyer, 2022; Drews et al., 2022). As Sordi and Dávila-Fernández (2023) point out, this pattern is also consistent with the conception of environmental protection as a luxury good (Abou-Chadi and Kayser, 2017), being very appealing but quickly deprioritized during economic downturns.

On the other hand, as climate change advances, households increasingly observe signals such as higher temperature levels, extreme weather events and related damages which can increase individual risk perception and affect individual support for climate policy (Moore et al., 2022; Ricke and Caldeira, 2014; Konisky et al., 2016; Goldberg et al., 2021; Zaval et al., 2014; Deryugina, 2013). However, the effect of increasing evidence of anthropogenic climate change on public support for climate policy is intricate. Humans are known for their cognitive biases which affect their perception and interpretation of increasing evidence of climate change. Studies show that individuals might quickly update their perception of normal weather conditions based on recent experience instead of comparing to pre-industrial trends which is known as the *shifting baselines effect* (Moore et al., 2019; Soga and Gaston, 2018; Moore et al., 2022). Moreover, there is evidence that humans tend to filter climate change-related information through pre-existing ideologies, rejecting information which contradicts their standing views, a phenomenon known as *biased assimilation* or *motivated reasoning* (Druckman and McGrath, 2019; McCright et al., 2014; Hazlett and Mildenberger, 2020; Little, 2019; Kahan, 2013; Moore et al., 2022; Douenne and Fabre, 2022; Bénabou and Tirole, 2016).

Lobbying also shapes individual sentiments towards green policies. Indeed, carbon pricing policies increase factor prices for fossil fuel-based energy products and prices of carbon-intensive intermediate and final products. Their implementation necessarily involves a redistribution of economic resources as production and consumption shift to a new, climate-neutral path. Independent of social welfare considerations, such a transition imposes significant private costs for industries with emission-intensive assets, such as fossil fuel plants, jeopardizing both their assets' value and political influence (Jenkins, 2014; Colgan et al., 2021). These industries are likely to oppose effective carbon pricing policies and engage in efforts to sway public opinion and downplay climate change concerns. Historically, industry-led scientific disinformation has been deployed to distort the dangers of tobacco consumption, the causes of acid rain or the role of chlorofluorocarbons on ozone depletion but the spread of scientific disinformation aimed at obstructing the emergency of climate change has been at an unprecedented scale (Farrell et al., 2019; Brulle, 2014; Dunlap et al., 2011; Farrell, 2016; Supran and Oreskes, 2017; Boussalis and Coan, 2016). Even though the oil industry has been informed of the impact of carbon dioxide on global warming since the 1950s (Franta, 2018), it invested millions of dollars to spread disinformation about climate change instead of taking responsibility and reducing its impact (Frumhoff et al., 2015; Bonneuil et al., 2021). The fossil fuel-based

Table 1
Initialization of households based on Eurobarometer survey (European Commission, 2019): correspondence between modelled variables and survey questions.

Variable	Survey question	Measurement	Value
es	D15A: What is your current occupation?	Choice of one out of 18 occupation categories (2 = Unemployed or temporarily not working)	$\begin{cases} 1 & \text{if D15A} = 2 \\ 0 & \text{otherwise} \end{cases}$
op	QB2: And how serious a problem do you think climate change is at this moment?	Scale from 1 (not at all a serious problem) to 10 (an extremely serious problem)	$\begin{cases} 1 & \text{if QB2} \leq 5 \\ 2 & \text{if } 5 < \text{QB2} \leq 9 \\ 3 & \text{if QB2} = 10 \end{cases}$

industry imposes severe political economy constraints to the implementation of effective climate policies but the political economy literature also documents a positive feedback effect (Pierson, 1993; Stokes, 2020; Moore et al., 2022) as the implementation of initial climate policy establishes powerful interests in the renewable-based industries to lobby in support of more stringent climate policies. The model accounts for these contesting dynamics as households are exposed to fossil and renewable-based industry-led (dis-)information campaigns that reflect the respective industry's political power and aim to promulgate viewpoints that are favourable to their industry interests.

Besides individual economic conditions, perception of climate change and exposure to industry-led (dis-)information campaigns, individual opinion is also strongly influenced by the social networks in which households are embedded at work, leisure or home (Latané, 1981; Akerlof, 1997; Mason et al., 2007; Moore et al., 2022). The dominant opinion on climate policy within one's peer group constitutes a social norm which is costly for individual households to violate but can shape public opinion in the long run (Bénabou and Tirole, 2006; McDonald and Crandall, 2015; Goldberg et al., 2020; Moore et al., 2022). The tendency towards social conformity can reinforce or undermine the effect of the above described factors, potentially leading to tipping points, i.e., qualitative and endogenous shifts in public opinion driven by self-reinforcing positive feedback mechanisms (Nyborg et al., 2016; Centola et al., 2018; Otto et al., 2020; Moore et al., 2022; Everall et al., 2023). Thus, the consideration of social dynamics is highly important to explore the interrelation between climate policy and public support and design politically feasible policies. Similar to Lipari et al. (2024), we represent social norms by households' reference groups (Bicchieri, 2005) and include them as determinant of individual policy opinion (Cole et al., 2022; Bond et al., 2012). There is ample evidence that social networks are highly stratified by socioeconomic class. The existence of reference groups gives rise to homophily in social networks which describes the tendency of individuals to interact more closely with others who share similar attributes, resulting in stronger mutual influence among similar individuals than with those who differ significantly in their beliefs and backgrounds (McPherson et al., 2001; Boguná et al., 2004; Currarini et al., 2009).

All these different channels considered, it is not clear how their interaction affects opinion dynamics, which channels are of particular importance and what this implies for policy design to successfully address the dilemma between political feasibility and environmental policy effectiveness (Kallbekken, 2023; Wicki et al., 2019). We argue that the opinion dynamics model developed in this study provides a powerful tool to explore these questions.

3.1.1. Agent types

Focusing on the EU, we model opinion dynamics across time t, measured in years, within a population of LS households which are distributed across $K = 26$ countries,[5] where $LS = \sum_{k=1}^{K} LS_k$ and LS_k denotes the national population. Each household i at time t is characterized by its employment status (es) and climate policy opinion (op) which is summarized by the profile

$$p_{i,t}^k = (es_{i,t}^k, op_{i,t}^k) \tag{1}$$

The employment status is modelled as a binary variable $es_{i,t} \in \{0,1\}$ where 1 indicates that the individual is unemployed. Climate policy opinion is a discrete variable $op_{i,t} \in \{1,2,3\}$ where 1 denotes opposition, 2 neutrality and 3 support. The (LS=24,603) households are initialized based on the empirical distribution within the EU region in 2019 according to Eurobarometer survey data (European Commission, 2019). Specifically, households in the opinion dynamics model are a 1:1 representation of Eurobarometer survey participants where each of the household's characteristics are derived from survey questions summarized in Table 1. Climate policy opinion is proxied by the question QB2 which asked respondents how serious a problem they think climate change is at this moment. We map the 10 point Likert scale onto the categories opposing, neutral or supporting climate policy which is common in the literature due to a lack of more precise and context-specific opinion data, particularly covering more than one country (see Moore et al., 2022). Note that our mapping according to which households are accounted as supporters only if they view climate change as an extremely serious problem is deliberately conservative. While climate change concern is a valuable indicator, it remains a proxy for actual support of stringent climate policies. By setting a high threshold for the "support" category, we ensure that we capture only those respondents with the highest level of concern, thereby minimizing the influence of the bias due to socially desirable responding, where respondents might overstate their concern due to societal expectations. In Section 5.2, we conduct a sensitivity analysis using a less conservative threshold, defining supporters as those with a score above 8.

[5] As of the time of writing of this article, there are 27 EU member states. However, Croatia has not been a member state in the beginning of our calibration period, i.e., 2011. Hence, our data is limited to the remaining 26 countries.

Moreover, we model two ideal-typical groups of asset holders in the energy sector which hold opposing economic interests and engage in lobbying. The two groups represent the political interest of fossil fuel-based and renewable-based asset holders (denoted by F and R, respectively), aiming to develop and promulgate viewpoints that are favourable to their industry's interests. For example, this can be interpreted as industry-led (dis-)information campaigns (Farrell et al., 2019). However, their political power $\rho_{tp,t} \in (0,1)$ with $tp = \{F, R\}$ changes over time and in accordance with their asset shares in the energy production capacity depending on the implemented climate policy.

3.1.2. Country-specific social networks

Households are connected to country-specific social networks. Their generation follows the Erdős–Rényi model $G(n,p)$ (Erdős and Rényi, 1960), where a link between each distinct pair of households in a given country is established with probability $p = \frac{\ell}{LS-1}$, and $n = LS$ denotes the number of households in the national network. A more detailed description of resulting networks is provided in Appendix B.2.

As opinion dynamics are known to be influenced by the underlying social network structure (i.e., mixing pattern and linkage rules) (Sîrbu et al., 2017), we additionally consider alternative algorithms for network construction and investigate sensitivity to the average degree ℓ in Sections 5.1 and 5.4. Specifically, we explore homophily-based social networks where households interact more closely with others who share similar attributes including social class, policy opinion and employment status. To disentangle the effect of topology and homophily, we compare resulting opinion dynamics to the case of random networks that preserve the degree sequence of the corresponding homophilic social network.

3.1.3. Timeline of events

As motivated in Section 3.1, individuals may change their opinion on climate change mitigation policy to adjacent opinion types depending on (i) individual economic conditions, (ii) perceived evidence of climate change, (iii) lobbying influence and (iv) social influence. Households may directly react to macroeconomic costs of mitigation policy if they become unemployed. They perceive evidence of climate change based on the mean surface temperature increase which depends on cumulative anthropogenic emissions in the atmosphere and leads to more frequent and severe extreme weather events. Depending on the political power dynamics between the fossil fuel- and renewable-based asset holders, households are targeted with industry-led (dis-)information campaigns aimed at influencing people's awareness of climate change. Finally, the influence of peers within the social network can either reinforce or weaken the effect of the individual determinants for one's policy opinion. Hence, we specifically account for the fact that individuals are embedded in several interconnected spheres (i.e., economic, climate, political and social) which change over time and affect public policy support. During each time step, individuals may change their policy opinion to adjacent opinion types, determined by the interaction of the four channels.

At each time step t, the following sequence of events is computed which are described in more detail below. First, external information from the economic and environmental spheres is updated. Second, people's tendency to adjust individual climate change concern based on short-term economic conditions can negatively influence the policy opinion of the unemployed. Third, increasingly emerging signals of climate change in individuals' everyday experience may influence households' policy opinion via changes in risk perception, but humans' cognitive biases such as the shifting baselines effect or biased assimilation might well complicate their perception of climate change. Fourth, powerful incumbents in the energy sector lobby against more stringent climate policies trying to refute or obstruct scientific evidence of anthropogenic climate change. As climate policies proceed, strong interests of renewable-based asset holders can emerge who lobby for increased awareness of climate change and more stringent climate policy. Fifth, individuals may be influenced via exchanges within their social network, where current social norms are costly to violate but can shape public opinion over the long run. Finally, it is the interaction of the four channels that determines whether a household ultimately updates its policy opinion or not.

3.1.4. Update external information from economic and environmental spheres (DSK)

Steps 2–4 above reflect how changes in the (politico-)economic and environmental spheres may feedback to opinion dynamics about climate policy in the population. Therefore, the opinion dynamics model first updates relevant exogenous variables (i.e., mean surface temperature increase ΔT_t, change in the unemployment rate $\hat{U}_t$ and share of green/fossil assets in the energy sector $\rho_{tp,t}$) and translates the change in the unemployment rate to the level of individual households. As we will demonstrate in this study, these variables which are exogenous in the opinion dynamics model can be empirical data (e.g., to validate the model) or endogenous variables of an IAM (e.g., to study the interrelation between climate policy scenarios and opinion dynamics). The change in employment is mapped to the individual household level via a two-step procedure to differentiate between employee- and job-turnover. First, the employee-turnover measures the rate at which employees leave their company and are replaced by new employees in a given year (Eurostat, 2024). In the model, ETO_t randomly selected employees, drawn from a uniform distribution, become unemployed, whose positions are subsequently replaced by randomly selected unemployed households, where

$$ETO_t = toL_t \tag{2}$$

The turnover rate is denoted by to and L_t denotes the number of employed households at time t. Second, the job-turnover measures the net change in employment between two points in time (i.e., total number of jobs created less the number of jobs which have disappeared in a given year). If the change in the unemployment rate is positive (i.e., $\hat{U}_t \geq 0$), JTO_t randomly selected employees, drawn from a uniform distribution become unemployed. Otherwise, JTO_t unemployed households are randomly selected to get a job.[6]

$$JTO_t = |\hat{U}_t| LS \tag{3}$$

3.1.5. Macroeconomic transition costs

Macroeconomic transition risks of climate policy may materialize and influence public support for climate policy via unemployment. Each household i may decrease her policy opinion based on

$$unem_{i,t} = \begin{cases} \nu & \text{if } es_{i,t} = 1 \\ 0 & \text{if } es_{i,t} = 0 \end{cases} \tag{4}$$

where the parameter $\nu \in (-1, 0)$ denotes the unemployment impact.

3.1.6. Climate change perception

The climate change perception feedback allows households to change their policy opinion in response to experienced climate change. However, humans are known for their imperfect cognition. Following Moore et al. (2022), we account for the presence of the shifting baseline effect according to which the evaluation of the mean surface temperature increase compared to pre-industrial ΔT_t may change over time as older conditions are forgotten. In the presence of the shifting baseline effect (modelled as a dummy variable $Base$ with value 1), the mean surface temperature increase is perceived only relative to a baseline of a weighted average over the last 2–8 years, allowing for a quick update of perceived normal conditions based on recent experience. Hence, temperature increase ΔT_t may be conceived imperfectly as ΔT_t^*, where

$$\Delta T_t^* = \begin{cases} \Delta T_t & \text{if } Base = 0 \\ \Delta T_t - \sum_{i=8}^{2} \beta_i \Delta T_{t-i}, & \text{if } Base = 1 \end{cases} \tag{5}$$

Note that β is a vector denoting the parametrization of the weighted average in the shifting baselines effect which are taken from Moore et al. (2019, 2022). Each household i perceives climate change which may influence its policy opinion via

$$cc_{i,t} = \eta \Delta T_t^* \tag{6}$$

where the parameter $\eta \in (0, 1)$ denotes the climate change evidence effectiveness which measures the strength of this channel.

3.1.7. Lobbying

The energy sector is assumed to spend constant annual real funds to influence public concern about climate change. Hence, lobbyists target households but the distribution of funds across the two lobbyist groups changes over time with their asset holdings in the energy sector. Their relative lobbying power $\rho_{tp,t}$ is assumed to be proportional to their asset holdings in the current production capacity. In fact, $\rho_{t,F} LS$ randomly selected households, drawn from a uniform distribution, receive the fossil fuel-based industry-led (dis-)information campaign. Each household i may decrease its support for climate policy via the fossil lobbying influence

$$Flob_{i,t} = \begin{cases} -\lambda & \text{if } U_{i,t}^F < \rho_{t,F} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

where $\lambda \in (0, 1)$ denotes the lobbying impact parameter and $U_{i,t}^F$ is a random draw from a uniform distribution $U(0, 1)$. The renewable-based industry-led (dis-)information campaign may positively influence the targeted households' policy opinion and is implemented analogously with

$$Rlob_{i,t} = \begin{cases} \lambda & \text{if } U_{i,t}^R < \rho_{t,R} \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

3.1.8. Social influence

Social conformity represents a social pressure or persuasive force which may induce individuals to change their policy opinion based on interactions within their social network. Each household i (implemented by a loop over all households in random order) exchanges views on climate policy with a randomly selected neighbour j who may influence i's opinion via social influence

$$soc_{i,t} = \begin{cases} 0 & \text{if } op_{i,t} = op_{j,t} \\ F & \text{if } op_{i,t} < op_{j,t} \\ -F & \text{if } op_{i,t} > op_{j,t} \end{cases} \tag{9}$$

where $F \in (0, 1)$ denotes the persuasive force parameter.

