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Opinion Dynamics meet Agent-based Climate Economics: An Integrated Analysis of Carbon Taxation

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Abstract

The paper introduces an integrated approach, blending Opinion Dynamics with a Macroeconomic Agent-Based Model (OD-MABM). It aims 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 panel survey data to the Dystopian Schumpeter meeting Keynes model (DSK). Opinion dynamics regarding stringent 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 (mis-)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 while effective carbon tax policies initially lead to a decline in public support due to substantial macroeconomic transition costs, they concurrently drive 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, gradually diminishing as the transition unfolds. Second, hybrid revenue recycling strategies that combine green subsidies with climate dividends successfully address this intertemporal tradeoff, broadening public support right from the introduction of the carbon tax.

Keywords: Climate change, mitigation policy, opinion dynamics, agent-based models, transition risks

JEL-Codes: C63; H31; Q43; Q50

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Declarations of interest: none

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.

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.

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.

Our key finding reveals a crucial intertemporal tradeoff 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 favorably 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 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 behavior 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

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

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 tradeoffs 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) and Peng et al. (2021) or Beckage et al. (2022) 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 (comp. 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 agent-based evolutionary economics 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)[4] add a social layer to the DSK by linking it to a simple two-party election model. Climate policies are implemented by a green 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 (mis-)information campaigns.[5] Moreover, we employ an elaborate estimation procedure to calibrate the opinion dynamics model to Eurobarometer panel survey data over 2011-2019 and illustrate descriptive output validation of the model for the 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

[2] originally developed by Flaschel (2015)

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

[4] Working paper by Di Benedetto, Wieners and von der Heydt forthcoming.

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

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 revenue usage, 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 removing politico-economic barriers.

3 An Integrated Opinion Dynamics-MABM Approach

To study dynamic public support for climate policy, we employ two Agent-Based Models (ABMs): an opinion dynamics model and a climate-macroeconomic model. We apply 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.

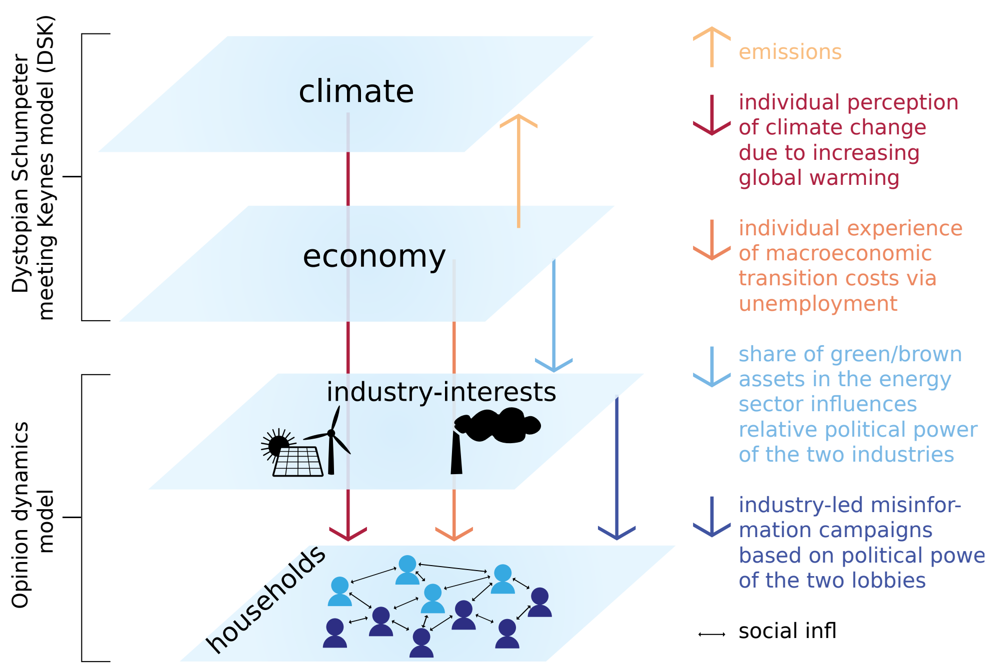


Figure 1: Overview of the integrated Opinion Dynamics - Macroeconomic Agent-Based Model approach (OD-MABM)

The dynamics in the economic and climate system affect public support for climate policy in the population 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 homophilic 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 (comp. 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 Figure 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 behaviors 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 panel data very well (comp. the principle of descriptive output validation discussed by Tesfatsion (2017)), and suggest a new benchmark in the field by providing insights on opinion dynamics over a duration hitherto unexplored in similar studies.

The model goes beyond modeling public support for climate change as a simple reaction to economic impacts alone. In particular, we include four relevant dimensions which are illustrated in Figure 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); (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 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 potentially 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 equilibrium. 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 misinformation 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 misinformation 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 misinformation about climate change instead of taking responsibility and reducing its impact (Frumhoff et al., 2015; Bonneuil et al., 2021). The fossil fuel-based industry thus imposes powerful political economy constraints to the implementation of effective climate policies. However, the political economy literature also documents a positive feedback effect (Pierson, 1993; Stokes, 2020; Moore et al., 2022) where the implementation of initial climate policy establishes powerful interests in the renewable-based industries to lobby in support of more stringent climate policies and climate change awareness. The model accounts for these contesting dynamics as households are exposed to fossil and renewable-based industry-led scientific (mis-)information campaigns that reflect the respective industry's political power and aim to promulgate viewpoints that are favourable to their industry interests.

While individual economic conditions, perception of climate change and exposure to industry-led (mis-)information campaigns are relevant, individual opinions are 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 individual 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 policy interventions. 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 the requirements of an advantageous policy mix to address the dilemma between political feasibility and environmental policy effectiveness (Kallbekken, 2023; Wicki et al., 2019). The opinion dynamics model developed in this study provides a powerful tool to address 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[6], where $LS = \sum_{k=1}^{K} LS_k$ and LS_k measures national population. Each household i is characterized by its employment status (es), social class (c) and climate policy opinion (op) which is summarized by the profile

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

The employment status is modelled as a binary variable $es_{i,t} \in \{0, 1\}$ where 1 indicates that the individual is unemployed. Moreover, we account for household heterogeneity in terms of their subjective social class which is represented by the discrete variable $c_i \in \{1, 2, 3, 4, 5\}$ whose value increases from lower to upper class and represents a grouping based on similar social factors such as income, wealth, education or occupation[7]. Climate policy opinion is a discrete variable $op_{i,t} \in \{1, 2, 3\}$ where 1 denotes opposition, 2 neutrality and 3 support. Note that each household's social class is assumed to remain constant over the transition period while the employment status and opinion may change over time. The (LS=26,019) 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 (comp. Moore et al. (2022)).

[6]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.

[7]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.

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)	$\begin{cases} 1 & \text{if D15A} = 2 \\ 0 & \text{otherwise} \end{cases}$
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)	$\begin{cases} 1 & \text{if working} \\ 2 & \text{lower middle} \\ 3 & \text{middle} \\ 4 & \text{upper middle} \\ 5 & \text{higher} \end{cases}$
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)	$\begin{cases} 1 & \text{if QB2} \leq 5 \\ 2 & \text{if } 5 < \text{QB2} \leq 9 \\ 3 & \text{if QB2} = 10 \end{cases}$

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

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 (mis-)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 National homophily-based social networks

Households interact in fixed national homophily-based social networks. For each country k, there is an undirected graph $G = (V, E)$ where $V = \{v_1, v_2, ..., v_{LS}\}$ denotes the set of LS households in a country and E denotes the set of links among households. Each household $v_i \in V$ is associated with a normalized characteristics vector

$$A^i = (a_1^i, a_2^i, a_3^i) = (\frac{es_{i,0}}{2}, \frac{c_i}{5}, \frac{op_{i,0}}{3}) \tag{2}$$

and is connected to ℓ other households. The weighted probability of connecting v_i to v_j (for $i \neq j$) depends on their similarity $\sigma(v_i, v_j)$ and is given by

$$P(v_i, v_j) = \frac{\sigma(v_i, v_j)}{\sum_{n=1, n\neq i}^{N} \sigma(v_i, v_n)} \tag{3}$$

with

$$\sigma(v_i, v_j) = \frac{1}{3} \sum_{m=1}^{3} (1 - |a_m^i - a_m^j|) \in (0, 1) \tag{4}$$

The network is then generated by the following process. For each household $v_i \in V$, ℓ households from $V \setminus \{v_i\}$ are selected with the probability distribution

$$\{P(v_i, v_1), P(v_i, v_2), ..., P(v_i, v_N)\} \setminus \{P(v_i, v_i)\} \tag{5}$$

and a link between v_i and each of the selected households is created. After iterating over all v_i, the resulting graph constitutes the social network G.