[6] The number of unemployed is expressed by $(LS - L_t)$.

Table 2
Opinion dynamics model parameters. The empirically calibrated parameter estimates for F, η, ν, λ and corresponding 95% confidence intervals are based on an estimation using a random forest algorithm with the help of the "freelunch" package by Carrella (2021). Note that the assumed average degree ℓ roughly corresponds to the size of an individual's support clique in general social networks (Dunbar and Spoors, 1995). Employee turnover varies across various dimensions (e.g. occupation, sector, gender, age, education, country) and is chosen to represent a reasonable value in the mid-range documented by Eurostat (2024).

	Description	Parameter values	Calibration
LS	Number of households	24,603	Eurobarometer survey respondents (European Commission, 2019)
ℓ	Average degree	4	Dunbar and Spoors (1995)
to	Employee turnover	0.07	Eurostat (2024)
F	Persuasive force	$\in (0,1)$	0.127 [0, 0.246]
$Base$	Shifting baselines	$\begin{cases} 1 & \text{if on} \\ 0 & \text{if off} \end{cases}$	Moore et al. (2022)
$\vec{\beta}$	Parametrization of shifting baselines	$(0.23, 0.2, 0.17, 0.14, 0.11, 0.09, 0.06)$	Moore et al. (2019, 2022)
η	Climate change evidence impact	$\in (0,1)$	0.255 [0.152, 0.361]
ν	Unemployment impact	$\in (-1,0)$	−0.145 [−0.608, 0]
λ	Lobbying impact	$\in (0,1)$	0.019 [0, 0.081]

Table 3
Opinion dynamics model inputs.

	Description	DSK variable	Value
ΔT_t	Mean surface temperature increase [°C]	$\Delta Temp_t$	$\in (-0.7, 6)$
$\hat{U}_t$	Change in the unemployment rate	$\hat{U}_t$	$\in (0,1)$
$\rho_{F,t}$	Share of fossil assets in the energy sector	$\frac{\mathfrak{K}^{de}_{e,t}}{\mathfrak{K}_{e,t}}$	$\in (0,1)$
$\rho_{R,t}$	Share of green assets in the energy sector	$\frac{\mathfrak{K}^{ge}_{e,t}}{\mathfrak{K}_{e,t}}$	$\in (0,1)$

3.1.9. Update climate policy support

The interaction of the four channels determines whether a household i in country k will ultimately change its opinion about climate policy. Specifically, each household updates its policy opinion based on the probability measure

$$p_{i,t} = unem_{i,t} + cc_{i,t} + Flob_{i,t} + Rlob_{i,t} + soc_{i,t} \tag{10}$$

The opinion next period becomes

$$op_{i,t+1} = \begin{cases} op_{i,t} + 1 & \text{if } p_{i,t} \geq 0,\ op_{i,t} < 3,\ B(p_{i,t}) = 1 \\ op_{i,t} - 1 & \text{if } p_{i,t} < 0,\ op_{i,t} > 1,\ B(|p_{i,t}|) = 1 \\ op_{i,t} & \text{else} \end{cases} \tag{11}$$

where $B(p)$ denotes a random draw from a Bernoulli distribution with parameter p. Thus, only if the positive influences outweigh the negative ones and the probability measure is positive, a household may increase its policy support. Likewise, if the negative influences outweigh the positive ones, the probability measure is negative and the individual household may decrease its policy opinion. Table 2 provides an overview of the model parameters including the calibrated values. Table 3 summarizes the exogenous model inputs which we first obtain from empirical data to calibrate the model parameters and then obtain from the coupled climate-macroeconomic module (DSK-SFC model) to simulate opinion dynamics for a variety of climate policy scenarios. A detailed description of the calibration procedure and empirical validation is provided in the next Section 3.2 and in Section 4.1, respectively.

3.2. Calibration of the OD model

We calibrate the opinion dynamics model by fitting it to the observed empirical dynamics in the EU countries over the period 2011–2019. To this end, we combine the 2011, 2013, 2015, 2017 and 2019 waves of the European Commission's Eurobarometer Survey (GESIS, 2023) which monitors public opinion and includes information about the unemployment status of each respondent, hence approximating the share of unemployed per country (and $\hat{U}_t$ in the model). We take into account 26 countries which have been a member both in 2011 and at the writing of this article (i.e., all – as of 2024 – current members minus Croatia). We link this dataset with data on the global temperature anomalies with respect to the 1901–2000 average (ΔT_t, for Environmental Information, 2023) and country specific shares of energy from renewable sources as percentage of gross final energy consumption (Eurostat, 2023) to proxy $\rho_{R,t}$ and $\rho_{F,t} = 1 - \rho_{R,t}$.

We then initialize our model using data from 2011 and search for the parameter combination that best reproduces the dynamics until 2019 (i.e., the end of the calibration period). In doing so, we employ the reference table algorithms implemented in the "freelunch" package for R by Carrella (2021). Specifically, we draw 50,000 parameter combinations, where each parameter (i.e., persuasive force F, climate change evidence effectiveness η, unemployment impact ν, lobbying impact λ) is drawn from a uniform distribution between 0 and 1 (or, in the case of ν, between −1 and 0). We then use each combination to run the model separately for each country with a 1:1 representation of survey participants and agents in our model. Afterwards, we try to estimate the set of parameters that best reproduces the empirical patterns of the weighted means of supporters, opponents and neutrals in the EU countries in the years of 2013, 2015, 2017 and 2019. To do so, we try to use each of the following algorithms implemented by Carrella (2021): OLS, Random Forest, Quantile Random Forest, Rejection ABC, loclinear ABC, Semiautomatic ABC, GAM and Neural Network ABC.[7] The results of the empirical calibration and validation are described in Section 4.1.

3.3. The Dystopian Schumpeter meeting Keynes model

The *Dystopian Schumpeter meeting Keynes model* (DSK) (Lamperti et al., 2018) is a macroeconomic agent-based integrated-assessment model born within the *Schumpeter meeting Keynes* (K+S) family (Dosi et al., 2010), which extends the macroeconomic structure of the K+S by incorporating a stylized energy sector and a climate box. The DSK represents one of the first attempts to produce a macroeconomic agent-based model (MABM) with an integrated assessment element and an energy sector (Ponta et al., 2018; Rengs et al., 2020; Ciola et al., 2023), constituting an important step forward in the ecological and energy economics literature. Indeed, MABMs offer significant advantages relative to other energy or climate macroeconomic models. For example, by encompassing both short and long-run dynamics within a single framework MABMs enable the study of the effects of climate shocks and transition policies at business cycle frequencies, which is not possible with traditional IAMs. Moreover, MABMs allow for investigating long-term growth effects, which are challenging to capture in traditional business cycle macro models, such as Dynamic Stochastic General Equilibrium Models (DSGEs).[8] MABMs also allow for out-of-equilibrium dynamics, which are of particular interest when studying the effect of potentially disruptive shocks and thanks to their inherent micro disaggregation they are particularly well-suited for studying distributional consequences of climate and energy shocks.

More specifically, we use the most recent DSK vintage denominated DSK-SFC (Reissl et al., 2024) where the model accounting system has been thoroughly revised and harmonized with the stock-flow consistent paradigm (Godley and Lavoie, 2006), which is nowadays a cornerstone in macro agent-based modelling (Caiani et al., 2016). This has improved the model's ability to track financial flows across economic agents and sectors, enhancing the integration between the financial and real sides of the model.

3.3.1. DSK-SFC: the model in a nutshell

In this section, we offer a brief overview of the model, emphasizing the key sectors and behavioural rules crucial for understanding the specific application outlined in the paper. A more comprehensive model description is available in Appendix D and in the original DSK description (Lamperti et al., 2018; Reissl et al., 2024).

The model comprises a consumption goods sector wherein consumption firms (C-Firms) engage in the production and sale of a homogeneous good utilizing labour, physical capital and energy. C-Firms invest in physical capital to uphold a productive capacity aligned with expected demand and ask for credit whenever internal resources prove insufficient to finance planned production and investment.

Capital items are purchased from the capital goods sector, where capital firms (K-Firms) manufacture them utilizing labour and energy. These capital items exhibit heterogeneity in terms of embedded labour productivity, energy efficiency and emission intensity. Consequently, capital items of distinct technological vintages incur varying production costs for C-Firms. In the pursuit of profit (imperfect) maximization, K-Firms innovate their production techniques for greater efficiency, as well as their supplied capital vintage to enhance attractiveness in the capital market.

The energy sector is consolidated into one single agent that produces energy through a combination of renewable and fossil fuel-based technologies. The energy sector innovates its production technology to reduce production and installation costs and invests in green capital stock whenever it proves cost-effective compared to fossil fuel-based technologies.

The household sector is aggregated in a single agent who consumes and receives income in the form of wages, unemployment benefits, government transfers, interests on deposits, and dividends from the private sector.

The government levies taxes on profits and income, collects the carbon tax, pays unemployment benefits, provides transfers to households and firms, and emits bonds to finance public deficits.

Finally, banks extend credit to C-Firms, buy government bonds, and take deposits of firms and households. The central bank sets the policy rate and clears the bond market whenever supply exceeds demand.

Households Households are represented as an aggregated entity, whose size coincides with the total labour supply.[9] They acquire income through various channels, including labour income, unemployment benefits, dividends from firms, banks, and the energy sector, and occasional lump-sum transfers from the government (see Section 3.4.2). Aggregate nominal demand is a function of households' income and wealth:

$$C_{d,t} = \alpha_1(W_t + UB_t + TR_t^H - Tax_t^H) + \alpha_2(Div_{t-1} + iD_{h,t}) + \alpha_3 D_{h,t-1} \tag{12}$$

Where W_t is the total wage bill, UB_t are unemployment benefits, TR_t^H are government transfers, Tax_t^H are taxes, and α_1 is the exogenous propensity to consume out of labour income; Div_{t-1} are dividends, $iD_{h,t}$ are interest payments on deposits, and α_2 is the exogenous propensity to consume out of dividend and capital income; $D_{h,t-1}$ is the stock of deposits held by households and α_3 is the exogenous propensity to consume out of wealth.[10] We posit $\alpha_1 > \alpha_2$, indicating a greater propensity to consume out of labour income compared to dividends and capital income.[11] Additionally, we assume that government transfers are treated akin to wages, implying their allocation towards workers.

[7] Note that loclinear ABC produced estimates which were drastically out of bounds and thus had to be discarded in the subsequent analysis.

[8] See Benigno and Fornaro (2018) for an attempt to introduce economic growth in an otherwise standard DSGE framework.

[9] Note that the labour supply in the DSK does not directly relate to the Eurobarometer survey which we use to initialize the households in the opinion dynamics model. For the sake of simplicity, we chose the consistent notation across the two models LS to denote the total number of households in the opinion dynamics model and the total labour supply in the DSK.

[10] Note that households' wealth is held exclusively in the form of bank deposits.

Consumption good firms C-Firms plan production to meet expected demand. This planned production guides investment decisions and determines the corresponding labour demand. Once production happens and C-Firms inventory stock has been replenished, prices are set as markups over the unit cost of production:

$$p_{c,t} = (1 + \mu_{c,t}) uc_{c,t} \tag{13}$$

Where $p_{c,t}$ is the price set by firm c in time t, $\mu_{c,t}$ is the mark-up, and $uc_{c,t}$ is the unit cost of production. Since each capital vintage κ available to firm c embeds its own unit costs of production $uc_{\kappa,t}$, the unit cost of production $uc_{c,t}$ faced by firm c is a weighted average defined as:

$$uc_{c,t} = \sum_{\kappa \in \Phi^{u}_{\kappa,c,t}} uc_{\kappa,t} \frac{\mathfrak{K}_{\kappa,c,t}}{\mathfrak{K}_{c,t}} \tag{14}$$

Where $\Phi^{u}_{\kappa,c,t}$ is the set of vintages available to firm c actually employed in production, $\mathfrak{K}_{\kappa,c,t}$ is the amount of production achieved by κ when employed at full capacity, and $\mathfrak{K}_{c,t}$ is c's productive capacity. Finally, each $uc_{\kappa,t}$ is determined by the technical characteristics of vintage κ (labour productivity and energy efficiency) and the factor prices:

$$uc_{\kappa,t} = \frac{w_t}{Pr_\kappa} + \frac{p_{e,t}}{EE_\kappa} \tag{15}$$

Where w_t is the wage rate, Pr_κ is the κ-specific labour productivity, $p_{e,t}$ is the energy price, and EE_κ is the κ-specific energy efficiency.

Energy sector The energy sector, represented by a single agent, provides energy to K and C-Firms using a blend of green and brown technologies. Following the original DSK framework, we assume that green technology is emission-free, with zero production costs but a positive expansion cost. In contrast, brown technologies embed an emission intensity, incur fossil fuel and carbon tax operating costs, and involve costless expansion investments. Furthermore, the model allows for different vintages of green and brown technologies. Among green technology vintages, variations exist in the embedded unit cost of production, whereas for brown technology vintages, distinctions arise in thermal efficiency, as well as emission intensity.

The energy sector employs an on-demand production system with a preference for lower-cost technology vintages over higher-cost ones. Consequently, brown technologies are activated only after green ones. The uniform energy price charged to K and C-Firms reflects marginal pricing and is given by:

$$p_{e,t} = \mu_{e,t} + mc_{e,t} \tag{16}$$

Where $\mu_{e,t}$ is a markup, which is assumed to grow at the same pace as nominal wages, and $mc_{e,t}$ is the production cost embedded in the marginal vintage employed in production.

The total productive capacity in the energy sector, $\mathfrak{K}_{e,t}$, is the sum of brown capacity, $\mathfrak{K}^{de}_{e,t}$, and green capacity, $\mathfrak{K}^{ge}_{e,t}$. The energy sector adjusts its productive capacity by investing to meet actual demand. When investing, the sector must decide whether to increase brown or green capacity based on the relative profitability of available vintages at each point in time. Let us call the installation cost of green capital belonging to vintage κ^{ge} $c_{\kappa^{ge}}$ and the operation cost of brown capital belonging to vintage κ^{de} $c_{\kappa^{de}}$, with:

$$c_{\kappa^{de},t} = \frac{p_{f,t-1}}{TE_{\kappa^{de}}} + \tau^{Em,E}_t EF_{\kappa^{de}} \tag{17}$$

Where $p_{f,t-1}$ is the fossil fuel price, $TE_{\kappa^{de}}$ is the thermal efficiency, $\tau^{Em,E}_t$ is the carbon tax, and $EF_{\kappa^{de}}$ is the emission intensity. Then, the energy sector compares the operation cost of the most efficient brown vintage ($c^{min}_{\kappa^{de}}$) with the installation cost of the best green vintage ($c^{min}_{\kappa^{ge}}$) and invests in brown capital whenever the following condition is met:

$$c^{min}_{\kappa^{de},t} < \frac{c^{min}_{\kappa^{ge},t}}{b^e} \tag{18}$$

Where b^e is a payback period parameter. Conversely, if the condition in Eq. (18) is not satisfied, the energy sector is motivated to invest entirely in green capital. However, there is a limit to the amount of green investment allowed at each point in time. We assume this limit to be a proportion ς^e_t of the existing green capital, net of depreciated green capital. The maximum green investment is thus $\varsigma^e_t \mathfrak{K}^{ge}_{t-1} + scrap^{ge}_{t-1}$, with $scrap^{ge}_{t-1}$ representing the green capital scrapped right before investment occurs. Unlike former DSK applications, we endogenize ς^e_t, linking the limit of green investment to the profitability differential between brown and green capital:

$$\varsigma^e_t = \arctan\left(A^{\varsigma} \frac{c^{min}_{\kappa^{de},t} b^e - c^{min}_{\kappa^{ge},t}}{c^{min}_{\kappa^{ge},t}} \right) \tag{19}$$

Where A^{ς} is a scaling parameter.

[11] We implicitly assume that capital income is mostly concentrated at the top of the personal income distribution (Ranaldi, 2022) and that the propensity to consume out of income is decreasing in the relative income (Kaldor, 1955; Duesenberry, 1962; Dynan et al., 2004).

Climate box The model comprises a climate box which translates cumulative emissions into global temperature anomaly. Since the model is calibrated to resemble to European economy (see Section 3.3.2), only a fraction of emissions are generated endogenously, whereas the rest is assumed exogenous, representing emissions coming from the rest of the world. We assume a linear relationship between cumulative emission and temperature anomaly, such that:

$$Temp_t = Y_1 + Y_2 \mathscr{E}_t^{\Sigma} \tag{20}$$

Where $\mathscr{E}_t^{\Sigma}$ are cumulative emissions up to period t; Y_1 is the exogenous temperature anomaly intercept; Y_2 is the exogenous temperature anomaly sensitivity to cumulative emissions.

3.3.2. DSK-SFC: calibration

The calibration of the DSK model aims to capture the qualitative features and empirical patterns typical of a European Union-like economy—i.e., an advanced economy with limited natural resources and a relatively modest share of global emissions. Specifically, the climate module is calibrated to ensure that global emissions align with the temperature anomaly projections for 2020–2100 as described in the IPCC AR6 scenario database (Byers et al., 2022)[12] (see Table F.1 in Appendix F). The fossil fuel sector is modelled as an external entity. It trades with the energy sector, and notably, it contributes its revenues to the domestic economy by a negligible amount (see Appendix D.5). Consequently, expenditures on fossil fuels are effectively treated as imports. Total emissions are the sum of endogenously generated emissions and exogenous emissions coming from the foreign sector. The pattern and magnitude of external/exogenous emissions are calibrated to qualitatively match the EU27 share of global emissions.

As is customary in the MABM literature, we conduct a quarterly calibration of the model. This process aims to produce time series data for major macroeconomic aggregates consistent with well-established macroeconomic stylized facts at business cycle frequency and growth rates. Table F.1 and Figure F.1 in Appendix F describe our validation results from 100 simulation runs, where each simulation contains a 200-period transient discarded from the analysis. The model produces auto- and cross-correlations functions for the filtered time series which are broadly in line with the data. Volatilities respect the hierarchical order observed in real-world time series, with investment being more volatile than GDP, consumption and inflation. However, unemployment and investment turns out to be too much volatile relative to GDP compared to what is usually found empirical data. Finally, our simulated economy grows at an average rate broadly in line with an SSP2 scenario for European countries under the current climate policy framework.

3.4. Climate and stabilization policies

We impose a battery of different carbon tax scenarios and relative green transition paths on the DSK-SFC. In a nutshell, we design a carbon tax whose real value increases linearly in time. Moreover, we impose a starting point in time for the carbon tax, an initial value, and a predefined maximum real value that the carbon tax can achieve. We then generate a variety of carbon taxes by changing the slope of the carbon tax increase and its initial value for various starting times. The transition speed is endogenous with respect to the particular carbon tax implemented. Moreover, different carbon taxes feedback differently in the macroeconomic dynamics, implying different macroeconomic costs and opinion dynamics over the transition period.

As a next step, we test whether carbon tax revenue recycling may strengthen public support for effective carbon taxation over the transition period. More specifically, we evaluate the role of earmarking a certain share of revenues from carbon taxation to be directly returned back to society via lump-sum transfers to households.

Finally, we investigate the effect of subsidizing green investment in the energy sector. We assume that the government commits to subsidize a certain share of green investment in every period and determines a share of carbon tax revenues to be recycled back to society when preparing the government budget. However, the government only pays climate dividends to households if total earmarked carbon tax revenues exceed the promised subsidy for the energy sector.

3.4.1. Carbon tax

The government imposes a carbon tax on the energy sector, whose corresponding revenue is:

$$CTAX_t = \tau_t^{Em,E} Em_{E,t} \tag{21}$$

Where $\tau_t^{Em,E}$ is the monetary amount charged per unit of emission and $Em_{E,t}$ are emissions generated by the energy sector.[13]

The carbon tax takes effect at a given point in time, t_0^{clim}, and increases linearly in real terms thereafter:

$$\begin{cases} \tau_t^{Em,E} = 0 & \text{If} \quad t < t_0^{clim} \\ \tau_t^{Em,E} = \frac{cpi_{t-1}}{cpi_0} min\left\{ \tau^{Em,E,max}, \quad \left[\tau_{t_0^{clim}}^{Em,E} + g^{\tau,Em}\left(t - t_0^{clim}\right) \right] \right\} & \text{Otherwise} \end{cases} \tag{22}$$

Where $\tau^{Em,E,max}$ denotes the real maximum value attainable by the carbon tax, cpi_t represents the general price level at time t, and $\tau_{t_0^{clim}}^{Em,E}$ is the initial carbon tax value.

A carbon tax profile is characterized by the pair $(t_0^{clim}, g^{\tau,Em})$, indicating both the introduction time of the carbon tax and its linear trend.

[12] We consider different carbon budget scenarios, ranging from 400 to 3000 $GtCO_2$.

[13] Total emissions in the energy sector are determined by the amount of brown capital utilized in a specific period and the vintages involved. In particular, the emission intensities associated with the vintages employed in energy production play a pivotal role in determining total emissions.

Table 4
Overview of 133 simulated policy scenarios: 25 pure carbon tax schemes, 27 carbon tax scenarios with climate dividends, 81 carbon tax with hybrid revenue recycling schemes. Note that different revenue recycling schemes were simulated only for ambitious tax schemes that combine t_0^{clim} and $g^{\tau,Em}$ which are indicated with an asterisks.

Carbon tax scheme				
Introduction time t_0^{clim}				
2020*	2025*	2030*	2035	2040
Linear trend $g^{\tau,Em}$				
very low	low	medium*	high*	very high*
1×10^{-6}	5×10^{-6}	1×10^{-5}	5×10^{-5}	1×10^{-4}
Revenue recycling scheme				
Share of total carbon tax revenues earmarked for redistribution ρ^{ctax}				
0	0.1	0.5	1	
Green subsidies ρ^{gsubs}				
	0	0.2	0.5	0.8
No recycling	Climate dividends	Green investment subsidies and climate dividends		
$\rho^{ctax} = 0$	$\rho^{ctax} > 0$	$\rho^{ctax} > 0$		
$\rho^{gsubs} = 0$	$\rho^{gsubs} = 0$	$\rho^{gsubs} > 0$		

3.4.2. Carbon tax recycling

Carbon tax revenues can be recycled in the economy through lump-sum transfers to workers or green investment subsidies to the energy sector. In our recycling experiments, we assume that a fraction ρ^{ctax} of total carbon tax revenues is reinstated into economic circulation by the government.

In the first battery of policy experiments, we assume no green investment subsidies but explore different configurations of lump-sum recycling to households, i.e., different ρ^{ctax} values. In this policy experiment the lump-sum transfer to households is therefore defined as:

$$TR_t^H = \rho^{ctax} CTAX_{t-1} \tag{23}$$

In a subsequent round of policy experiments, green subsidies are introduced. This involves the government providing an amount equal to a specified percentage of green investment as a tax rebate to the energy sector. Funded by the carbon tax revenue, this subsidy results in a reduction in the amount of transfers directed to workers:

$$\begin{cases} TR_t^E = \rho^{gsubs} c_{\kappa^{ge}}^{min} EI_t^{ge} \\ TR_t^H = \rho^{ctax} CTAX_{t-1} - TR_t^E \end{cases} \tag{24}$$

Where $c_{\kappa^{ge}}^{min}$ is the unit cost of green investment, EI_t^{ge} is green investment, and therefore $c_{\kappa^{ge}}^{min} EI_t^{ge}$ is the nominal green investment. Note that ρ^{gsubs} directly lowers the cost of investing in green capital, and therefore the profitability of green technologies relative to brown ones. It follows that the limit to green investment specified in Eq. (19) can be rewritten as:

$$\varsigma_t^e = \arctan\left(A^{\varsigma} \frac{c_{\kappa^{de},t}^{min} b^e - (1 - \rho^{gsubs}) c_{\kappa^{ge},t}^{min}}{(1 - \rho^{gsubs}) c_{\kappa^{ge},t}^{min}} \right) \tag{25}$$

Table 4 provides an overview of the 133 carbon tax scenarios considered in this analysis. We study 25 pure carbon tax schemes that are characterized by the pair $(t_0^{clim}, g^{\tau,Em})$. For the nine ambitious carbon tax schemes, whose introduction time t_0^{clim} and linear trend $g^{\tau,Em}$ are indicated with an asterisks in Table 4, we apply a battery of different revenue recycling schemes. Specifically, we investigate the effect of three different configurations of climate dividends and nine configurations of hybrid revenue recycling that combines green subsidies and climate dividends.

4. Results

4.1. Calibration and validation of the OD model

As a start, we validate our approach by conducting an empirical analysis based on OLS and fixed effects models using the data that we employ to calibrate our model (as described in Section 3.2). To do so, we use the stacked data set of the Eurobarometer survey (GESIS, 2023) 2011–2019 and couple it with the country-level data on the share of green energy capacity, as well as with data on temperature anomalies to estimate six different models, all using the individual's climate change concern (which we use in our agent-based model to proxy the individual's stance on climate policy) as a dependent variable.

Table 5 reports the estimation results using the “fixest” package for R (Bergé, 2018). The standard errors in (2), (3), (5) and (6) are clustered by the country. We find evidence for all channels that we hypothesize based on the literature discussed in section 3.1: First, social influence: A higher share of opponents in the previous period decreases the climate change concern in the current period. This effect is statistically significant across all of our specifications. Furthermore, we find a significant positive effect of the share of supporters in the previous period in the absence of country fixed effects.

Second, while we do not find a significant “direct effect” of unemployment (i.e., unemployed are not significantly less likely concerned about climate change when controlling for the other factors), we do find a negative 'social effect' of unemployment when accounting for country fixed effects. This means that a higher rate of unemployment in the previous observation period decreases climate change concern in the current period.

Third, we observe that respondents who live in countries which have a higher capacity share of green energy are significantly more concerned about climate change when accounting for country fixed effects. We argue that this proxies the impact of lobbying.

Finally, we find that responses in years which are hotter are on average more concerned about climate change. However, this effect is not statistically significant when accounting for country fixed effects. In the baseline analysis shown in Table 5, we rely on global temperature anomalies. However, we explore the impact of using EU-level or national temperature anomalies in Appendix A. While our results are similar for EU-level temperature anomalies, the impact of country-level temperature anomalies is not statistically significant when clustering the standard errors by country.

In addition to the four channels in our model, we find evidence that the climate change concern varies with self-described social class. In particular, self-described middle-class, upper-middle class and (in most specifications) upper-class survey respondents exhibit significantly higher climate change concern than self-described lower-class respondents. One reason for this dynamic could be that lower-class respondents perceive a trade-off between their (economic) welfare and climate change mitigation policies, and are less likely to be able to ‘afford’ the latter. Another potential explanation why we may observe class-specific differences (or why they are pronounced) could be social homophily. If people who perceive themselves to belong to the middle-class or above are more concerned about climate change and more likely connected to other people with a similar social background, homophily could multiply this effect within this group of the population. This is why we explore how our agent-based model behaves in a homophilic network instead of a random network in Section 5.4.

This simple, preliminary empirical analysis encourages us to calibrate our opinion dynamics model with the same data.

As described in Section 3.2, we employ the “freelunch” package by Carrella (2021) for the programming language R to empirically calibrate our model. We test all eight algorithms provided by this package (OLS, Random Forest, Quantile Random Forest, Rejection ABC, loclinear ABC, Semiautomatic ABC, Neural Network ABC and GAM) and rank them according to the ability of the point estimates to reproduce the empirical patterns. Following Carrella (2021), we further also conduct a 5-fold cross-validation exercise to investigate the ability of the estimation procedures to predict simulated data when trained with a different subset of the simulations and present the results in Appendix C.

Table 6 shows the point estimates and 95% confidence interval produced by each algorithm, as well as the RMSE. We calculate the RMSE according to Eq. (26), where N_t is the weighted mean of neutrals in all EU countries in a given year (i.e., $N_t = \sum_i w_i n_{i,t}$). The weights w_i are derived from the Eurobarometer variable 'weight EU28' which seek to weight each survey response in a way that it is representative for the whole EU. Similarly, S_t denotes the weighted mean of supporters and O_t the weighted mean of opponents in year t. Likewise, N_t^{emp}, S_t^{emp}, O_t^{emp} denote the weighted EU-wide empirical shares of neutrals, supporters and opponents:

$$RMSE = \sqrt{\frac{1}{3t}\sum_t((S_t - S_t^{emp})^2 + (O_t - O_t^{emp})^2 + (N_t - N_t^{emp})^2)} \tag{26}$$

We run the model with each parameter combination obtained from the point estimates of the eight estimation procedures, as well as with a 'constant predictor' scenario, in which the opinions are static over time for each country with 1,000 different random seeds and calculate this RMSE for every random seed.

We report the point estimates and confidence intervals (both as produced by the “freelunch” package) and the mean and standard deviation of the RMSE as described above in Table 6. Since loclinear ABC produces clearly erroneous estimation results which are by far out of bounds and which perform the worst in terms of RMSE, we refrain from reporting them.

Fig. 2 shows simulated and empirical opinion dynamics – depicted by lines and dots respectively – for each country over the calibration period using the point estimates of the random forest regression algorithm. For many countries, e.g. Lithuania, Sweden, Belgium, Slovenia, Spain, Italy and Germany, opinion dynamics are replicated with high precision (i.e. $RMSE < 0.05$). For some countries including Slovakia, Cyprus, Latvia and Greece, we observe larger quantitative deviations (i.e. $0.09 < RMSE < 0.14$) but the qualitative dynamics are usually matched well. Notably, the RMSE of the total EU is much lower than the RMSE in every single country. This is because the model simultaneously overestimates the share of, e.g., neutrals in some countries and underestimates them in other countries.

4.2. Interaction between carbon tax schemes and public support over the transition period

A later introduction of the carbon tax t_0^{clim} implies that the full transition in the energy sector is achieved at a later point in time, while a higher slope of the carbon tax $g^{t,Em}$ accelerates the green transition. Similarly, the share of green assets in the energy sector starts growing with the introduction of the carbon tax, where steeper carbon tax pathways are associated with faster diffusion of green technologies in the energy sector which are assumed to increase the lobbying power of renewable based asset holders. To trigger a decarbonization process which is fast enough to comply with EU climate targets, extremely high carbon taxes are required

Table 5
Estimation results for the individuals' climate change concern in the Eurobarometer survey data from 2011–2019 using OLS and Fixed Effects models without and with clustering the standard errors by countries.