3.1.3 Timeline of events

As described 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 react to macroeconomic costs of mitigation policy, proxied by the unemployment rate. They perceive evidence of climate change based on the mean surface temperature increase (ΔT_t) 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 ($\rho_{tp,t}$), households are targeted with industry-led (mis)information campaigns aimed at influencing the acceptance of the reality of climate change. 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 t, 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., ΔT_t, $\widehat{U}_t$, $\rho_{tp,t}$) and translates the change in the unemployment rate $\widehat{U}_t$ 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 a climate-macroeconomic model (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. 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

$$ETO_t = toL_t \tag{6}$$

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., $\widehat{U}_t \geq 0$), JTO_t randomly selected employees, drawn from a uniform distribution become unemployed. Otherwise, JTO_t unemployed households are randomly selected to get a job[8].

$$JTO_t = |\widehat{U}_t| LS \tag{7}$$

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

$$unem_{i,t} = \begin{cases} -\nu & \text{if } es_{i,t} = 1 \\ 0 & \text{if } es_{i,t} = 0 \end{cases} \tag{8}$$

where the parameter $\nu \in (0, 1)$ 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

$$\Delta T_t^* = \begin{cases} \Delta T_t & \text{if } Base = 0 \\ \Delta T_t - \sum_{i=8}^{2} \beta_i \Delta T_{t-i}, & \text{if } Base = 1 \end{cases} \tag{9}$$

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

$$cc_{i,t} = \eta \Delta T_t^* \tag{10}$$

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

[8]The number of unemployed is expressed by $(LS_t - L_t)$.

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 a constant share of households $\bar{\tau}$ but the distribution of funds across the two lobbyist groups changes over time with their assets' revaluation in the wake of implemented climate policy. Their relative lobbying power $\rho_{tp,t}$ is assumed to be proportional to their asset holdings in the current production capacity. In fact, $\bar{\tau}\rho_{t,F}LS$ randomly selected households, drawn from a uniform distribution, receive the fossil fuel-based industry-led (mis)information campaign. Each household i may decrease its support for climate policy via the fossil lobbying influence

$$Flob_{i,t} = \begin{cases} -\lambda & \text{if } U_{i,t}^F < \bar{\tau}\rho_{t,F} \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

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 (mis)information campaign may positively influence the targeted households' policy opinion and is implemented analogously with

$$Rlob_{i,t} = \begin{cases} \lambda & \text{if } U_{i,t}^R < \bar{\tau}\rho_{t,R} \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

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

$$soc_{i,t} = \begin{cases} 0 & \text{if } op_{i,t} = op_{j,t} \\ F & \text{if } op_{i,t} < op_{j,t} \\ -F & \text{if } op_{i,t} > op_{j,t} \end{cases} \tag{13}$$

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

3.1.9 Update climate policy support

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

$$p_{i,t} = unem_{i,t} + cc_{i,t} + Flob_{i,t} + Rlob_{i,t} + soc_{i,t} \tag{14}$$

The opinion next period becomes

$$op_{i,t+1} = \begin{cases} op_{i,t} + 1 & \text{if } p_{i,t} \geq 0,\ op_{i,t} < 3,\ B(p_{i,t}) = 1 \\ op_{i,t} - 1 & \text{if } p_{i,t} < 0,\ op_{i,t} > 1,\ B(|p_{i,t}|) = 1 \\ op_{i,t} & \text{else} \end{cases} \tag{15}$$

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, and 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 results is provided in the next section 3.2 and in section 4.1, respectively.

	Description	Parameter values	Calibration
LS	Number of households	26,019	Eurobarometer survey respondents
ℓ	Connectivity parameter	2	
to	Employee turnover	0.07	
F	Persuasive force	$\in (0,1)$	0.20 [0.00, 0.54]
$Base$	Shifting baselines	$\begin{cases} 1 & \text{if on} \\ 0 & \text{if off} \end{cases}$	
$\vec{\beta}$	Parametrization of shifting baselines	$(0.23, 0.2, 0.17, 0.14, 0.11, 0.09, 0.06)$	
η	Climate change evidence impact	$\in (0,1)$	0.27 [0.14, 0.41]
ν	Unemployment impact	$\in (0,1)$	0.11 [0.00, 0.28]
$\bar{\tau}$	Share of targeted citizens by lobbying	0.10	
λ	Lobbying impact	$\in (0,1)$	0.15 [0.00, 0.42]

Table 2: Opinion dynamics model parameters. The empirically calibrated parameter estimates and correspondng 95% confidence intervals are based on random forest, the best performing estimation algorithm.

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

Table 3: Opinion dynamics model inputs

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 (European Commission 2014, 2017, 2018, 2019; European Commission and European Parliament 2021) which monitors public opinion and includes information about the unemployment status of each respondent, hence approximating the share of unemployed per country (and $\widehat{U}_t$ in the model). We take into account 26 countries which have been a member in 2011 and at the writing of this article (i.e., all current members minus Croatia). We link this dataset with data on the global temperature anomalies with respect to the 1901-2000 average (ΔT_t, National Centers 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 100,000 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. 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 comparing a vector consisting of 208 observations (i.e., 26 countries multiplied by 2 to account for supporters and opponents, multiplied by 4 for the years of 2011, 2013, 2015 and 2019) with a $100,000 \times 208$ matrix produced by the simulations. 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.[9]. 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 (ABM) with an integrated assessment element and an energy sector (Ponta et al., 2018; Rengs et al., 2020; Ciola et al., 2023) and constitutes an important step forward in the ecological and energy economics literature. Indeed, MABMs offers 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 the Dynamic Stochastic General Equilibrium Model (DSGE) [10]. 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[11] where the model accounting system has been thoroughly revised and harmonized with the stock-flow consis-

[9] We also tried to use GAM and Neural Network ABC, but had to exclude the former because it was computationally too expensive and the latter because it was not able to deal with the size of the target vector.

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

[11] The DSK-SFC model description will be made available in a forthcoming working paper by Reissl, Fierro, Lamperti, and Roventini.

tent 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 (G) and in the original DSK description (Lamperti et al., 2018).

The model comprises a consumption goods sector wherein consumption firms (C-Firms) engage in the production and sale of a homogeneous good utilizing labor, 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 labor and energy. These capital items exhibit heterogeneity in terms of embedded labor 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 provide deposits for 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 labor supply[12]. They acquire income through various channels, including labor 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:

$$C_{d,t} = \alpha_1(W_t + UB_t + TR_t^H - Tax_t^H) + \alpha_2(Div_{t-1} + iD_{h,t}) + \alpha_3 D_{h,t-1} \tag{16}$$

[12]Note that the labor 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 labor supply in the DSK.

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 labor 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[13]. We posit $\alpha_1 > \alpha_2$, indicating a greater propensity to consume out of labor income compared to dividends and capital income[14]. Additionally, we assume that government transfers are treated akin to wages, implying their allocation towards workers.

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

$$p_{c,t} = (1 + \mu_{c,t})uc_{c,t} \tag{17}$$

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:

$$uc_{c,t} = \sum_{\kappa \in \Phi^u_{\kappa,c,t}} uc_{\kappa,t} \frac{\mathfrak{K}_{\kappa,c,t}}{\mathfrak{K}_{c,t}} \tag{18}$$

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 (labor productivity and energy efficiency) and the factor prices:

$$uc_{\kappa,t} = \frac{w_t}{Pr_\kappa} + \frac{p_{e,t}}{EE_\kappa} \tag{19}$$

Where w_t is the wage rate, Pr_κ is the κ-specific labor 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:

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

[14] We implicitly assume that capital income is mostly concentrated at the 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).

$$p_{e,t} = \mu_{e,t} + mc_{e,t} \tag{20}$$

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:

$$c_{\kappa^{de},t} = \frac{p_{f,t-1}}{TE_{\kappa^{de}}} + \tau^{Em,E}_t EF_{\kappa^{de}} \tag{21}$$

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:

$$c^{min}_{\kappa^{de},t} < \frac{c^{min}_{\kappa^{ge},t}}{b^e} \tag{22}$$

Where b^e is a payback period parameter. Conversely, if the condition in eq.(22) 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:

$$\varsigma^e_t = \arctan\left(A^{\varsigma}\frac{c^{min}_{\kappa^{de},t} b^e - c^{min}_{\kappa^{ge},t}}{c^{min}_{\kappa^{ge},t}}\right) \tag{23}$$

Where A^{ς} is a scaling parameter.

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:

$$Temp_t = \Upsilon_1 + \Upsilon_2 \mathscr{E}^{\Sigma}_t \tag{24}$$

Where $\mathscr{E}^{\Sigma}_t$ are cumulative emissions up to period t; Υ_1 is the exogenous temperature anomaly intercept; Υ_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).[15] (see table 8 in appendix B). 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 G.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 8 and Figure 8 in appendix B 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.

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

3.4.1 Carbon tax

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

$$CTAX_t = \tau_t^{Em,E} Em_{E,t} \tag{25}$$

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[16].

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

$$\begin{cases} \tau_t^{Em,E} = 0 & \text{If} \quad t < t_0^{clim} \\ \tau_t^{Em,E} = \frac{cpi_{t-1}}{cpi_0} min\left\{\tau^{Em,E,max}, \ \left[\tau_{t_0^{clim}}^{Em,E} + g^{\tau,Em}\left(t - t_0^{clim}\right)\right]\right\} & \text{Otherwise} \end{cases} \tag{26}$$

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.

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:

$$TR_t^H = \rho^{ctax} CTAX_{t-1} \tag{27}$$

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:

$$\begin{cases} TR_t^E = \rho^{gsubs} c_{\kappa^{ge}}^{min} EI_t^{ge} \\ \\ TR_t^H = \rho^{ctax} CTAX_{t-1} - TR_t^E \end{cases} \tag{28}$$

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.(23) can be rewritten as:

$$\varsigma_t^e = \arctan\left(A^{\varsigma} \frac{c_{\kappa^{de},t}^{min} b^e - (1 - \rho^{gsubs}) c_{\kappa^{ge},t}^{min}}{(1 - \rho^{gsubs}) c_{\kappa^{ge},t}^{min}}\right) \tag{29}$$

[16] 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 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.

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**		
$\rho^{ctax} = 0$	$\rho^{ctax} > 0$	$\rho^{ctax} > 0$		
$\rho^{gsubs} = 0$	$\rho^{gsubs} = 0$	$\rho^{gsubs} > 0$		

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 scheme. 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.

4 Results

4.1 Calibration and validation of the OD model

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 six different algorithms (OLS, Random Forest, Quantile Random Forest, Rejection ABC, loclinear ABC, Semiautomatic ABC) and rank them according to i) their ability to identify parameters using a 5-fold cross-validation exercise as well as the coverage of the confidence intervals produced by them, and ii) the mean root of the squared error of the predicted vs. empirical values for 2013, 2015, 2017 and 2019 (i.e., descriptive output validation, see Tesfatsion, 2017).

For our cross-validation exercises, we use the two metrics provided by the freelunch package (Carrella, 2021), namely 'performance', which quantifies the improvement in point estimates for predictions compared to a scenario where one simply guesses the average value of the distribution (see the definition in the appendix A, Equation (33)), and 'coverage' which detects how often the true parameter is contained in the 95% confidence interval produced by the method.

The performance may reach a maximum value of 1 (for perfectly identified variables), but may even reach negative values for mis-identified variables. Carrella (2021) cite a performance of lower than 0.1 as 'serious identification failure' and a performance lower than 0.3 as an 'identification failure'. As it can be seen in Table 6 in the appendix A, every method tested can identify every parameter, although Rejection ABC performs much worse than all other algorithms in terms of performance.

Table 5 shows the point estimates and 95% confidence interval produced by each algorithm, as well as the RMSE in terms of absolute number of people when running the model for each of the 26 countries using the point estimates of the six algorithms. We can see that random forest regression outperforms all other methods in terms of the RMSE, we therefore choose this method to estimate the parameters.[17]

algorithm	persuasive force	evidence effect	unemployment effect	lobbying effect	RMSE
random forest	0.2 (-0.137 – 0.542)	0.274 (0.143 – 0.407)	0.108 (-0.073 – 0.284)	0.149 (-0.152 – 0.423)	5.57
quantile random forest	0.225 (0.034 – 0.606)	0.284 (0.142 – 0.435)	0.105 (0.007 – 0.265)	0.126 (0.005 – 0.725)	5.80
loclinear abc	0.055 (0.052 – 0.059)	0.078 (0.071 – 0.091)	0.214 (0.202 – 0.228)	-0.256 (-0.258 – -0.253)	5.83
semiautomatic abc	0.166 (0.007 – 0.517)	0.265 (0.015 – 0.695)	0.313 (0.015 – 0.846)	0.194 (0.011 – 0.56)	5.93
rejection abc	0.356 (0.034 – 0.959)	0.363 (0.081 – 0.623)	0.31 (0.016 – 0.882)	0.407 (0.022 – 0.953)	6.13
linear regression	-0.12 (-0.279 – 0.001)	0.0 (-0.07 – 0.061)	0.132 (0.03 – 0.239)	-0.151 (-0.267 – -0.036)	10.54

Table 5: Parameter estimates and 95% confidence intervals for each of the six algorithms and the sum of the root mean squared errors of supporters, opponents and neutrals, ordered by the RMSE in ascending order.

Simulating the opinion dynamics using the best calibration for the 2011-2019 period, we find that the model performs very well in terms of descriptive output validation. Figure 2 shows that the opinion dynamics of large countries such as Germany, France, Italy and Spain are replicated with high precision. Fore some countries including Cyprus, Greece, Estonia, Latvia and Slovakia, we observe larger quantitative deviations but the qualitative dynamics are matched well. The two main reasons for the heterogeneous model performance across EU countries relate to cross-country differences and to our calibration approach. Consistent with the macroeconomic model, which captures the EU27 economy as an aggregate, the calibration procedure aims at minimizing the difference between the simulated and empirical data in terms of the population-weighted average opinion shares. Thus, the forecast error of the calibrated opinion dynamics model is higher for small countries by construction. Second, the calibration approach reflects our aim to develop a general model which is useful to explore opinion dynamics related to climate policy in the EU. We chose not to calibrate country-specific parameters as our policy experiments are also simulated

[17] We choose the RMSE of the opinion dynamics in the calibrated model vs. the empirical data instead of other metrics, such as the performance in cross-validation, since this metric measures how well-suited the set of parameters produced by a given algorithm is to mimic the empirical patterns, while the performance measures how well an algorithm can identify parameters solely based on simulated data, without any connection to empirical data.

at the EU level, meaning that our analysis does not differentiate for cross-country differences in macroeconomic transition risks.

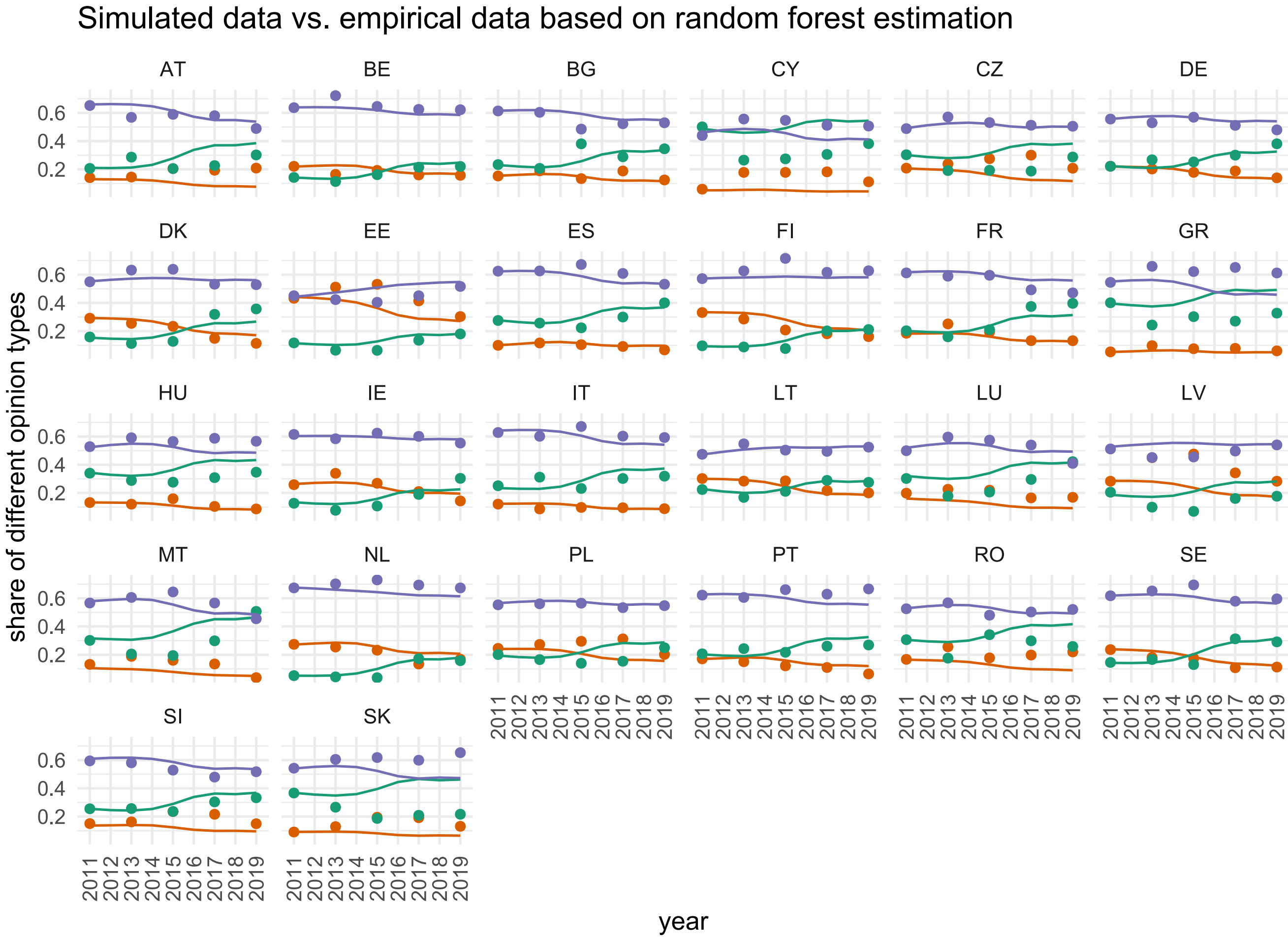


Figure 2: Descriptive output validation of the opinion dynamics model. Purple indicates neutrals, green indicates supporters and orange indicates opponents. Lines represent simulated data (average of 100 Monte Carlo experiments), points correspond to Eurobarometer survey data.