	Direct effect of unemployment			Social effect of unemployment		
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	6.933***	6.933***		6.983***	6.983***	
	(0.067)	(0.282)		(0.072)	(0.286)	
Unemployed	−0.011	−0.011	−0.021			
	(0.027)	(0.045)	(0.041)			
Unemployment rate in t − 1				−0.394*	−0.394	−3.050*
				(0.187)	(1.011)	(1.229)
Green capacity share	0.201***	0.201	9.324**	0.191**	0.191	8.933**
	(0.060)	(0.211)	(2.954)	(0.060)	(0.218)	(2.558)
Temperature anomaly	1.185***	1.185***	0.488	1.171***	1.171***	0.373
	(0.059)	(0.279)	(0.317)	(0.059)	(0.274)	(0.299)
Share of supporters in t − 1	1.052***	1.052*	0.105	1.054***	1.054*	−0.116
	(0.112)	(0.503)	(0.648)	(0.112)	(0.500)	(0.691)
Share of opponents in t − 1	−9.393***	−9.393***	−4.053*	−9.445***	−9.445***	−4.676**
	(0.204)	(0.803)	(1.495)	(0.206)	(0.801)	(1.371)
Lower-middle class	−0.018	−0.018	−0.022	−0.020	−0.020	−0.022
	(0.023)	(0.038)	(0.037)	(0.023)	(0.038)	(0.037)
Middle class	0.084***	0.084	0.093*	0.078***	0.078*	0.093*
	(0.015)	(0.042)	(0.037)	(0.015)	(0.037)	(0.037)
Upper-middle class	0.190***	0.190**	0.227***	0.182***	0.182**	0.234***
	(0.031)	(0.058)	(0.058)	(0.031)	(0.051)	(0.058)
Upper class	0.217***	0.217	0.242*	0.208***	0.208	0.235*
	(0.060)	(0.112)	(0.115)	(0.060)	(0.113)	(0.113)
Num.Obs.	96 649	96 649	96 649	96 649	96 649	96 649
R2	0.066	0.066	0.075	0.066	0.066	0.075
R2 Adj.	0.066	0.066	0.074	0.066	0.066	0.075
R2 Within			0.016			0.017
R2 Within Adj.			0.016			0.017
AIC	411 879.9	411 879.9	411 000.4	411 875.6	411 875.6	410 935.3
BIC	411 974.7	411 974.7	411 332.1	411 970.4	411 970.4	411 267.1
RMSE	2.04	2.04	2.03	2.04	2.04	2.03
Std.Errors	IID	by: country	by: country	IID	by: country	by: country
FE: country			X			X

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

Table 6
Parameter estimates and 95% confidence intervals for each algorithm and the RMSE produced when running the model 1,000 times with the point estimates, compared to a 'constant predictor' scenario in which opinions stay constant.

#	Algorithm	Persuasive Force	Evidence Effect	Unemployment Effect	Lobbying Effect	RMSE (mean)	RMSE (std. dev.)
1	Random Forest	0.127	0.255	−0.145	0.019	0.01620	0.00097
		(−0.004 – 0.246)	(0.152 – 0.361)	(−0.608 – 0.326)	(−0.032 – 0.081)		
2	Quantile Random Forest	0.11	0.262	−0.139	0.016	0.01870	0.00156
		(0.004 – 0.468)	(0.114 – 0.525)	(−0.563 – −0.007)	(0.001 – 0.06)		
3	Neural Network ABC	0.032	0.005	−0.281	−0.035	0.03779	0.00160
		(−0.029 – 0.116)	(−0.025 – 0.057)	(−0.529 – −0.032)	(−0.06 – −0.005)		
4	Rejection ABC	0.423	0.666	−0.47	0.097	0.03989	0.00209
		(0.015 – 0.972)	(0.174 – 0.985)	(−0.974 – −0.019)	(0.005 – 0.242)		
5	Constant Predictor	0.0	0.0	0.0	0.0	0.04151	0.00000
		(0.0 – 0.0)	(0.0 – 0.0)	(0.0 – 0.0)	(0.0 – 0.0)		
6	Semiautomatic ABC	0.593	0.525	−0.306	0.144	0.10591	0.00366
		(0.028 – 0.988)	(0.031 – 0.967)	(−0.942 – −0.011)	(0.004 – 0.665)		
7	GAM	−0.071	−0.117	−0.548	−0.036	0.12322	0.00195
		(−0.221 – 0.101)	(−0.197 – −0.026)	(−0.992 – −0.075)	(−0.096 – 0.032)		
8	Linear Regression	0.264	−0.181	0.515	0.147	0.22141	0.00304
		(0.042 – 0.599)	(−0.451 – −0.022)	(0.043 – 1.019)	(0.057 – 0.255)		

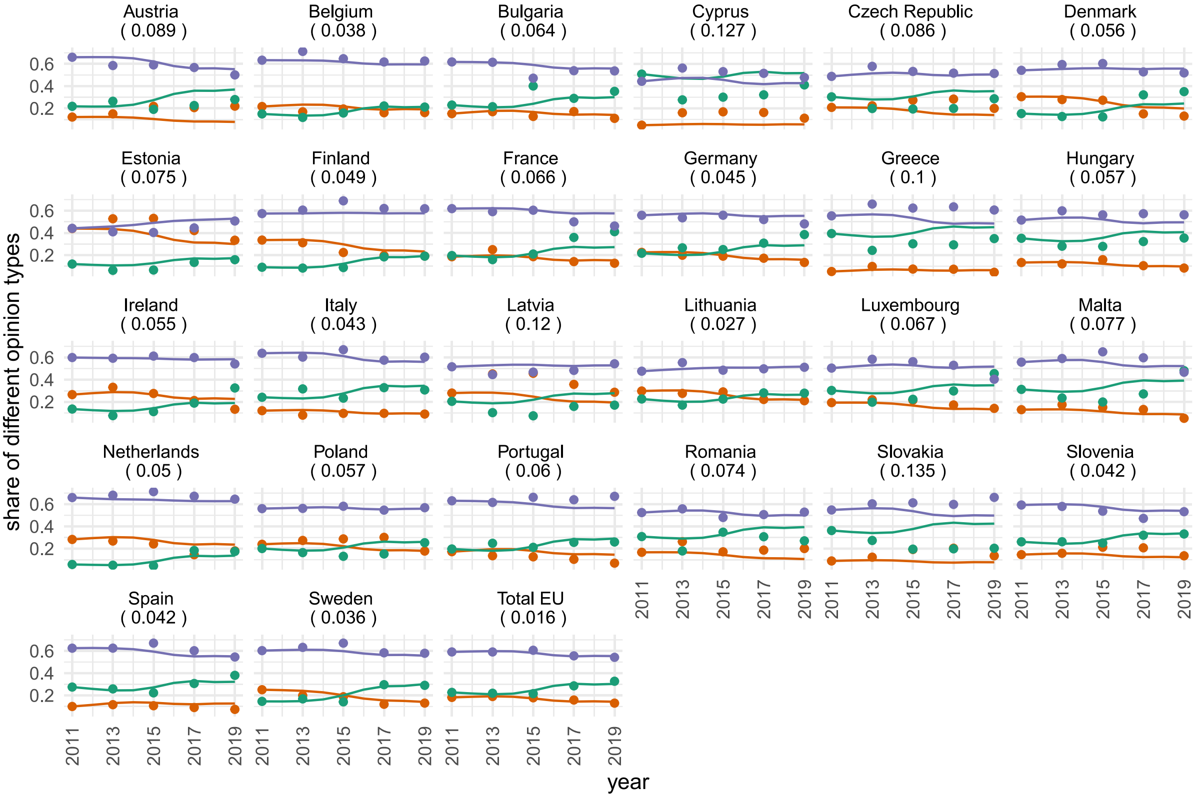


Fig. 2. Descriptive output validation of the opinion dynamics model based on random forest estimation. The RMSE is reported in parentheses. Purple indicates neutrals, green indicates supporters and orange indicates opponents. Lines represent simulated data (average of 100 Monte Carlo experiments), points correspond to Eurobarometer survey data. Total EU represents the population-weighted average of individual countries.

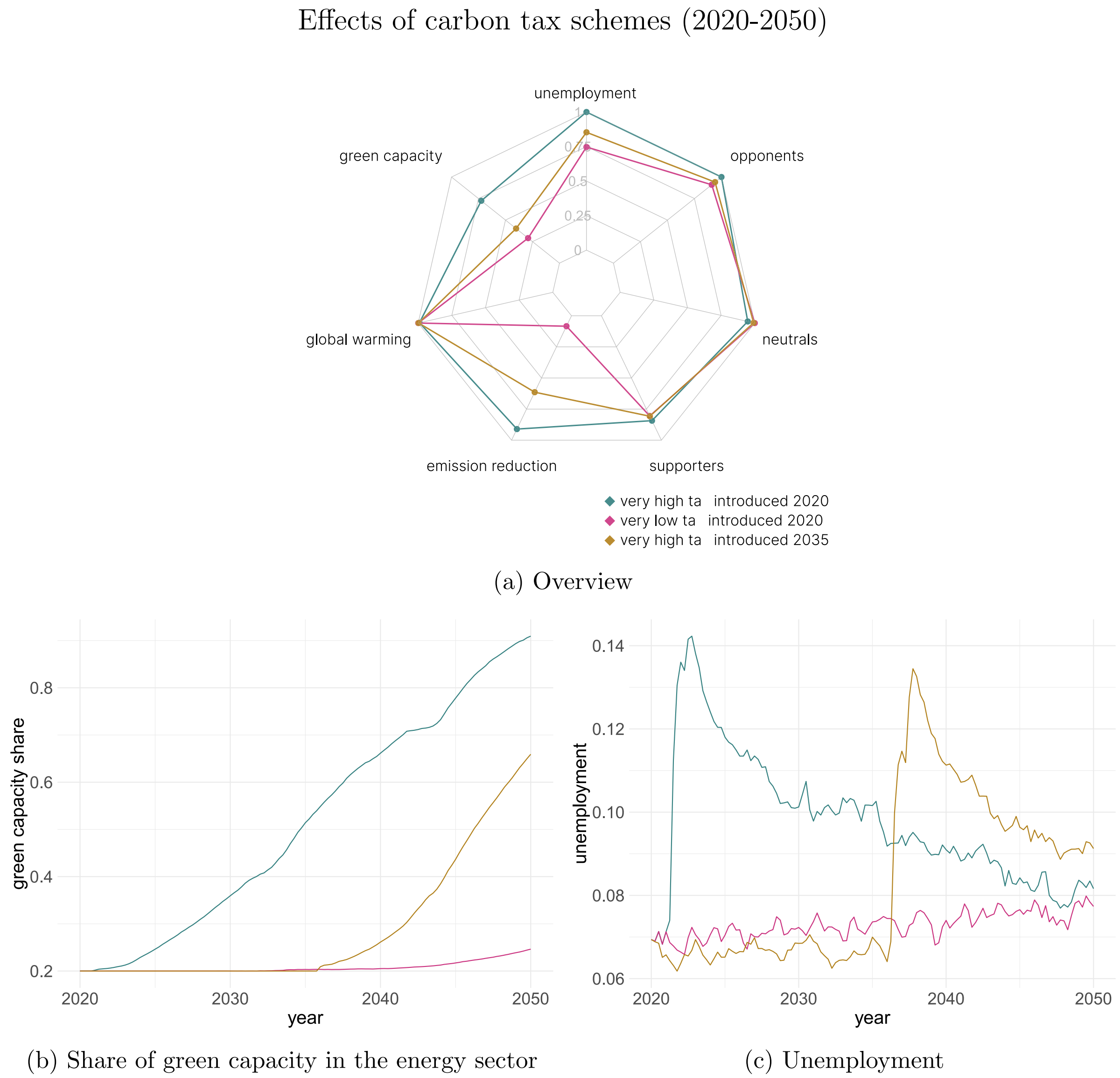
which involve a high risk of a severe unemployment crisis caused by a surge in energy prices, large drops in investment and a rise in bankruptcy rates (see also Wieners et al., 2022; Lamperti and Roventini, 2022; Lamperti et al., 2022).

The transmission mechanism from the carbon tax to the macroeconomy in our model operates as follows: a carbon tax raises the production cost of energy generated by brown capital and therefore the energy price,[14] as long as brown vintages are utilized in production. C-Firms pass through the increased energy prices to the general price level,[15] leading to a reduction in real wages. This results in a generalized lack of aggregate demand, leading to high unemployment and weak economic growth.

Looking at long-run opinion dynamics over the transition period 2020–2050 associated with different carbon tax schemes (see Fig. 3), we find that modest carbon taxes are not only insufficient to trigger the decarbonization in the energy sector but also constrain public support by sustaining fossil asset holders' lobbying power. A low carbon price sustains fossil assets in the energy sector and thus their respective asset holders' lobbying power to influence public opinion, e.g. by financing climate change denial campaigns. Conversely, stringent carbon tax pathways increase green asset holders' lobbying power, activating a positive feedback effect in which powerful interests to promote the reality of climate change are established. In short, the lobbying power of green asset holders increases the higher the slope of the carbon tax $g^{t,Em}$ and the earlier it is introduced (i.e., the lower t_0^{clim}). However, this positive feedback effect is likely to be counteracted by the macroeconomic transition costs of climate policy. A sufficiently high carbon tax is likely to trigger a serious unemployment crisis which limits overall public support for climate policy as immediate economic concerns may outweigh long-run concerns such as climate change. However, an ambitious early mitigation policy accelerates the economic and lobbying tipping point towards increasing support after which the unemployment crisis is over and green asset holders have the higher lobbying power. Over the long run (i.e.,2020–2050), average support for climate policy does not differ substantially between the very low and very high carbon tax scenarios. However, an ambitious carbon tax gives rise to short-run dynamics that question the political feasibility.

[14] Recall the energy price setting Eq. (16) which specifies that the production cost of the marginal vintage utilized in energy production serves as the foundation for determining the energy price.

[15] Recall the price setting Eq. (13) implying that for a given markup, cost-push shocks are entirely passed through. Note also, that in the K+S basic framework, markups are insensitive to cost-push shocks.



(a) Overview

(b) Share of green capacity in the energy sector

(c) Unemployment

Fig. 3. Variables across three exemplary tax scenarios (average of 100 Monte Carlo experiments): (i) very high tax introduced 2020: $t_0^{clim} = 2020$, $g^{\tau,Em} = 1 \times 10^{-4}$; (ii) very low tax introduced 2020: $t_0^{clim} = 2020$, $g^{\tau,Em} = 1 \times 10^{-6}$; (iii) very high tax introduced 2035: $t_0^{clim} = 2035$, $g^{\tau,Em} = 1 \times 10^{-4}$. Additional information for plot (a): points summarize the mean value of a variable over 2020–2050 in a specific scenario relative to the maximum value across all simulated scenarios.

This is illustrated in Fig. 4. Disruptive macroeconomic shocks of a sufficiently high carbon tax initially increase the share of opponents and decrease the share of supporters in the population. Interestingly, this trend reverses after years when the economic and lobbying tipping points have been passed. During the latter period, low carbon tax pathways are associated with a persistently lower share of supporters and higher share of opponents than high carbon tax pathways. But reaching this desirable tipping point is likely to require complementary policies to mitigate macroeconomic transition risks. Comparing public support for climate policy over 2020–2035 across all simulated scenarios, we find that carbon tax pathways that are sufficient to trigger the energy sector decarbonization and reach the EU climate goals are the ones that achieve lowest public support and highest opposition. For example, the most effective carbon tax in terms of the energy transition (i.e., very high tax introduced in 2020) is associated with an average share of opponents that is 16% higher than in the scenarios which assume a very low carbon tax that is implemented only late in 2030 or no tax during this period. Similarly, the corresponding average share of supporters is 3% lower (see Figure G.1 in Appendix G).