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

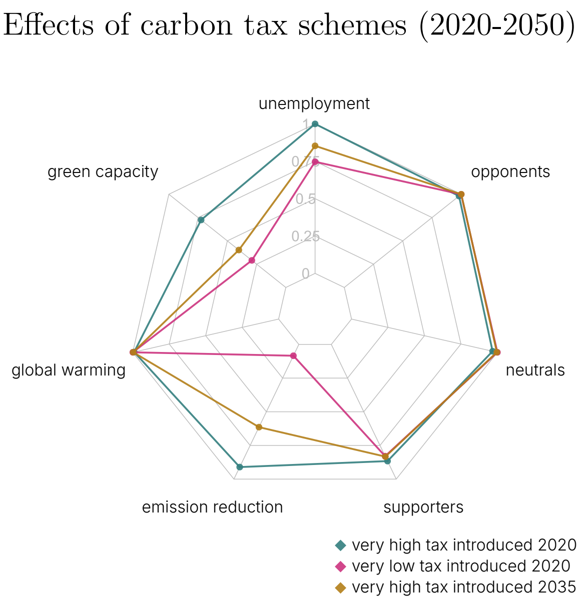
A later introduction of the carbon tax (t_0^{clim}) implies that the full transition in the energy sector is achieved at a later point in time, while a higher slope of the carbon tax ($g^{t,Em}$) accelerates the green transition. Similarly, the share of green assets in the energy sector starts growing 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 decarbonisation process which is fast enough to comply with EU climate targets, extremely high carbon taxes are required 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 (comp. also Wieners et al. (2022), Lamperti and Roventini (2022) and 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[18] as long as brown vintages are utilized in production. C-Firms pass through the increased energy prices to the general price level[19], leading to a reduction in real wages. This results in a generalized lack of aggregate demand, leading to high unemployment and weak economic growth.

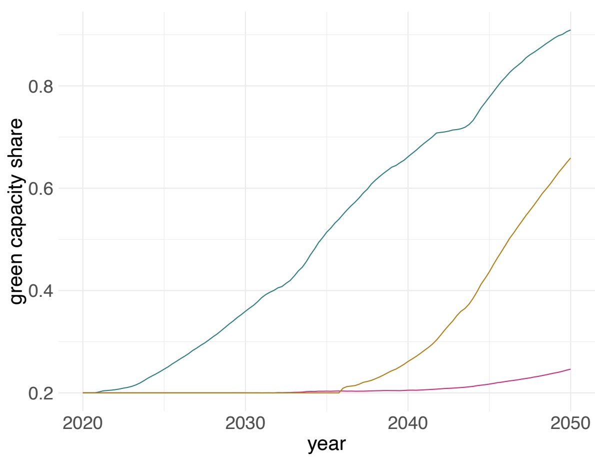
Looking at long-run opinion dynamics over the transition period 2020-2050 associated with different carbon tax schemes (comp. Figure 3), we find that modest carbon taxes are not only insufficient to trigger the decarbonisation in the energy sector but also constrain public support by sustaining fossil asset holders' lobbying power. A low carbon price sustains the profits of fossil asset holders which constitute the basis to invest in 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. A high carbon tax alters the distribution of profits in the energy sector in favor of green asset holders and ultimately removes the profits of fossil asset holders due to excessive capacity. Thus, the lobbying power of the green asset holders increases the higher the slope of the carbon tax ($g^{t,Em}$) and the earlier it is introduced (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), cumulative or 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.

[18]Recall the energy price setting Equation (20), which specifies that the production cost of the marginal vintage utilized in energy production serves as the foundation for determining the energy price.

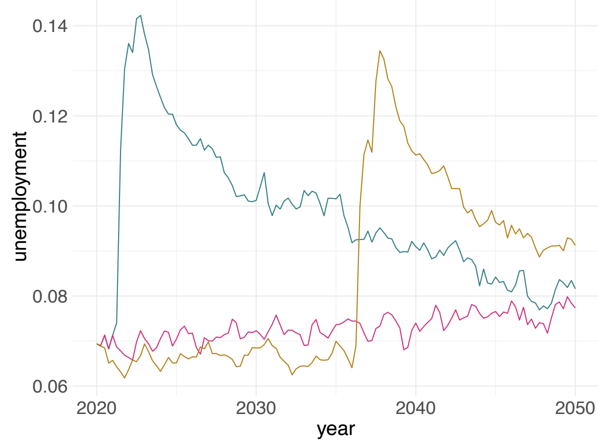
[19]Recall the price setting Equation (17) implying that for given markup, cost-push shock are entirely pass-through. Note also, that in the K+S basic framework, markups are insensitive to cost-push shocks.



(a) Overview



(b) Share of green capacity in the energy sector



(c) Unemployment

Figure 3: Variables across three exemplary tax scenarios: i) very high tax introduced in 2020 (blue); ii) very low carbon tax introduced in 2020 (pink); iii) very high carbon tax introduced in 2035 (yellow). 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 Figure 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 in the medium run after the economic and lobbying tipping points have been passed. During the latter period, low carbon tax pathways are associated with a persistently higher share of opponents and lower share of supporters 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 5% lower (comp. Figure 15 in appendix H).

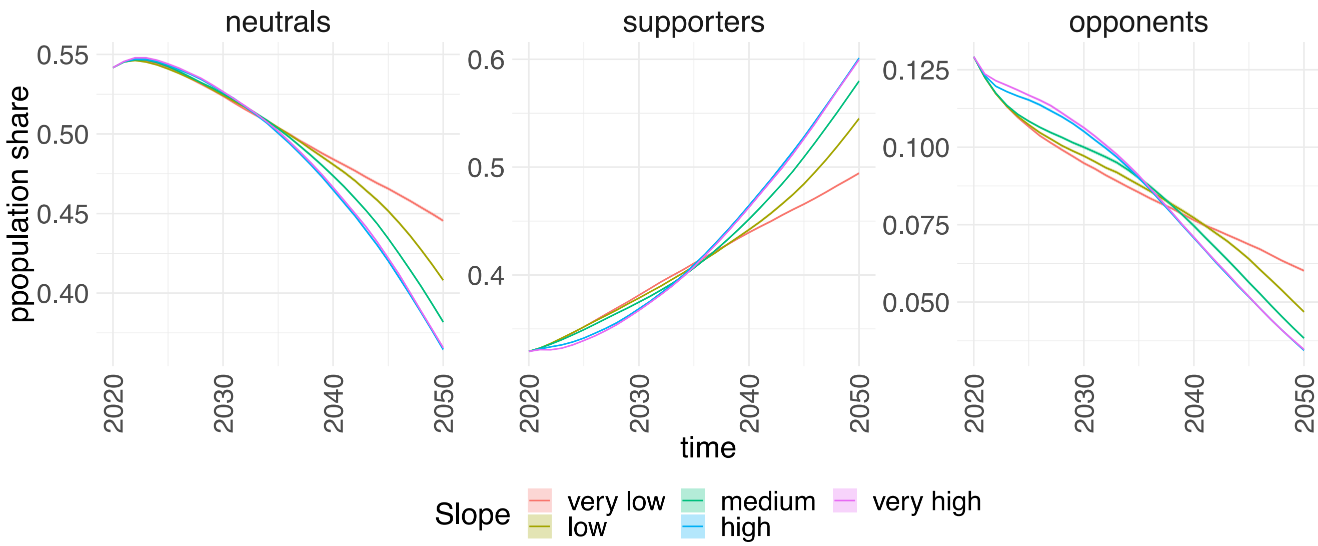


Figure 4: Share of opinion types across carbon tax schemes introduced in 2020 (based on 100 Monte Carlo experiments)

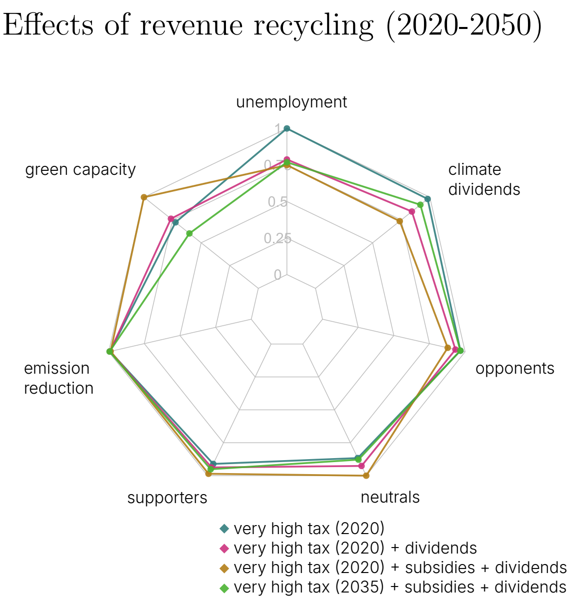
We argue that a policy mix, e.g. combining a carbon tax with redistributive policies such as climate dividends or green investment subsidies, should be evaluated with respect to two dimensions. The first dimension assesses the impact of the policy mix on the goals of the energy transition, determining 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 described above, specifically by shaping public opinion dynamics to garner support for it.

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

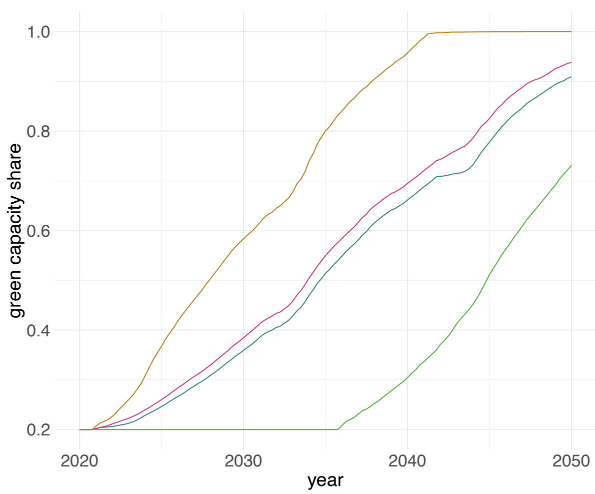
As discussed in section 4.2, the carbon tax affects the macroeconomy by diminishing the real value of wages. Distributing carbon tax revenues to households can offset the income loss caused by the carbon tax, thereby restoring an aggregate demand level conducive to low unemployment during the transition. 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.

Distributing climate dividends to households positively affects 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 of the policy mix (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 Figure 5 by contrasting the extreme cases of an early introduction of the very high carbon tax without a complementary recycling mechanism and the same carbon tax whose entire generated revenues are earmarked for recycling via climate 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 people are likely to share their concerns with their friends and family potentially leading to tipping point dynamics causing a much bigger drop in climate policy support over subsequent periods 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 the government's 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}, higher green investment subsidies ρ^{gsubs} accelerate 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 maximized for the policy mix which combines an early implementation of a very high carbon tax whose entire revenues are recycled back to society (i.e., $\rho^{ctax} = 1$) via high green investment subsidies ($\rho^{gsubs} = 0.8$) and (residual) climate dividends. This is illustrated in Figure 5 showing that the "best" policy mix outperforms the pure carbon tax and the climate dividend revenue recycling mechanism but also the scenario where the same policy mix is introduced with delay (i.e., in 2030).



(a) Overview



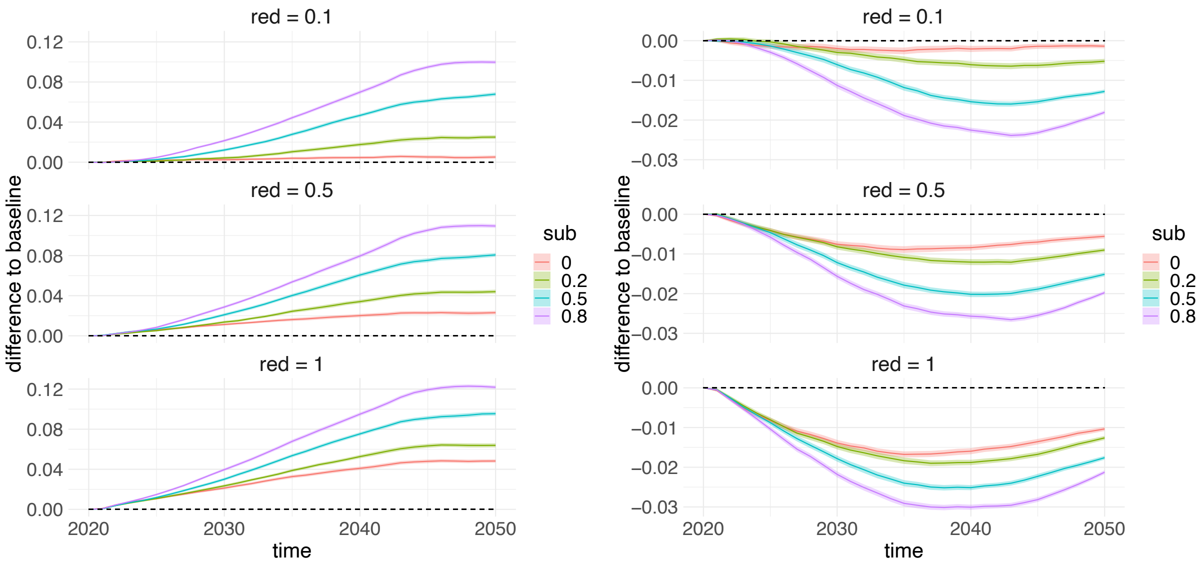
(b) Share of green capacity in the energy sector

(c) Unemployment

Figure 5: Variables across four exemplary tax scenarios: i) very high tax introduced in 2020 (blue, $\rho^{ctax} = \rho^{gsubs} = 0$); ii) very high tax introduced in 2020, all revenues recycled via climate dividends (pink, $\rho^{ctax} = 1$, $\rho^{gsubs} = 0$); iii) very high tax introduced in 2020, all revenues recycled via high green subsidies and climate dividends (yellow, $\rho^{ctax} = 1$, $\rho^{gsubs} = 0.8$); iv) very high tax introduced in 2035, all revenues recycled via high green subsidies and climate dividends (green, $\rho^{ctax} = 1$, $\rho^{gsubs} = 0.8$). 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.

Figure 6 displays the 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 maximizes the transition speed in the energy sector which translates into 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 these slopes record lower levels of public support and higher opposition during the transition period. Delaying the introduction of the policy mix is also detrimental in terms of maximizing support in the population as the positive effect on opinion dynamics start to unfold only at a later point in time.

Effects of revenue recycling (2020-2050)



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

Figure 6: Share of supporters and opponents across revenue recycling configurations defined by a combination of earmarked carbon tax revenues for redistribution to society (red = ρ^{ctax}) and green investment subsidy (sub = ρ^{gsubs}). Simulation results are based on 100 Monte Carlo experiments.

Finally, we want to decompose the relative importance of the different channels in changing the opinions of households. To this end, we depict the effects of unemployment, climate change, lobbying and social influence for each year in Figure 7, focusing on the policy scenario that generates highest public support over the transition period: early implementation of a (very) high carbon tax together with high green investment subsidies and climate dividends.

Since we are specifically interested in tracking changes in opinions, we focus on the four groups that changed their opinion in the respective period: Households decreasing their climate policy opinion from support to neutral ($G_{1,t}$) or from neutral to oppose ($G_{2,t}$) and those increasing their policy opinion from oppose to neutral ($G_{3,t}$) or from neutral to support ($G_{4,t}$). Please note that the composition of these groups changes each year. For example, an individual that changed her policy opinion from oppose to neutral last year in $t-1$ and thus belongs to the group $G_{3,t-1}$, cannot belong to the same group this year ($G_{3,t}$) 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 Equation 30, where j denotes the respective group that changed its opinion.

$$\begin{cases} \sum_{i \in G_j} unempl_i & \text{unemployment} \\ \sum_{i \in G_j} cc_i & \text{climate change} \\ \sum_{i \in G_j} Flob_i & \text{fossil lobbying} \\ \sum_{i \in G_j} Rlob_i & \text{green lobbying} \\ \sum_{i \in G_j} soc_i & \text{social influence} \end{cases} \tag{30}$$

The decomposition reveals the significant role of social influence. As can be seen in Figure 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. The impact of climate change, in turn, depends on the variable $cc_{i,t}$ which increases uniformly for all households over time with increasing temperature[20]. 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[21]. 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_4) and from support to neutral (group G_1) 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_2) and from oppose to neutral (G_3). 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, Figure 7 illustrates that the G_4 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 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 increases with the diffusion of renewables in the energy sector, thereby increasing resources and lobbying power of green asset holders to target more households with their campaign. The personal experience of unemployment exerts a negative pressure on policy support. Since the economy does not suffer from a severe unemployment crisis in the best-performing policy scenario (compared to a scenario which features a high carbon tax rate without redistribution), the impact of unemployment is rather small.