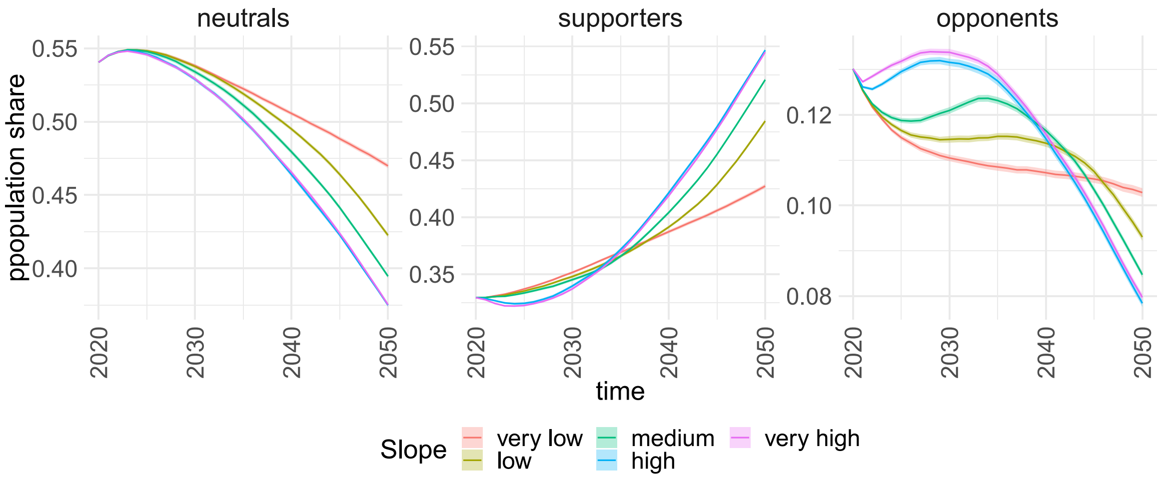


Fig. 4. Share of opinion types across carbon tax schemes introduced in 2020 (average of 100 Monte Carlo experiments).

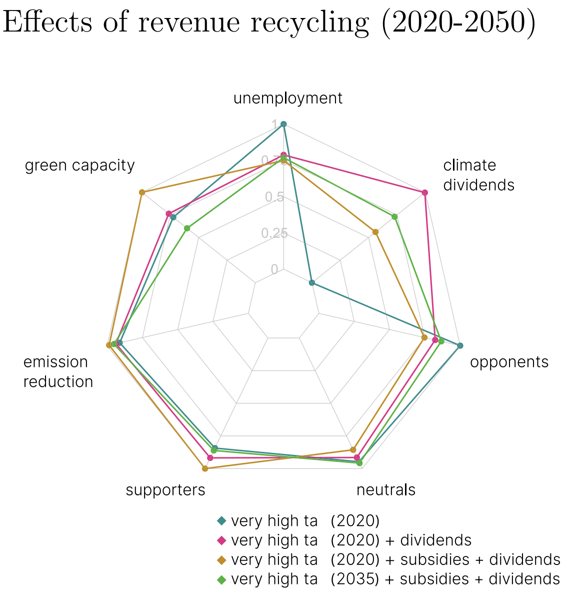
4.3. Role of complementary fiscal and redistributive policies to achieve a socio-politically feasible transition

These problematic properties of a pure carbon tax suggest that – in order to be politically feasible – it should be combined with stabilization policies that can be financed using generated carbon tax revenues. We argue that any such policy mix should be evaluated along two dimensions. The first dimension assesses the policy mix's impact on the goals of the energy transition, determining whether it aligns with, hinders, or potentially accelerates these objectives. The second dimension examines the policy mix's capacity to address the political feasibility concerns, specifically by shaping public opinion dynamics to garner support for it. This section evaluates alternative policy pathways and revenue recycling schemes across these dimensions.

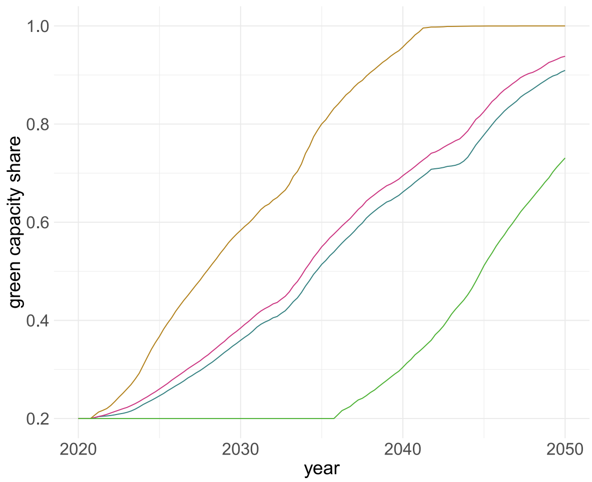
As discussed in Section 4.2, the carbon tax affects the macroeconomy by diminishing the real value of wages. Distributing carbon tax revenues to households can offset the income loss caused by the carbon tax, thereby restoring an aggregate demand level conducive to low unemployment during the transition. Additionally, when coupled with green investment subsidies, compensation to households can mitigate macroeconomic costs and expedite the transition. While green incentives reduce the portion of carbon tax revenues available for household transfers, it is important to note that a faster transition means an earlier decline in the energy price and, consequently, a quicker and endogenous recovery of real wages.

We find that distributing climate dividends to households increases public support for climate change mitigation. Climate dividends stabilize demand for private consumption leading to reduced unemployment over the transition period and a slightly accelerated decarbonization in the energy sector. This effect increases with the share of the carbon tax revenues that the government earmarks for recycling back to society ρ^{ctax}, and is observed across all simulated carbon tax pathways. With respect to timing, early implementation (i.e., low t_0^{clim}) is associated with lower opposition to and higher support for climate policy than delayed climate action. Compared to the pure carbon tax scenario, climate dividends thus constitute an effective revenue recycling mechanism to reduce opposition and promote support while perfectly aligning with, potentially even accelerating the energy transition. This effect is illustrated in a simplified way in Fig. 5 by contrasting the extreme cases of an early introduction of the very high carbon tax without a complementary recycling mechanism (labelled "*very high tax (2020)*") and the same carbon tax whose entire generated revenues are earmarked for recycling via climate dividends (labelled "*very high tax (2020) + dividends*"). The latter reduces average unemployment over the transition period substantially and slightly increases the average share of green capacity in the energy mix which affects opinion dynamics directly via the unemployment channel and higher average lobbying power of green asset holders (i.e., lobbying channel), respectively. However, these positive direct effects also propagate over time via endogenous social influence. For example, an unemployment crisis would not only affect the policy opinion of households that are directly hit and indeed become unemployed. These households are likely to share their concerns with friends and family, potentially triggering tipping point dynamics that result in a much larger decline in climate policy support over time due to second-order effects. Thus, curbing macroeconomic transition costs, e.g. by boosting demand via climate dividends, is essential to avoid detrimental direct and indirect effects to public support for climate policy.

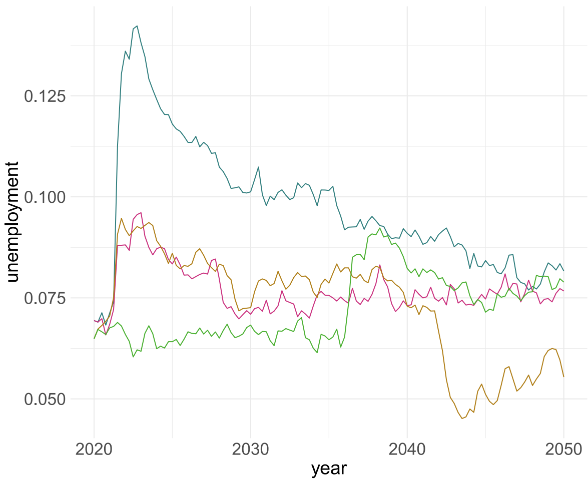
The alternative revenue recycling mechanism combines climate dividends with green investment subsidies. Specifically, the government commits to subsidize a certain share of green investment in the energy sector. If earmarked carbon tax revenues exceed green subsidies, the residual is redistributed directly to households in the form of lump-sum climate dividends. Different configurations of this revenue recycling scheme are described by possible combinations of the announced green investment subsidy ρ^{gsubs} and earmarked carbon tax revenues ρ^{ctax}. For a given share of earmarked carbon tax revenues ρ^{ctax}, a higher green investment subsidy ρ^{gsubs} accelerates the green transition in the energy sector without compromising positive employment effects as the accelerated diffusion of green capacity is accompanied by a faster reduction in energy prices. Comparing the opinion dynamics across all policy configurations, we find that political support is highest for the ambitious policy mix which combines an early



(a) Overview



(b) Share of green capacity in the energy sector

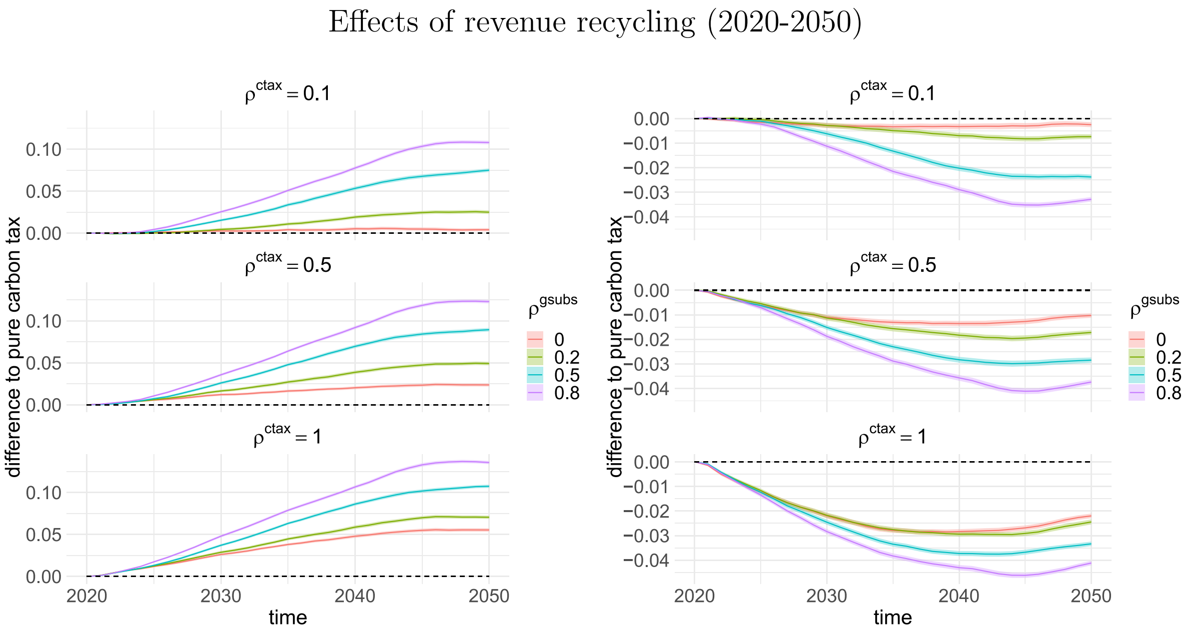


(c) Unemployment

Fig. 5. Variables across four exemplary tax scenarios (average of 100 Monte Carlo experiments): (i) very high tax (2020): $t_0^{clim} = 2020$, $g^{\tau,Em} = 1 \times 10^{-4}$, $\rho^{ctax} = \rho^{gsubs} = 0$); (ii) very high tax (2020) + dividends: $t_0^{clim} = 2020$, $g^{\tau,Em} = 1 \times 10^{-4}$, $\rho^{ctax} = 1$, $\rho^{gsubs} = 0$); (iii) very high tax (2020) + subsidies + dividends: $t_0^{clim} = 2020$, $g^{\tau,Em} = 1 \times 10^{-4}$, $\rho^{ctax} = 1$, $\rho^{gsubs} = 0.8$; (iv) very high tax (2035) + subsidies + dividends: $t_0^{clim} = 2035$, $g^{\tau,Em} = 1 \times 10^{-4}$, $\rho^{ctax} = 1$, $\rho^{gsubs} = 0.8$. Additional information for plot (a): points summarize the mean value of a variable over 2020–2050 in a specific scenario relative to the maximum value across all simulated scenarios.

implementation of a very high carbon tax whose entire revenues are recycled back to society (i.e., $\rho^{ctax} = 1$) via a high green investment subsidy ($\rho^{gsubs} = 0.8$) and residual climate dividends. This is illustrated in Fig. 5 showing that the policy mix labelled "*very high tax (2020) + subsidies + dividends*" outperforms the pure carbon tax (labelled "*very high tax (2020)*") and the simple revenue recycling mechanism based on climate dividends (labelled "*very high tax (2020) + dividends*") but also the scenario where the same policy mix is introduced with delay in 2035 (labelled "*very high tax (2035) + subsidies + dividends*").

Fig. 6 displays these dynamics, showing the share of supporters and opponents for different policy mixes for the case of a very high carbon tax implemented in 2020. Compared to the pure carbon tax, the revenue recycling mechanism combining high subsidies and climate dividends (i.e., $\rho^{ctax} = 1$, $\rho^{gsubs} = 0.8$) is associated with the steepest increase of the share of supporters and decrease of the share of opponents over the transition period as this policy mix effectively addresses unemployment and accelerates the transition in the energy sector which in turn strengthens the lobbying influence of the green asset holders. The main pattern of the dynamics does not change if we consider the high or medium carbon tax even though they are associated with lower support and



(a) Share of supporters   (b) Share of opponents

Fig. 6. Share of supporters and opponents across revenue recycling configurations defined by a combination of earmarked carbon tax revenues for redistribution to society (ρ^{ctax}) and green investment subsidy (ρ^{gsubs}). Simulation results are expressed as average of 100 Monte Carlo experiments and depicted as difference to the baseline of a very high carbon tax without revenue recycling where $t_0^{clim} = 2020$, $g^{\tau,Em} = 1 \times 10^{-4}$.

higher opposition during the transition period. Delaying the introduction of the policy mix is also detrimental as the positive effect on opinion dynamics start to unfold only at a later point in time.

Finally, we want to decompose the relative importance of the different channels for households to update their opinion. To this end, we depict the effects of unemployment, climate change, lobbying and social influence for each year in Fig. 7, focusing on the policy scenario that generates highest public support over the transition period: early implementation of the very high carbon tax together with a high green investment subsidy and climate dividends which are financed by the carbon tax revenues.