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

[21] 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

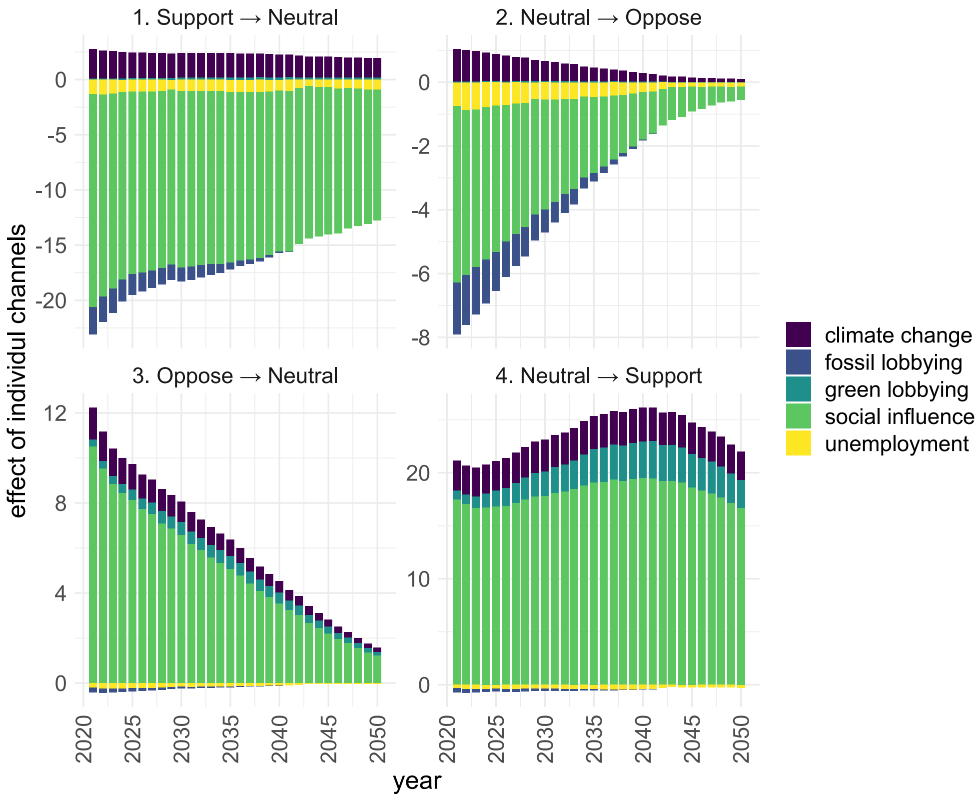


Figure 7: Relative importance of different channels to update opinion for the best policy scenario: very high tax introduced in 2020, all revenues recycled via high green subsidies and climate dividends (i.e., $\rho^{ctax} = 1$, $\rho^{gsubs} = 0.8$). Simulation results are based on 100 Monte Carlo experiments.

5 Robustness checks

5.1 Sensitivity analysis

In any simulation model, the choice of parameters plays a vital role in the outcomes. As described in sections 3.2 and 4.1, we do not choose the parameters arbitrarily, but rely on well-tested methods to choose. The main advantage 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 how well-identified the parameter is. We exploit this fact to check 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 10 in appendix D). In 9 out of 17 parameter combinations, the policy scenario in which the government quickly introduces a stringent carbon tax which is coupled with full redistribution and a high green investment subsidy 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 upper bound of the confidence interval 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, holistic government action and the other essentially simulates a case in which the government does very little, very late. Figure 9 in appendix D 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 high.

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 11 in appendix D shows that our results are robust to changes in the emission pathways of other countries.

To understand the influence of individual parameter values on policy support, we consider the best performing policy mix of introducing the very high carbon tax pathway in 2020 along with green investment subsidies and climate dividends and analyse how cumulative support for climate policy over the transition period (2020-2050) changes across the estimated parameters' confidence interval. As illustrated in Figure 10 in the appendix D, public support increases with the persuasive force F. A higher persuasive force increases the frequency to update one's policy opinion due to persuasion by peers as well as the speed through which positive and negative direct effects on policy opinion can propagate via the social network. The parameter η which measures the impact of perceived climate change on individual policy opinion positively affects public support. The inverse holds for the ν which measures the extent to which individual unemployment decreases climate change concern, where high parameter values reduce public support. In the scenario where the best policy mix is implemented and the green transition is achieved rather fast while successfully mitigating macroeconomic transition costs, public support increases with higher lobbying impact parameter λ. In general, public support increases with higher η, and lower ν.

5.2 Model extensions

We also experimented with including two cognitive biases that may be relevant in shaping opinion dynamics. First, 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 Equation (31), where ζ is a parameter denoting the social desirability bias.

$$p_{i,t} = \begin{cases} \zeta(soc_{i,t} + cc_{i,t} + unem_{i,t} + Flob_{i,t} + Rlob_{i,t}) & \text{if } op_{i,t} = op_t^{mod} \\ soc_{i,t} + cc_{i,t} + unem_{i,t} + Flob_{i,t} + Rlob_{i,t} & \text{else} \end{cases} \tag{31}$$

In our second extension, we introduce 'biased assimilation'. Here, agents are less likely to be affected by the climate change evidence effect if they are opposed to climate policies, but more likely if they already are supporters. 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 Equation (32).

$$cc_{i,t} = \begin{cases} \eta \Delta T_t^*(1-\mu) & \text{if } op_{i,t} = 1 \\ \eta \Delta T_t^* & \text{if } op_{i,t} = 2 \\ \eta \Delta T_t^*(1+\mu) & \text{if } op_{i,t} = 3 \end{cases} \quad (32)$$

We again attempt to fully calibrate 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 E for biased assimilation and appendix F 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 policy scenario 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 acceptance.

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.

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 are differently affected by macroeconomic transition risks (i.e., unemployment), climate change and industry lobbying which directly affects individual policy opinion who can either support, oppose or be neutral towards climate policy. Humans' tendency towards social conformity acts as significant multiplier of the above dimensions and constitutes an important determinant of opinion dynamics. We calibrated the model to Eurobarometer survey data over 2011-2019 to empirically identify the parameters and validate the model.

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 (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 favorable 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 for high green investment subsidies and climate dividends constitutes a successful strategy to address this intertemporal tradeoff. 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 psychological factors such as biased assimilation and social desirability bias.

A decomposition of related 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. Most notably, social influence constitutes the most important component to explain the non-linear change in public support in the baseline calibration of the opinion dynamics model as it facilitates the propagation of individual experience through social networks.

While this 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. In the context of research on climate change, it would be interesting 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.

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Appendix

A OD-Cross-validation

Apart from validating our parameter estimation method using the empirical data, we also conduct a 5-fold cross-validation exercise built into the "freelunch" package by Carrella (2021). This means that the whole dataset generated by running the model with randomly drawn parameters is split into five different datasets. Consecutively, four sub-datasets are then used to train the algorithm to predict the hold-out dataset for a total of five times (i.e., each sub-dataset serves as hold-out dataset once).

Carrella (2021) defines performance as (using the author's notation) in Equation 33, where $\hat{\theta}_j$ is the estimated parameter for training row j, θ^*_j is the real parameter of training row j, and $\bar{\theta}$ is the average parameter value in the whole training dataset.

$$Performance = 1 - \frac{\sqrt{\sum_j (\theta^*_j - \hat{\theta}_j)^2}}{\sqrt{\sum_j (\theta^*_j - \bar{\theta})^2}} \tag{33}$$

The maximum performance is 1, indicating perfect identification, but it can even reach negative values (indicating mis-identification). Carrella (2021) cites values below 0.1 as critical identification failures and values below 0.3 as identification failures. Table 6 shows the performance of each parameter for each algorithm.

algorithm	persuasive force	evidence effect	unemployment effect	lobbying effect
loclinear ABC	0.77	0.91	0.85	0.79
linear regression	0.76	0.89	0.84	0.78
quantile random forest	0.77	0.85	0.84	0.72
random forest	0.76	0.86	0.84	0.72
semiautomatic ABC	0.68	0.73	0.69	0.67
rejection ABC	0.50	0.69	0.42	0.33

Table 6: Performance in cross-validation exercises (algorithms ranked from the highest to the lowest mean performance)

We further assess coverage which shows how often the true parameter is contained in the interval given by the 95% confidence interval produced by each method which is summarized in Table 7. Accordingly, the best coverage is 0.95 (see Carrella, 2021). Linear regression performs best in terms of coverage, followed by random forest regression. Loclinear ABC is an outlier in that it produces by far the worst confidence bounds. While OLS and loclinear ABC produce confidence bounds which are too small (in the case of loclinear ABC drastically too small), the confidence bounds are too large for the other algorithms.

algorithm	persuasive force	evidence effect	unemployment effect	lobbying effect
linear regression	0.94	0.94	0.94	0.94
loclinear ABC	0.76	0.84	0.85	0.84
quantile random forest	0.99	0.99	0.99	0.99
random forest	0.97	0.97	0.98	0.97
rejection ABC	0.98	0.98	0.97	0.97
semiautomatic ABC	0.98	0.98	0.98	0.98

Table 7: Coverage in cross-validation exercises (in alphabetical order)

B DSK-validation

Figure 8: Auto-correlation functions (ACF) up to 8 lags for the main macroeconomic aggregates. Solid lines represent average auto-correlations across 100 simulation runs; red shaded areas are 95% confidence intervals.
Cross-correlation functions (CCF) for GDP and the other main macroeconomic aggregates up to 4 lags/leads. Solid lines represent average cross-correlations across 100 simulation runs; red shaded areas are 95% confidence intervals.

Table 8: Simulated business cycle and growth statistics

Standard deviation of GDP	0.021
Standard deviation of Consumption	0.0122
Standard deviation of Investment	0.1208
Standard deviation of Unemployment	0.0192
Standard deviation of Inflation	0.0191
Av. ann. GDP growth	0.0104
Av. ann. global emissions stock growth	0.0116
End of century temperature anomaly	3.186

C DSK-calibration

Table 9: Parameters table

Symbol	**Description**	**Value**
$N1$	Number of K-Firms	20
$N2$	Number of C-Firms	200
NB	Number of banks	10
ζ	Unemployment benefit ratio	0.4
τ_h	Tax rate on labour income	0
α_1	Propensity to consume out of wage & transfers income	0.965
α_2	Propensity to consume out of profit & interest income	0.3
α_3	Propensity to consume out of wealth	0.1
$\overline{\mathfrak{w}}$	Maximum per-period % change in the wage rate	0.025
ψ_1	Sensitivity of nominal wage to inflation gap	0.4
ψ_2	Sensitivity of wage to productivity	1
ψ_3	Sensitivity of nominal wage to unemployment	0.26
η^w	Parameter used for calculating weighted averages	0.76
μ^K	K-Firm mark-up	0.1
Γ	# brochures sent by K-Firms (fraction of current customers)	0.32
$\mathfrak{o}$	Share of K-Firm revenue dedicated to R&D	0.04
$\mathfrak{x}^K$	Share of K-Firm R&D dedicated to innovation	0.5
$\mathfrak{b}_1^K$	Parameter governing K-Firm probability of innovating	0.3
$\mathfrak{b}_2^K$	Parameter governing K-Firm probability of imitating	0.3
$\mathfrak{b}_3^K$	Shape parameter of beta distribution for capital vintage labour productivity innovation	1.5
$\mathfrak{b}_4^K$	Shape parameter of beta distribution for capital vintage labour productivity innovation	3
$\mathfrak{b}_5^K$	Lower bound for random capital vintage labour productivity innovation	-0.015
$\mathfrak{b}_6^K$	Upper bound for random capital vintage labour productivity innovation	0.015
$\mathfrak{b}_7^K$	Shape parameter of beta distribution for capital vintage energy efficiency innovation	1.5
$\mathfrak{b}_8^K$	Shape parameter of beta distribution for capital vintage energy efficiency innovation	3
$\mathfrak{b}_9^K$	Lower bound for random capital vintage energy efficiency innovation	-0.01
$\mathfrak{b}_{10}^K$	Upper bound for random capital vintage energy efficiency innovation	0.035

Table 9 – continued from previous page

Symbol	Description	Value
$\mathfrak{b}^K_{11}$	Shape parameter of beta distribution for capital vintage environmental friendliness innovation	1.5
$\mathfrak{b}^K_{12}$	Shape parameter of beta distribution for capital vintage environmental friendliness innovation	3
$\mathfrak{b}^K_{13}$	Lower bound for random capital vintage environmental friendliness innovation	-0.01
$\mathfrak{b}^K_{14}$	Upper bound for random capital vintage environmental friendliness innovation	0.02
$\mathfrak{b}^K_{15}$	Shape parameter of beta distribution for labour productivity of K-Firm production technique	1.5
$\mathfrak{b}^K_{16}$	Shape parameter of beta distribution for labour productivity of K-Firm production technique	3
$\mathfrak{b}^K_{17}$	Lower bound for random K-Firm production technique labour productivity innovation	-0.015
$\mathfrak{b}^K_{18}$	Upper bound for random K-Firm production technique labour productivity innovation	0.03
$\mathfrak{b}^K_{19}$	Shape parameter of beta distribution for energy efficiency of K-Firm production technique	1.5
$\mathfrak{b}^K_{20}$	Shape parameter of beta distribution for energy efficiency of K-Firm production technique	3
$\mathfrak{b}^K_{21}$	Lower bound for random K-Firm production technique energy efficiency innovation	-0.01
$\mathfrak{b}^K_{22}$	Upper bound for random K-Firm production technique energy efficiency innovation	0.05
$\mathfrak{b}^K_{23}$	Shape parameter of beta distribution for environmental friendliness of K-Firm production technique	1.5
$\mathfrak{b}^K_{24}$	Shape parameter of beta distribution for environmental friendliness of K-Firm production technique	3
$\mathfrak{b}^K_{25}$	Lower bound for random K-Firm production technique environmental friendliness innovation	-0.005
$\mathfrak{b}^K_{26}$	Upper bound for random K-Firm production technique environmental friendliness innovation	0.0025
b	Payback parameter	160
τ^K	Tax rate on K-Firm profit	0.1
δ^K	K-Firm dividend payout rate	0.75
σ	C-Firm adaptive demand expectations parameter	0.16
$\mathfrak{Q}$	Maximum output producible with one unit of capital good	40
u	C-Firms' desired capacity utilization	0.8
$\overline{\lambda}$	C-Firm maximum capacity growth	0.25
Δ^μ	C-Firm mark-up adjustment coefficient	0.01

Table 9 – continued from previous page

Symbol	Description	Value
ϕ	C-Firm maximum borrowing coefficient	10
ω_1	Weight of relative price in C-Firm competitiveness	20
ω_2	Weight of relative ability to satisfy demand in C-Firm competitiveness	1
ω_3	Parameter limiting size of period-to-period change in C-Firm market share	0.8
χ	Sensitivity of C-Firm market share to competitiveness	-1.39
τ^C	Tax rate on C-Firm profits	0.1
Δ	C-Firm dividend payout rate	0.75
υ_B	Bank deposit interest rate markdown	1
cm	Credit multiplier	0.05
$\mathfrak{v}$	Sensitivity of credit multiplier to bank fragility	0
$\mathfrak{M}$	Individual bank lending rate mark-up parameter	0.1
μ^B	Bank baseline loan rate mark-up	0.7
τ^B	Tax rate on bank profits	0.1
δ^B	Bank dividend payout rate	0.5
ξ_{GB}	Share of government bonds which must be repaid in each period	1
υ_{GB}	Markdown parameter for government bond interest rate	0
r	Central bank lending rate intercept	0.04
$\underline{r}$	Central bank rate lower bound	1e-6
ι_1	Taylor rule smoothing parameter	0.74
ι_1	Taylor rule inflation sensitivity	1.23
ι_1	Taylor rule unemployment sensitivity	0.17
$\pi*$	Central bank target inflation rate	0.02015
$U*$	Central bank target unemployment rate	0.05
υ_{CB}	Markdown parameter for central bank deposit rate	1
A^{ς}	Upper bound on per-period expansion of green energy capacity scaling parameter	0.1
b^e	Energy sector payback period parameter	10
δ^F	Fossil fuel sector dividend payout rate	0.01

D Sensitivity Analysis

We conduct two types of sensitivity analyses to check the robustness of our policy recommendations to i) parameter uncertainty in the opinion dynamics model, and ii) uncertainty regarding the emissions produced by the rest of the world.

In order to deal with the parameter uncertainty in the OD model, we propose to study extreme parameter combinations given by the bounds of the confidence interval. If we had only one parameter, we could study whether our main policy recommendation holds if the parameter is not set at its point estimate, but at its lower and its higher bound. For two parameters of interest, we would have to check the situation in which both are at the lower bound, both are at the higher bound or (each) one is at the lower and the other at the higher bound. Since we have four parameters of interest, this leaves us with $2^4 = 16$ parameter combinations plus the baseline scenario.[22]

[22] As the lower bound of the confidence intervals is negative for the random forest estimates with regard to the persuasive force, the unemployment effect and the lobbying effect, but a negative coefficient does not make sense economically, we assume the absence of this effect (equal to a coefficient of zero) to be the lower bound of the estimates.