Since we are specifically interested in tracking opinion changes, we focus on the four different groups of households which update their opinion in the respective period: Households decreasing their climate policy opinion from support to neutral ($G_{s\to n,t}$) or from neutral to oppose ($G_{n\to o,t}$) and those increasing their policy opinion from oppose to neutral ($G_{o\to n,t}$) or from neutral to support ($G_{n\to s,t}$). Please note that the composition of these groups changes each year. For example, an individual that changed her policy opinion from oppose to neutral in $t-1$ and thus belongs to the group $G_{o\to n,t-1}$, cannot belong to the same group in the subsequent period t ($G_{o\to n,t}$) or might not even update her opinion again (i.e., might not belong to any of the four groups in t). We measure the group specific effect of each channel as the total influence experienced by the group at time t by summing over all group members' individually experienced influence. This implies that larger groups are indicated by larger bars. For each year t, the (group-specific) effects of unemployment, climate change, fossil lobbying, green lobbying and social influence are thus quantified by Eq. (27), where j denotes the respective group.

$$\begin{cases} \sum_{i\in G_j} unempl_i & \text{unemployment} \\ \sum_{i\in G_j} cc_i & \text{climate change} \\ \sum_{i\in G_j} Flob_i & \text{fossil lobbying} \\ \sum_{i\in G_j} Rlob_i & \text{green lobbying} \\ \sum_{i\in G_j} soc_i & \text{social influence} \end{cases} \tag{27}$$

This decomposition reveals the significant role of social influence. As we can see in Fig. 7, social influence constitutes the most important component to explain opinion change. We must be aware of the fact that it is endogenous to the opinion dynamics module of our model. Hence, humans' tendency towards social conformity acts as a significant multiplier to reinforce the dynamics stemming from the economy and the climate, i.e. unemployment, lobbying and global warming. This effect is known in the literature as "social multiplier" (Glaeser et al., 2003). Without the external drivers, social influence on its own would merely cause the numerically largest group to grow until the whole society would follow a uniform opinion, as we can see in a robustness check illustrated by Figure H.1 in Appendix H.1. The impact of climate change, in turn, depends on the variable $cc_{i,t}$ which increases uniformly for all

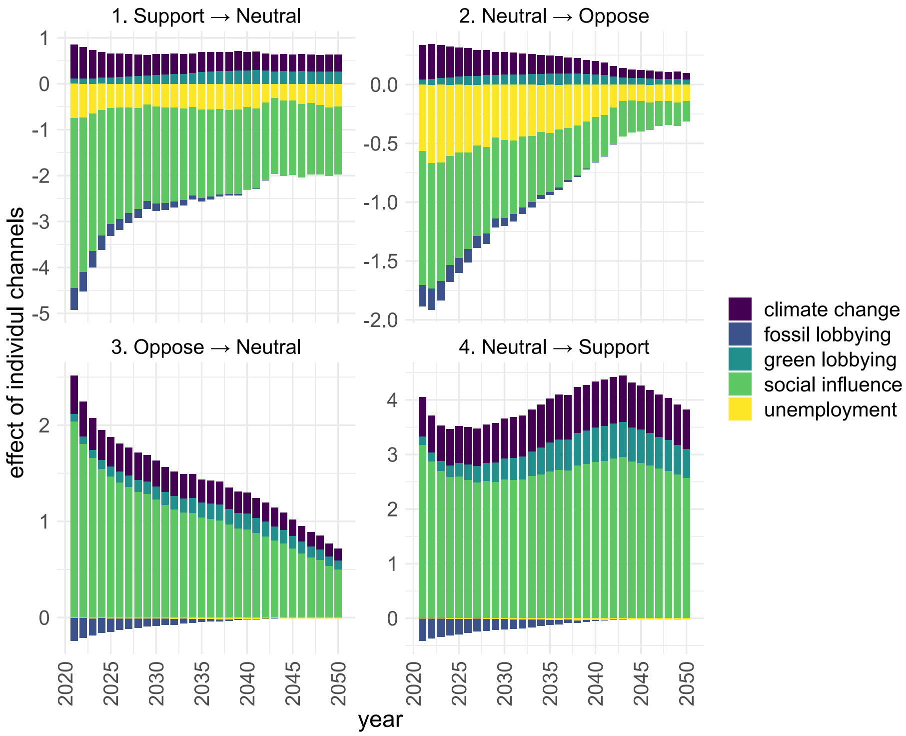


Fig. 7. Relative importance of different channels to update opinion for the ambitious policy scenario (average of 100 Monte Carlo experiments): very high tax introduced in 2020, all revenues recycled via high green subsidies and climate dividends (i.e., $\rho^{ctax} = 1$, $\rho^{gsubs} = 0.8$).

households over time with increasing temperature.[16] Over the transition period 2020–2050, $cc_{i,t}$ increases by 44% even if the EU achieves its climate targets as climate change and its perception depends on cumulative global emissions and emissions from the rest of the world are assumed to be exogenous in our simulations.[17] Differences in the relative importance of climate change across groups within a given year are thus only driven by group size, indicating that changing from neutral to support (group $G_{n\to s}$) and from support to neutral (group $G_{s\to n}$) constitute the largest groups across the transition period. The share of opponents decreases over time which is also reflected by the decreasing group sizes of households changing their opinion from neutral to oppose ($G_{n\to o}$) and from oppose to neutral ($G_{o\to n}$). Within a group, differences in the relative importance of climate change across time are a combination of increasing $cc_{i,t}$ and changing group sizes. Also in this respect, Fig. 7 illustrates that the $G_{n\to s}$ on average constitutes the largest group in the best-performing policy mix scenario. Differences across time and groups are more difficult to interpret as they can be attributed to changing $cc_{i,t}$ and group sizes. Fossil lobbying is a determinant for policy opinion change towards decreasing support. Under the best policy mix, the influence of fossil lobbying is gradually phased out by 2040 with the declining lobbying power of the fossil fuel-based industry leading to less households that are targeted by the anti-climate campaign. In contrast, we find that green lobbying is a relevant determinant for households which update their policy opinion towards increasing support. It quickly increases with the introduction of the high carbon tax which increases resources and lobbying power of green asset holders to target more households with their campaign. Finally, personal experience of unemployment exerts a negative pressure on policy support which is contained compared to the scenario without complementary stabilization policies.

5. Robustness checks

5.1. Sensitivity to model parameters

Exploring the confidence interval of parameter estimates In any simulation model, the choice of parameters plays a vital role for the outcomes. As described in Sections 3.2 and 4.1, we do not choose the parameters arbitrarily, but rely on well-tested algorithms to calibrate the parameters to fit our simulation outputs to empirical data using the "freelunch" package (Carrella, 2021). One of the main advantages of this approach is that it does not only provide point estimates, but also confidence intervals for each parameter, which may be smaller or larger, depending on the algorithm and how well-identified the parameter is. We exploit this fact to check

[16] The stochastic nature of the mean surface temperature in the DSK-SFC implies only small fluctuations around the linearly increasing temperature.

[17] We study the effect of exogenous emission pathways in the DSK-SFC on opinion dynamics as part of the sensitivity analysis provided in Section 5.1.

Table 7
Initialization of households based on Eurobarometer survey (European Commission, 2019): correspondence between modelled variables and survey questions.

Variable	Survey question	Measurement	Value
op	QB2: And how serious a problem do you think climate change is at this moment?	Scale from 1 (not at all a serious problem) to 10 (an extremely serious problem)	$\begin{cases} 1 & \text{if QB2} \le 4 \\ 2 & \text{if } 5 \le \text{QB2} \le 8 \\ 3 & \text{if QB2} > 8 \end{cases}$

whether 'extreme' parameter combinations which are located at the edge of the confidence intervals produce different insights than our main analysis relying on the point estimates. Since we are confronted with four parameters that have a lower and an upper bound, respectively, we test $2^4 = 16$ parameter combinations in addition to the baseline configuration presented above.

We visualize the results of this sensitivity analysis in a two-fold way. We first rank each of the 133 policy scenarios according to their cumulative support for climate policies in the period until 2050 (see Table H.1 in Appendix H.2). In 9 out of 17 parameter combinations, the policy scenario in which the government quickly introduces a stringent carbon tax whose revenues are recycled in the form of a high green investment subsidy and climate dividends fares best in terms of cumulative support (both looking at the period until 2035 and until 2050). These parameter combinations are all characterized by a positive lobbying impact. The only other policy scenario that is ranked first more than once (more specifically, four times) is where the government enacts a very weak carbon tax policy very late (i.e., a scenario which clearly fails with regard to the climate goals). This is true for parameter combinations where the unemployment impact is at the lower bound of the confidence interval (implying a particularly strong effect) and where the lobbying impact is zero. We then look in detail at the results of these two scenarios, which we can imagine as 'extreme ends' of the policy space, as one implies rapid, comprehensive government action and the other essentially simulates a case in which the government does very little, very late. Figure H.2 in Appendix H.2 shows that the policy in which the government acts strongly and rapidly does not only rank first in 9 out of 17 combinations, but performs only slightly worse in 4 out of 17 other combinations. However, it performs much worse in those simulations where the lobbying impact is zero and the unemployment impact is strong.

Finally, Figure H.3 in the Appendix H.2 illustrates how different combinations of estimated parameters within the confidence interval affect public support for climate policy during the transition period if the government quickly introduces a stringent carbon tax and uses generated revenues for a high green investment subsidy and climate dividends. In this scenario, support increases with higher values of persuasive force $F \in (0,1)$, evidence impact $\eta \in (0,1)$, lobbying impact $\lambda \in (0,1)$ and unemployment impact $\nu \in (-1,0)$ with the most favourable conditions for policy support occurring at the upper confidence bounds of these parameters.

Sensitivity to average degree in social networks In the main analysis, the average degree in the country-specific social networks ℓ is assumed to be 4. To explore how the overall level of connectedness of the social network affects opinion dynamics in the ambitious policy scenario, we compare opinion dynamics under varying levels of average degree ℓ. As illustrated in Figure L.2a in Appendix L, higher connectivity accelerates the reduction of opponents and increase of supporters in the population and vice versa.

Sensitivity to employee turnover Similarly, the employee turnover rate to is assumed to be 0.07 in the main analysis. While employee turnover varies across multiple dimensions like occupation, sector, gender, age, education or country, the parameter is chosen to represent a reasonable value in the mid-range documented by Eurostat (2024). Exploring sensitivity of opinion dynamics to this parameter in the ambitious policy scenario, we find that a higher employee turnover marginally reduces the share of "extreme" opinion types supporters and opponents while increasing the share of neutrals in the population (see Figure H.4 in Appendix H.3). Put differently, higher turnover reduces polarization via increased noise in the opinion dynamics model which exerts negative pressure on policy support of those who become (temporarily) unemployed and positive influence on support of those who start a job.

Sensitivity to emission pathways of the rest of the world We further conduct a sensitivity analysis to understand how the model dynamics react to changes in the emission pathways in countries outside of the EU, which are exogenous to the model. Table H.2 in Appendix H shows that our results are robust to changes in the emission pathways of other countries. Regardless of the emissions pathways assumed for the rest of the world, the ambitious policy mix beats other carbon tax regimes.

5.2. Alternative definition of opinion types

To check whether our analysis is robust to alternative thresholds defining the three opinion types based on reported climate change concern in the Eurobarometer survey, we test an alternative definition of the climate policy opinion op. As summarized in Table 7, this specification is less conservative since households are accounted as supporters if their climate change concern is higher than 8, compared to 10 in the main analysis (see Table 1). This implies a higher share of supporters and a lower share of opponents and neutrals in the base year.

Again, we fully calibrate the model using the estimation algorithms provided by the "freelunch" package (Carrella, 2021) and rank them, together with a 'constant predictor' scenario, according to their ability to reproduce the weighted mean share of supporters, neutrals and opponents in the EU in the period between 2013 and 2019. Results are shown in Table I.1 in Appendix I.

Applying the same scenario-based analysis to the newly estimated opinion dynamics model, we find that our results are robust to changes of these thresholds. Again, it is the ambitious policy mix (i.e., quick introduction of stringent carbon tax and full revenue recycling in the form of high green investment subsidy and climate dividends) which performs best in terms of political support during the transition period. As shown in Figure I.1 in Appendix I, opinion dynamics across different carbon tax schemes without revenue recycling exhibit a very similar pattern as in the main analysis. In both cases, the share of opponents (supporters) is largest (smallest) for high-slope carbon tax pathways until the economic and lobbying tipping points are reached. However, the lower share of opponents in the base year prevents an initial spike in opponents following the introduction of a stringent carbon tax. Consequently, hybrid revenue recycling continues to increase support and decrease opposition but the extent of the latter is somewhat lower (see Figure I.2 in Appendix I). Finally, the relative importance of different channels to update opinion across the different groups remain the same but reflect changes in group size due to alternative opinion definition (see Figure I.3 in Appendix I).

5.3. Cognitive biases

We also experiment with including two cognitive biases that may be relevant in shaping opinion dynamics. First, we introduce 'biased assimilation'. Here, agents are less likely to be affected by climate change evidence if they oppose climate policy, but more likely if they already support it. The extent of this effect is governed by the biased assimilation parameter $\mu \in (0,1)$. In this case, the equation describing the climate change evidence effect is given by Eq. (28).

$$cc_{i,t} = \begin{cases} \eta \Delta T_t^*(1-\mu) & \text{if } op_{i,t} = 1, \Delta T_t^* > 0 \\ \eta \Delta T_t^*(1+\mu) & \text{if } op_{i,t} = 1, \Delta T_t^* < 0 \\ \eta \Delta T_t^* & \text{if } op_{i,t} = 2 \\ \eta \Delta T_t^*(1+\mu) & \text{if } op_{i,t} = 3, \Delta T_t^* > 0 \\ \eta \Delta T_t^*(1-\mu) & \text{if } op_{i,t} = 3, \Delta T_t^* < 0 \end{cases} \tag{28}$$

In our second extension, we include a 'social desirability bias' in which agents are less likely to switch away from the modal opinion op_t^{mod} (i.e., the opinion that is held by the plurality of the population) than from other opinions. In this case, the equation governing the change of opinion is changed according to Eq. (29), where ζ is a parameter denoting the social desirability bias.

$$p_{i,t} = \begin{cases} \zeta(unem_{i,t} + cc_{i,t} + Flob_{i,t} + Rlob_{i,t} + soc_{i,t}) & \text{if } op_{i,t} = op_t^{mod} \\ unem_{i,t} + cc_{i,t} + Flob_{i,t} + Rlob_{i,t} + soc_{i,t} & \text{else} \end{cases} \tag{29}$$

We again fully calibrate the model empirically using the reference table algorithms included by the "freelunch" package provided by Carrella (2021). The results of the calibration are given in the Appendix (see Appendix J for biased assimilation and Appendix K for the social desirability bias). While the extensions do not improve the fit to the empirical data, our main policy conclusions are robust to these extensions, as the ambitious policy mix which combines a very high tax rate with full redistribution of revenues via a high green investment subsidy and climate dividends paid to households fares best in terms of public support.

Note that the decomposition of the relative importance of the different channels to update policy opinion looks markedly different in the presence of social desirability bias (see Figure K.2 in Appendix K) than in the baseline model and the model with biased assimilation. While social influence plays a much smaller role as explicit channel to shape opinion of agents, 'social influence' in a wider sense also plays a very important role in this model in the sense that agents are less likely to change their opinion away from the modal opinion. Hence, the influence of the peer group is smaller in this model but the influence of the society as a whole is larger.

5.4. Alternative network topologies

To explore the effect of the social network structure on opinion dynamics, we consider two alternative network topologies. First, we extend the model to include a homophily-based social network for each country where households are more likely to interact with others who share similar attributes including social class, policy opinion and employment status. To gain a deeper understanding of the role of homophily for opinion dynamics, we then use the configuration model to generate random country-specific networks from the given degree sequence obtained from the respective homophilic network.

Homophily-based social networks As described in Section 3.1, real-world social networks often feature a mixing pattern that is homophilic, which describes the tendency of individuals to associate and bond with others who are similar to themselves in various attributes such as beliefs, values, education or social status. To account for the ample evidence that social networks are stratified by socioeconomic class and the result from our empirical analysis that climate change concern is correlated with class, we extend the household attributes by subjective social class[18] using Eurobarometer survey data (see Table 8). Social class is denoted by $c_i \in \{1,2,3,4,5\}$ and its (time-invariant) value increases from lower to upper class. The profile of a household i living in country k then reads

$$p_{i,t}^k = (es_{i,t}^k, c_i^k, op_{i,t}^k) \tag{30}$$

Table 8
Initialization of households based on Eurobarometer survey (European Commission, 2019): correspondence between modelled social class and survey questions.

Variable	Survey question	Measurement	Value
c	D63: Do you see yourself and your household belonging to…?	Scale ranging from 1 (The working class of society) to 5 (The higher class of society)	$\begin{cases} 1 & \text{if working} \\ 2 & \text{lower middle} \\ 3 & \text{middle} \\ 4 & \text{upper middle} \\ 5 & \text{higher} \end{cases}$

The distribution of the social class as well as the correlation between the employment status, social class and opinion – measured by Cramér's V – is summarized in Appendix B.1 by Figure B.1 and Table B.1, respectively.

To construct country-specific homophily-based social networks, we follow the network generation procedure by Hager et al. (2025) which we describe in detail in Appendix B.3. Each country's network is represented as an undirected graph where links between households are determined by the similarity of their characteristics. The probability of a link between two households is weighted by their similarity, calculated based on the normalized attributes policy opinion, social class and employment status. For each household, connections are formed by selecting a given number of other households according to this probability distribution, resulting in a social network with a specified average degree ℓ.

Country-specific networks based on configuration model Second, we study a network type that preserves the degree distribution of the homophilic social network, but where the probability to connect with each other does not depend on the agents' other characteristics. Following the configuration model (Newman, 2010), each household is initially assigned a degree based on the number of links it would have in a homophilic network with the same average degree ℓ. The network is then constructed by iteratively linking households to match their assigned degrees (see Appendix B.4).

A more detailed description of the resulting country-specific social networks based on homophily and the configuration model is provided in Appendix B.3 and B.4, respectively.

We again calibrate the model with homophilic networks using the reference table algorithms included in the "freelunch" package provided by Carrella (2021). The results are summarized in Table L.1 in Appendix L. Also in this case, parameters estimated by the random forest algorithm yield the smallest RMSE in the descriptive output validation. However, homophilic networks do not improve the fit to empirical data when compared to random networks. We then use the same parameter estimates and run the model with the configuration network. The resulting fit is highly similar (see Table L.1 in Appendix L).

To explore the sensitivity of our main conclusions to the social network type, we compare opinion dynamics across all three network topologies for two scenarios: (i) early introduction of a very high carbon tax without revenue recycling and (ii) an ambitious policy mix combining (i) with hybrid revenue recycling in the form of a high green subsidy and residual climate dividends. We find that network type has a minor influence overall, primarily affecting the share of opponents (see Table L.2 in Appendix L). Without revenue recycling, the increase of the share of opponents following the introduction of the stringent carbon tax is most pronounced for random social networks. Since households in random networks are connected without regard to similarity, these networks facilitate more diverse interactions, exposing individuals to different viewpoints about climate policy and leading to faster opinion changes. Conversely, homophilic networks contain the rise in opposition after the introduction of the carbon tax and the concurrent increase in unemployment. Configuration networks, which preserve the degree sequence of the respective national homophilic network but randomize the connections, are associated with only a slightly lower share of opponents compared to random networks, underscoring the role of homophily in decelerating opinion change in response to negative exogenous effects such as unemployment (see Figure L.1a). For the ambitious policy mix, the share of opponents decreases most rapidly in homophilic networks, as the influence from lobbying and the economy prompts opponents to update their opinion towards increased support. This, in turn, promotes feedback effects from social influence, as these households are more likely to interact with and influence other opponents (see Figure L.1b).

6. Concluding remarks

Carbon pricing is the benchmark of decarbonization policies within the economics profession, but public opposition to ambitious carbon taxes around the world has clearly demonstrated serious political feasibility concerns. Moreover, studying climate change mitigation policies in the economy depicted as complex evolving system points to the potential of significant macroeconomic transition risks that need to be addressed by an adequate policy mix. Yet, only few attempts exist to integrate dynamic representation of the socio-political spheres into integrated-assessment models to better understand barriers to public support and which policy elements are conducive to broaden it over the transition period without compromising climate goals.

[18] Even though objective criteria are to be preferred in many cases, subjective social class is assumed as reliable indicator to proxy a homophilic social network structure (McPherson et al., 2001) which is described in 3.1.2.

This paper developed a novel agent-based opinion dynamics model that explicitly accounts for complex interactions among social, political, economic and climate systems to study public support for climate change mitigation policy. Heterogeneous households can either support, oppose or be neutral towards climate policy. Over time, they are differently affected by macroeconomic transition risks (i.e., unemployment), climate change and industry lobbying which have a direct influence on individual policy opinion. Humans' tendency towards social conformity acts as significant multiplier of the above dimensions. To empirically identify the parameters and validate the opinion dynamics model, we calibrated the model to Eurobarometer survey data over 2011–2019.

To investigate the co-evolution of opinion dynamics and climate change mitigation policy, we proposed an integrated Opinion Dynamics-Macroeconomic Agent-based model framework that links our opinion dynamics model to the Dystopian Schumpeter meeting Keynes model (Reissl et al., 2024; Lamperti et al., 2018), a simulated EU-like economy. After studying a battery of 133 policy scenarios that combine different carbon tax schemes and revenue recycling mechanisms, the following results stand out.

Even though environmentally effective carbon tax schemes on their own are most likely politically infeasible due to their macroeconomic costs which immediately reduce public support in the population, we show that they would promote a favourable social tipping point in the longer run, when the economic weight of the fossil industry and hence their lobbying power decreases, and the economic and political weight of the renewable energy sector increases.

Sustaining public support in the short run requires complementary policies to mitigate the economic fallout of the carbon tax. Carbon tax revenues can serve as a means to this end. Specifically, we find that a hybrid revenue recycling scheme which uses the generated revenues to finance a high green investment subsidy and climate dividends constitutes a successful strategy to address this intertemporal trade-off. This finding is robust across a wide range of the parameter space and also holds under extensions of the opinion dynamics model that account for additional cognitive biases such as biased assimilation and social desirability bias.

For such an ambitious policy scenario, the decomposition of opinion dynamics into the different channels reveals that low unemployment contains people's anxiety that climate policy threatens their job (opportunities). The fast diffusion of green technologies in the energy sector eventually breaks the lobbying power of fossil fuel-based asset holders and increases the political power of green asset holders to influence public opinion. Increasing evidence of climate change positively affects policy support via increased risk perception. Notably, social influence constitutes the most important component to amplify opinion change in the baseline calibration of the model as it facilitates the propagation of individually experienced job loss, industry-led (dis-)information campaigns and perceived climate change through social networks.

While this study is one of the first attempts to systematically integrate an opinion dynamics model and a macroeconomic agent-based model, this approach leaves plenty of promising avenues for further research. First, it would be interesting to consider the co-evolution of climate change concern and household consumption preferences which would likely increase effectiveness of a carbon tax (Konc et al., 2021). Second, another fruitful avenue is to implement a bidirectional link between the opinion dynamics model and the DSK model, where the opinion dynamics feed back into the policies enacted in the DSK. Such an approach could combine the benefits of an approach that focuses on the 'supply side' of policies (e.g., by means of an election model) and the 'demand side' (such as ours) to further enhance our understanding of the complex interplay between economy, climate, policy and opinions.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Open access funding provided by University of Graz. The authors would like to express their gratitude to the participants of the (i) Interdisciplinary Uncertainty Conference at CeUS 2023 (Bielefeld), (ii) WEHIA 2023 (Koper), (iii) Workshop on Complex System Approaches to 21st Century Challenges 2023 (Santa Fe), (iv) Climate Finance & Macroeconomics seminar series at EIEE (Milan), (v) EPOC International Doctoral Workshop 2024 (Venice) and (vi) seminar series of the Institute of Economics at Sant'Anna School of Advanced Studies 2024 (Pisa) for helpful comments and suggestions. We would like to thank Ernesto Carrella for his inspiration regarding the calibration of the opinion dynamics model; Silvia Pianta for kindly sharing a pre-processed, cleaned and formated dataset of the Eurobarometer survey; Richard Sturn, Christian Gehrke and Jordan Everall for their participation in discussions of the ideas incorporated and reported in the paper manuscript. All remaining errors are our own.

Online appendix

The appendix of this article can be found online at https://doi.org/10.1016/j.jebo.2024.106816.

Data availability

The code, publicly available data, and replication instructions are available at https://github.com/teresa-lackner.

References

Abou-Chadi, T., Kayser, M.A., 2017. It's not easy being green: Why voters punish parties for environmental policies during economic downturns. Elect. Stud. 45, 201–207.
Akerlof, G.A., 1997. Social distance and social decisions. Econometrica 1005–1027.

Balint, T., Lamperti, F., Mandel, A., Napoletano, M., Roventini, A., Sapio, A., 2017. Complexity and the economics of climate change: a survey and a look forward. Ecol. Econom. 138, 252–265.
Beckage, B., Lacasse, K., Winter, J.M., Gross, L.J., Fefferman, N., Hoffman, F.M., et al., 2020. The Earth has humans, so why don't our climate models? Clim. Change 163 (1), 181–188.
Beckage, B., Moore, F.C., Lacasse, K., 2022. Incorporating human behaviour into Earth system modelling. Nat. Hum. Behav. 6 (11), 1493–1502.
Bénabou, R., Tirole, J., 2006. Incentives and prosocial behavior. Am. Econ. Rev. 96 (5), 1652–1678.
Bénabou, R., Tirole, J., 2016. Mindful economics: The production, consumption, and value of beliefs. J. Econ. Perspect. 30 (3), 141–164.
Benegal, S.D., 2018. The impact of unemployment and economic risk perceptions on attitudes towards anthropogenic climate change. JESS 8 (3), 300–311.
Benigno, G., Fornaro, L., 2018. Stagnation traps. Rev. Econ. Stud. 85 (3), 1425–1470.
Benjamin Wehrmann, J.W., 2024. Q&A – What the German top court's 'debt brake' ruling means for climate policy. https://www.cleanenergywire.org/factsheets/qa-what-german-top-courts-debt-brake-ruling-means-climate-policy. (Accessed 11 February 2024).
Bergé, L., 2018. Efficient estimation of maximum likelihood models with multiple fixed-effects: the R package FENmlm. CREA Discussion Papers, (13).
Bicchieri, C., 2005. The Grammar of Society: The Nature and Dynamics of Social Norms. Cambridge University Press.
Black, S., Parry, I.W., Zhunussova, K., 2023. Is the Paris agreement working? A stocktake of global climate mitigation. Staff Clim. Notes 2023 (002).
Blanchard, O., Gollier, C., Tirole, J., 2023. The portfolio of economic policies needed to fight climate change. Annu. Rev. Econ. 15 (1), 689–722.
Boguná, M., Pastor-Satorras, R., Díaz-Guilera, A., Arenas, A., 2004. Models of social networks based on social distance attachment. Phys. Rev. E 70 (5), 056122.
Bond, R.M., Fariss, C.J., Jones, J.J., Kramer, A.D., Marlow, C., Settle, J.E., Fowler, J.H., 2012. A 61-million-person experiment in social influence and political mobilization. Nature 489 (7415), 295–298.
Bonneuil, C., Choquet, P.L., Franta, B., 2021. Early warnings and emerging accountability: Total's responses to global warming, 1971–2021. Global Environ. Change 71, 102386.
Boussalis, C., Coan, T.G., 2016. Text-mining the signals of climate change doubt. Global Environ. Change 36, 89–100.
Brulle, R.J., 2014. Institutionalizing delay: foundation funding and the creation of US climate change counter-movement organizations. Clim. Change 122, 681–694.
Brulle, R.J., Carmichael, J., Jenkins, J.C., 2012. Shifting public opinion on climate change: an empirical assessment of factors influencing concern over climate change in the US, 2002–2010. Clim. Change 114 (2), 169–188.
Byers, E., Krey, V., Kriegler, E., Riahi, K., Schaeffer, R., Kikstra, J., Lamboll, R., Nicholls, Z., Sandstad, M., Smith, C., van der Wijst, K., Al Khourdajie, A., Lecocq, F., Portugal-Pereira, J., Saheb, Y., Stromann, A., Winkler, H., Auer, C., Brutschin, E., Gidden, M., Hackstock, P., Harmsen, M., Huppmann, D., Kolp, P., Lepault, C., Lewis, J., Marangoni, G., Müller-Casseres, E., Skeie, R., Werning, M., Calvin, K., Forster, P., Guivarch, C., Hasegawa, T., Meinshausen, M., Peters, G., Rogelj, J., Samset, B., Steinberger, J., Tavoni, M., van Vuuren, D., 2022. AR6 Scenario Database. Zenodo, https://doi.org/10.5281/zenodo.5886911.
Caiani, A., Godin, A., Caverzasi, E., Gallegati, M., Kinsella, S., Stiglitz, J., 2016. Agent based-stock flow consistent macroeconomics: Towards a benchmark model. J. Econom. Dynam. Control 69, 375–408.
Carattini, S., Carvalho, M., Fankhauser, S., 2018. Overcoming public resistance to carbon taxes. Wiley Interdiscip. Rev. Clim. Change 9 (5), e531.
Carrella, E., 2021. No free lunch when estimating simulation parameters. J. Artif. Soc. Soc. Simul. 24 (2).
Castro, J., Drews, S., Exadaktylos, F., Foramitti, J., Klein, F., Konc, T., Savin, I., van den Bergh, J., 2020. A review of agent-based modeling of climate-energy policy. Wiley Interdiscip. Rev. Clim. Change 11 (4), e647.
Centola, D., Becker, J., Brackbill, D., Baronchelli, A., 2018. Experimental evidence for tipping points in social convention. Science 360 (6393), 1116–1119.
Ciola, E., Turco, E., Gurgone, A., Bazzana, D., Vergalli, S., Menoncin, F., 2023. Enter the MATRIX model: a multi-agent model for transition risks with application to energy shocks. J. Econom. Dynam. Control 146, 104589.
Cole, J.C., Ehret, P.J., Sherman, D.K., Van Boven, L., 2022. Social norms explain prioritization of climate policy. Clim. Change 173 (1–2), 10.
Colgan, J.D., Green, J.F., Hale, T.N., 2021. Asset revaluation and the existential politics of climate change. Int. Organ. 75 (2), 586–610.
Currarini, S., Jackson, M.O., Pin, P., 2009. An economic model of friendship: Homophily, minorities, and segregation. Econometrica 77 (4), 1003–1045.
Dávila-Fernández, M.J., Sordi, S., Cafferata, A., 2023. How do you feel about going green? Modelling environmental sentiments in a growing open economy. J. Econ. Interact. Coord. 1–39.
Dechezleprêtre, A., Fabre, A., Kruse, T., Planterose, B., Chico, A.S., Stantcheva, S., 2022. Fighting Climate Change: International Attitudes Toward Climate Policies. Technical Report, National Bureau of Economic Research.
Dell, M., Jones, B.F., Olken, B.A., 2012. Temperature shocks and economic growth: Evidence from the last half century. Am. Econ. J.: Macroecon. 4 (3), 66–95.
Deryugina, T., 2013. How do people update? The effects of local weather fluctuations on beliefs about global warming. Clim. Change 118, 397–416.
Di Benedetto, A., Wieners, C.E., von der Heydt, A.S., 2024. Feasible Climate Policies in a Democracy with a Climate-Denying Party. Technical Report, arXiv preprint arXiv:2403.07681.
Dosi, G., Fagiolo, G., Roventini, A., 2010. Schumpeter meeting keynes: A policy-friendly model of endogenous growth and business cycles. J. Econ. Dyn. Control 34 (9), 1748–1767.
Douenne, T., Fabre, A., 2022. Yellow vests, pessimistic beliefs, and carbon tax aversion. Am. Econ. J.: Econ. Policy 14 (1), 81–110.
Drews, S., Savin, I., Van Den Bergh, J.C., Villamayor-Tomás, S., 2022. Climate concern and policy acceptance before and after COVID-19. Ecol. Econom. 199, 107507.
Druckman, J.N., McGrath, M.C., 2019. The evidence for motivated reasoning in climate change preference formation. Nature Clim. Change 9 (2), 111–119.
Duesenberry, J.S., 1962. Income, Saving and the Theory of Consumer Behavior. Harvard University Press.
Dunbar, R.I., Spoors, M., 1995. Social networks, support cliques, and kinship. Hum. Nat. 6, 273–290.
Dunlap, R.E., McCright, A.M., et al., 2011. Organized climate change denial. Oxf. Handb. Clim. Change Soc. 1, 144–160.
Dynan, K.E., Skinner, J., Zeldes, S.P., 2004. Do the rich save more? J. Polit. Econ. 112 (2), 397–444.
for Environmental Information, N.C., 2023. Global climate at a glance - time series data. URL: https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/global/time-series. (Accessed 13 October 2023).
Erdős, P., Rényi, A., 1960. On the evolution of random graphs. Publ. Math. Inst. Hung. Acad. Sci. 5 (1), 17–60.
European Commission, 2019. Eurobarometer 91.3. URL: https://doi.org/10.4232/1.13372. (Accessed 13 October 2023).
Eurostat, 2023. Share of energy from renewable sources. URL: https://ec.europa.eu/eurostat/databrowser/view/NRG_IND_REN/default/table. (Accessed 13 October 2023).
Eurostat, 2024. European Union Labour Force Survey (EU LFS). Recently Hired Workers. URL: https://www.cedefop.europa.eu/en/tools/skills-intelligence/indicators#detailed-employment-by-occupation. (Accessed 8 July 2024).
Everall, J.P., Donges, J.F., Otto, I.M., 2023. The Pareto effect in tipping social networks: from minority to majority. EGUsphere 2023, 1–38.
Farrell, J., 2016. Corporate funding and ideological polarization about climate change. Proc. Natl. Acad. Sci. 113 (1), 92–97.
Farrell, J., McConnell, K., Brulle, R., 2019. Evidence-based strategies to combat scientific misinformation. Nat. Clim. Change 9 (3), 191–195.
Fisher-Vanden, K., Weyant, J., 2020. The evolution of integrated assessment: Developing the next generation of use-inspired integrated assessment tools. Ann. Rev. Resour. Econ. 12, 471–487.
Flaschel, P., 2015. Goodwin's MKS system: a baseline macro model. Camb. J. Econ. 39 (6), 1591–1605.
Franta, B., 2018. Early oil industry knowledge of CO2 and global warming. Nature Clim. Change 8 (12), 1024–1025.
Frumhoff, P.C., Heede, R., Oreskes, N., 2015. The climate responsibilities of industrial carbon producers. Clim. Change 132 (2), 157–171.

GESIS, 2023. Eurobarometer data service. URL: https://www.gesis.org/en/eurobarometer-data-service/home. (Accessed 13 October 2023).
Glaeser, E.L., Sacerdote, B.I., Scheinkman, J.A., 2003. The social multiplier. J. Eur. Econom. Assoc. 1 (2–3), 345–353.
Godley, W., Lavoie, M., 2006. Monetary Economics: an Integrated Approach to Credit, Money, Income, Production and Wealth. Springer.
Goldberg, M.H., Gustafson, A., Ballew, M.T., Rosenthal, S.A., Leiserowitz, A., 2021. Identifying the most important predictors of support for climate policy in the United States. Behav. Public Policy 5 (4), 480–502.
Goldberg, M.H., van der Linden, S., Leiserowitz, A., Maibach, E., 2020. Perceived social consensus can reduce ideological biases on climate change. Environ. Behav. 52 (5), 495–517.
Hafner, S., Anger-Kraavi, A., Monasterolo, I., Jones, A., 2020. Emergence of new economics energy transition models: a review. Ecol. Econom. 177, 106779.
Hager, T., Mellacher, P., Rath, M., 2025. Gender Norms and Network Structure: A Model of the Intra-Household Division of Labor. Fem. Econ., forthcoming.
Hazlett, C., Mildenberger, M., 2020. Wildfire exposure increases pro-environment voting within democratic but not republican areas. Am. Political Sci. Rev. 114 (4), 1359–1365.
Hurst, M., Dittmar, H., Bond, R., Kasser, T., 2013. The relationship between materialistic values and environmental attitudes and behaviors: A meta-analysis. J. Environ. Psychol. 36, 257–269.
IPCC, 2023. Summary for policymakers. In: Core Writing Team, Lee, H., Romero, J. (Eds.), Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III To the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC, Geneva, Switzerland, pp. 1–34. http://dx.doi.org/10.59327/IPCC/AR6-9789291691647.001, URL https://www.ipcc.ch/report/ar6/syr/downloads/report/IPCC_AR6_SYR_SPM.pdf.
Isley, S.C., Lempert, R.J., Popper, S.W., Vardavas, R., 2015. The effect of near-term policy choices on long-term greenhouse gas transformation pathways. Global Environ. Change 34, 147–158.
Jenkins, J.D., 2014. Political economy constraints on carbon pricing policies: What are the implications for economic efficiency, environmental efficacy, and climate policy design? Energy Policy 69, 467–477.
Kachi, A., Bernauer, T., Gampfer, R., 2015. Climate policy in hard times: are the pessimists right? Ecol. Econom. 114, 227–241.
Kahan, D.M., 2013. Ideology, motivated reasoning, and cognitive reflection. Judgm. Decis. Mak. 8 (4), 407–424.
Kahn, M.E., Kotchen, M.J., 2011. Business cycle effects on concern about climate change: the chilling effect of recession. Clim. Change Econ. 2 (03), 257–273.
Kaldor, N., 1955. Alternative theories of distribution. Rev. Econ. Stud. 23 (2), 83–100.
Kalkuhl, M., Wenz, L., 2020. The impact of climate conditions on economic production. Evidence from a global panel of regions. J. Environ. Econ. Manage. 103, 102360.
Kallbekken, S., 2023. Research on public support for climate policy instruments must broaden its scope. Nature Clim. Change 13 (3), 206–208.
Känzig, D.R., 2023. The Unequal Economic Consequences of Carbon Pricing. Technical Report, National Bureau of Economic Research.
Keppo, I., Butnar, I., Bauer, N., Caspani, M., Edelenbosch, O., Emmerling, J., Fragkos, P., Guivarch, C., Harmsen, M., Lefevre, J., et al., 2021. Exploring the possibility space: Taking stock of the diverse capabilities and gaps in integrated assessment models. Environ. Res. Lett. 16 (5), 053006.
Klenert, D., Mattauch, L., Combet, E., Edenhofer, O., Hepburn, C., Rafaty, R., Stern, N., 2018. Making carbon pricing work for citizens. Nature Clim. Change 8 (8), 669–677.
Konc, T., Drews, S., Savin, I., van den Bergh, J.C., 2022. Co-dynamics of climate policy stringency and public support. Global Environ. Change 74, 102528.
Konc, T., Savin, I., van den Bergh, J.C., 2021. The social multiplier of environmental policy: Application to carbon taxation. J. Environ. Econ. Manage. 105, 102396.
Konisky, D.M., Hughes, L., Kaylor, C.H., 2016. Extreme weather events and climate change concern. Clim. Change 134, 533–547.
Lamperti, F., Bosetti, V., Roventini, A., Tavoni, M., 2019a. The public costs of climate-induced financial instability. Nature Clim. Change 9 (11), 829–833.
Lamperti, F., Dosi, G., Napoletano, M., Roventini, A., Sapio, A., 2018. Faraway, so close: Coupled climate and economic dynamics in an agent-based integrated assessment model. Ecol. Econom. 150, 315–339.
Lamperti, F., Mandel, A., Napoletano, M., Sapio, A., Roventini, A., Balint, T., Khorenzhenko, I., 2019b. Towards agent-based integrated assessment models: examples, challenges, and future developments. Reg. Environ. Change.
Lamperti, F., Monasterolo, I., Roventini, A., 2019c. Climate risks, economics and finance: Insights from complex systems. In: The Systemic Turn in Human and Natural Sciences: A Rock in the Pond. Springer, pp. 97–119.
Lamperti, F., Roventini, A., 2022. Beyond climate economics orthodoxy: impacts and policies in the agent-based integrated-assessment DSK model. Eur. J. Econ. Econ. Policies Interv. 19 (3), 357–380.
Lamperti, F., Wieners, C., Buizza, R., Dosi, G., Roventini, A., 2022. Macroeconomic policies to stay below 2 C with sustainable growth.
Latané, B., 1981. The psychology of social impact. Am. Psychol. 36 (4), 343.
Lipari, F., Lázaro-Touza, L., Escribano, G., Sánchez, Á., Antonioni, A., 2024. When the design of climate policy meets public acceptance: an adaptive multiplex network model. Ecol. Econom. 217, 108084.
Little, A.T., 2019. The distortion of related beliefs. Am. J. Political Sci. 63 (3), 675–689.
Magacho, G., Espagne, E., Godin, A., Mantes, A., Yilmaz, D., 2023. Macroeconomic exposure of developing economies to low-carbon transition. World Dev. 167, 106231.
Mason, W.A., Conrey, F.R., Smith, E.R., 2007. Situating social influence processes: Dynamic, multidirectional flows of influence within social networks. Pers. Soc. Psychol. Rev. 11 (3), 279–300.
McCright, A.M., Dunlap, R.E., Xiao, C., 2014. The impacts of temperature anomalies and political orientation on perceived winter warming. Nat. Clim. Change 4 (12), 1077–1081.
McDonald, R.I., Crandall, C.S., 2015. Social norms and social influence. Curr. Opin. Behav. Sci. 3, 147–151.
McPherson, M., Smith-Lovin, L., Cook, J.M., 2001. Birds of a feather: Homophily in social networks. Ann. Rev. Sociol. 27 (1), 415–444.
Meckling, J., Kelsey, N., Biber, E., Zysman, J., 2015. Winning coalitions for climate policy. Science 349 (6253), 1170–1171.
Meckling, J., Sterner, T., Wagner, G., 2017. Policy sequencing toward decarbonization. Nat. Energy 2 (12), 918–922.
Mellacher, P., 2021. Opinion dynamics with conflicting interests. GSC Discussion Papers No. 28.
Meng, K.C., Rode, A., 2019. The social cost of lobbying over climate policy. Nature Clim. Change 9 (6), 472–476.
Mercure, J.-F., Pollitt, H., Edwards, N.R., Holden, P.B., Chewpreecha, U., Salas, P., Lam, A., Knobloch, F., Vinuales, J.E., 2018. Environmental impact assessment for climate change policy with the simulation-based integrated assessment model E3ME-FTT-GENIE. Energy Strategy Rev. 20, 195–208.
Mercure, J.-F., Sharpe, S., Vinuales, J.E., Ives, M., Grubb, M., Lam, A., Drummond, P., Pollitt, H., Knobloch, F., Nijsse, F.J., 2021. Risk-opportunity analysis for transformative policy design and appraisal. Global Environ. Change 70, 102359.
Meyer, A.G., 2022. Do economic conditions affect climate change beliefs and support for climate action? Evidence from the US in the wake of the great recession. Econ. Inq. 60 (1), 64–86.
Montfort, S., Fesenfeld, L., Stadelmann-Steffen, I., Ingold, K., 2023. Policy sequencing can increase public support for ambitious climate policy. Policy Soc. 42 (4), 454–477.
Moore, F.C., Lacasse, K., Mach, K.J., Shin, Y.A., Gross, L.J., Beckage, B., 2022. Determinants of emissions pathways in the coupled climate–social system. Nature 603 (7899), 103–111.
Moore, F.C., Obradovich, N., Lehner, F., Baylis, P., 2019. Rapidly declining remarkability of temperature anomalies may obscure public perception of climate change. Proc. Natl. Acad. Sci. 116 (11), 4905–4910.

Moreno, A., Guevara, D., Andrade, J., Pierros, C., Godin, A., Yilmaz, S.D., Valdecantos, S., 2024. Low-carbon transition and macroeconomic vulnerabilities: A multidimensional approach in tracing vulnerabilities and its application in the case of Colombia. Int. J. Political Econ. 53 (1), 43–66.
Muth, D., 2023. Pathways to stringent carbon pricing: Configurations of political economy conditions and revenue recycling strategies. A comparison of thirty national level policies. Ecol. Econom. 214, 107995.
Newman, M., 2010. Networks: An Introduction. Oxford University Press.
Nyborg, K., Anderies, J.M., Dannenberg, A., Lindahl, T., Schill, C., Schlüter, M., Adger, W.N., Arrow, K.J., Barrett, S., Carpenter, S., et al., 2016. Social norms as solutions. Science 354 (6308), 42–43.
Otto, I.M., Donges, J.F., Cremades, R., Bhowmik, A., Hewitt, R.J., Lucht, W., Rockström, J., Allerberger, F., McCaffrey, M., Doe, S.S., et al., 2020. Social tipping dynamics for stabilizing Earth's climate by 2050. Proc. Natl. Acad. Sci. 117 (5), 2354–2365.
Pahle, M., Burtraw, D., Flachsland, C., Kelsey, N., Biber, E., Meckling, J., Edenhofer, O., Zysman, J., 2018. Sequencing to ratchet up climate policy stringency. Nature Clim. Change 8 (10), 861–867.
Palagi, E., Coronese, M., Lamperti, F., Roventini, A., 2022. Climate change and the nonlinear impact of precipitation anomalies on income inequality. Proc. Natl. Acad. Sci. 119 (43), e2203595119.
Peng, W., Iyer, G., Bosetti, V., Chaturvedi, V., Edmonds, J., Fawcett, A.A., Hallegatte, S., Victor, D.G., Van Vuuren, D., Weyant, J., 2021. Climate policy models need to get real about people—here's how. Nature 594 (7862), 174–176.
Pierson, P., 1993. When effect becomes cause: Policy feedback and political change. World Politics 45 (4), 595–628.
Ponta, L., Raberto, M., Teglio, A., Cincotti, S., 2018. An agent-based stock-flow consistent model of the sustainable transition in the energy sector. Ecol. Econom. 145, 274–300.
Ranaldi, M., 2022. Income composition inequality. Rev. Income Wealth 68 (1), 139–160.
Reissl, S., Fierro, L.E., Lamperti, F., Roventini, A., 2024. The dsk-sfc stock-flow consistent agent-based integrated assessment model. Available at SSRN 4766122.
Rengs, B., Scholz-Wäckerle, M., van den Bergh, J., 2020. Evolutionary macroeconomic assessment of employment and innovation impacts of climate policy packages. J. Econ. Behav. Organ. 169, 332–368.
Ricke, K.L., Caldeira, K., 2014. Natural climate variability and future climate policy. Nature Clim. Change 4 (5), 333–338.
Scruggs, L., Benegal, S., 2012. Declining public concern about climate change: Can we blame the great recession? Glob. Environ. Change 22 (2), 505–515.
Semieniuk, G., Campiglio, E., Mercure, J.-F., Volz, U., Edwards, N.R., 2021. Low-carbon transition risks for finance. Wiley Interdiscip. Rev. Clim. Change 12 (1), e678.
Sîrbu, A., Loreto, V., Servedio, V.D., Tria, F., 2017. Opinion dynamics: models, extensions and external effects. Particip. Sens. Opin. Collect. Aware. 363–401.
Soga, M., Gaston, K.J., 2018. Shifting baseline syndrome: causes, consequences, and implications. Front. Ecol. Environ. 16 (4), 222–230.
Sordi, S., Dávila-Fernández, M.J., 2023. The Green-MKS system: A baseline environmental macro-dynamic model. J. Econ. Behav. Organ. 212, 1056–1085.
Stokes, L.C., 2020. Short Circuiting Policy: Interest Groups and the Battle Over Clean Energy and Climate Policy in the American States. Oxford University Press, USA.
Supran, G., Oreskes, N., 2017. Assessing ExxonMobil's climate change communications (1977–2014). Environ. Res. Lett. 12 (8), 084019.
Tooze, A., 2023. Chartbook Carbon Notes 9 Slouching Towards a 2 Degree-Plus World. Chartbook, URL https://adamtooze.substack.com/p/chartbook-carbon-notes-9-slouching. (Accessed 18 December 2023).
van den Bergh, J.C., Savin, I., Drews, S., 2019. Evolution of opinions in the growth-vs-environment debate: Extended replicator dynamics. Futures 109, 84–100.
Wettengel, J., 2024. Germany's carbon pricing system for transport and buildings. https://www.cleanenergywire.org/factsheets/germanys-planned-carbon-pricing-system-transport-and-buildings. (Accessed 11 February 2024).
Weyant, J., 2017. Some contributions of integrated assessment models of global climate change. Rev. Environ. Econ. Policy.
Wicki, M., Fesenfeld, L., Bernauer, T., 2019. In search of politically feasible policy-packages for sustainable passenger transport: insights from choice experiments in China, Germany, and the USA. Environ. Res. Lett. 14 (8), 084048.
Wieners, C., Lamperti, F., Buizza, R., Dosi, G., Roventini, A., 2022. Macroeconomic policy for a rapid and orderly transition.
World Bank, 2023. Carbon pricing dashboard. https://carbonpricingdashboard.worldbank.org/map_data. (Accessed 11 February 2024).
Zaval, L., Keenan, E.A., Johnson, E.J., Weber, E.U., 2014. How warm days increase belief in global warming. Nature Clim. Change 4 (2), 143–147.