We can then investigate whether our main conclusions still hold by first analyzing which of the 133 policy scenario maximizes public support over the period until 2050 in each of the seventeen parameter combinations.[23] Table 10 shows the results of this analysis. We can see that the scenario which combines an early introduction of a high carbon tax rate with full redistribution and a high subsidy ranks first in 9 out of 17 parameter combinations. There is another mode at the end of the policy space, as the scenario in which the government acts extremely late with a very low tax rate is the "best" in terms of public support in four out of 17 combinations, even though this scenario by far misses the climate goals of the European Union.

policy scenario	ranked first	ranked second	ranked third	ranked fourth	ranked fifth
start = 2020, slope = 1e-04, red = 0.1, sub = 0.8	0	0	0	0	4
start = 2020, slope = 1e-04, red = 0.5, sub = 0.8	0	1	6	2	0
start = 2020, slope = 1e-04, red = 1, sub = 0.5	0	0	0	0	2
start = 2020, slope = 1e-04, red = 1, sub = 0.8	9	0	0	0	0
start = 2020, slope = 1e-05, red = 1, sub = 0.8	0	0	0	0	2
start = 2020, slope = 5e-05, red = 0.1, sub = 0.8	0	0	0	0	1
start = 2020, slope = 5e-05, red = 0.5, sub = 0.8	0	0	2	7	0
start = 2020, slope = 5e-05, red = 1, sub = 0.8	0	8	1	0	0
start = 2025, slope = 1e-05, red = 1, sub = 0	0	1	0	0	0
start = 2025, slope = 1e-05, red = 1, sub = 0.2	1	0	0	0	0
start = 2025, slope = 1e-06, red = 0, sub = 0	0	0	2	0	0
start = 2030, slope = 1e-05, red = 0.1, sub = 0.2	0	0	1	0	0
start = 2030, slope = 1e-05, red = 0.1, sub = 0.5	1	0	0	0	0
start = 2030, slope = 1e-05, red = 0.5, sub = 0.5	0	1	0	0	0
start = 2030, slope = 1e-05, red = 1, sub = 0.2	0	0	0	0	1
start = 2030, slope = 1e-05, red = 1, sub = 0.5	0	0	1	0	0
start = 2030, slope = 1e-06, red = 0, sub = 0	1	0	0	0	4
start = 2030, slope = 5e-05, red = 1, sub = 0.2	0	0	0	0	1
start = 2035, slope = 1e-06, red = 0, sub = 0	0	3	2	0	0
start = 2035, slope = 5e-06, red = 0, sub = 0	0	0	0	1	0
start = 2040, slope = 1e-04, red = 0, sub = 0	0	0	0	1	0
start = 2040, slope = 1e-05, red = 0, sub = 0	1	0	0	4	0
start = 2040, slope = 1e-06, red = 0, sub = 0	4	0	0	1	1
start = 2040, slope = 5e-06, red = 0, sub = 0	0	3	2	1	1

Table 10: Ranking of the policy scenarios in the sensitivity analysis. Policy scenarios are described by the combination of the i) introduction year when the carbon tax scheme is introduced (i.e., start which we denoted formally as t_0^{clim} in the main analysis; ii) the slope of the carbon tax $g^{\tau,Em}$; iii) share of earmarked carbon tax revenues red (i.e., ρ^{ctax}); and (iv) green subsidy sub (i.e., ρ^{gsubs}).

A closer look at the results tells us that the scenarios in which the main policy conclusion holds are the ones where the lobbying impact is positive. In order to get a better understanding of the differences between the two 'extreme' cases in terms of political support, we plot the cumulated share of opponents and the cumulated share of supporters in the period from 2020 to 2050 in Figure 9. We can see that the scenario in which the government does very little, very late, only fares considerably better if there is no lobbying impact and the unemployment impact is at the upper bound of the confidence interval. In all other parameter combinations, the policy scenario which combines an early introduction of a stringent carbon tax rate with full redistribution and a high subsidy fares better than or similar to the scenario in which the government acts very late and does very little.

[23] We also checked the ranking in the period until 2035, where the distribution of results is very similar, although a number of policy scenarios are ranked ex aequo, as the government does not act within the given time frame in these scenarios.

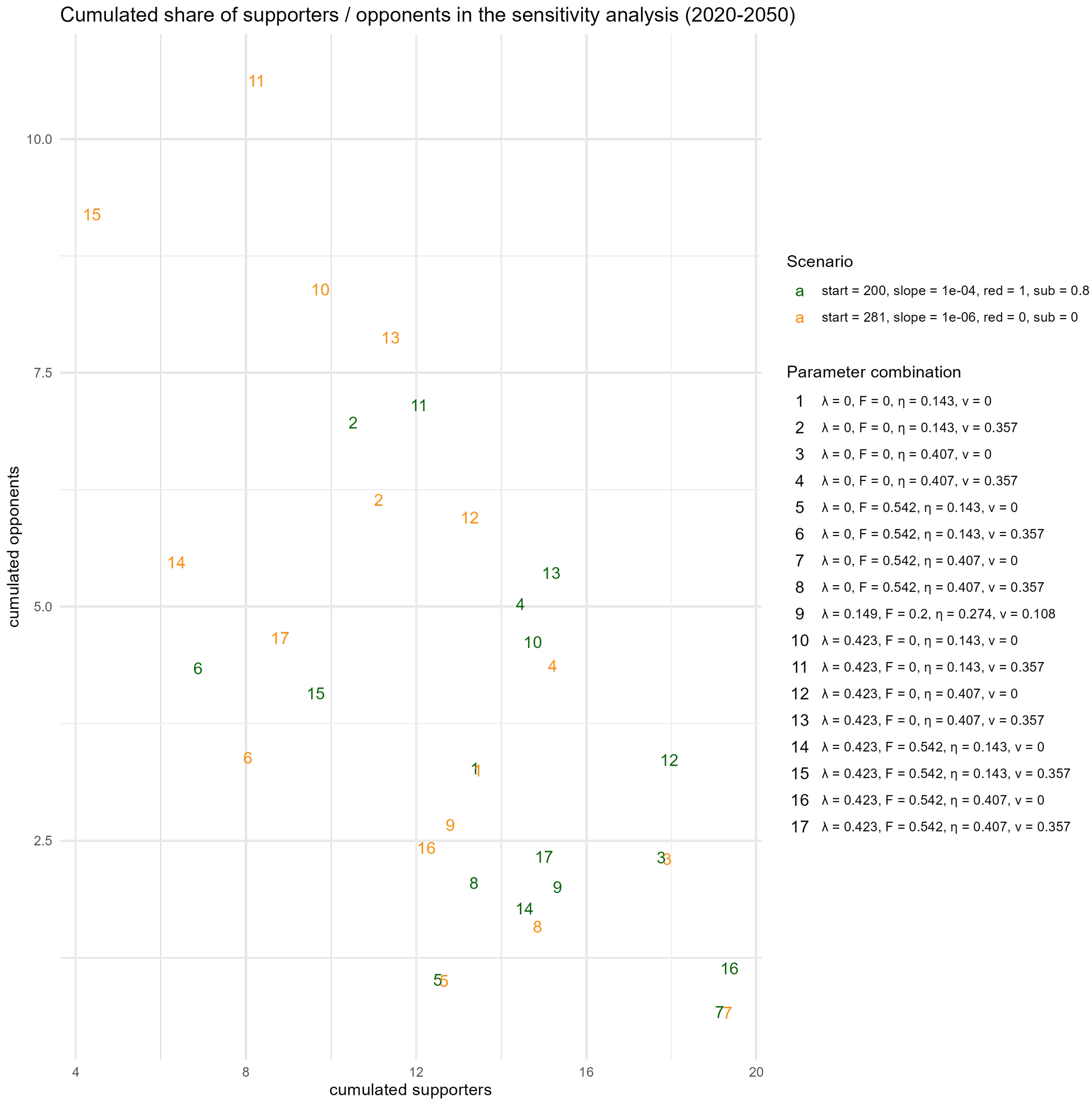

Figure 9: Supporters vs. Opponents for the two 'extreme' cases

Climate change itself has shown to be an important predictor of the support of climate policies, but is also highly dependent on emissions of countries outside of the EU, which are exogenous to our model. Thus, we also conduct a second sensitivity analysis in which we check whether our main policy conclusions hold in alternative emission pathways of the 'rest of the world' by comparing the policy scenario that has fared best in our main analysis (i.e., a high carbon tax rate ans full redistribution of the tax revenue including a high subsidy for investment in green energy plants) with four different carbon tax regimes without redistribution. Towards this end, we vary the calibrated slope parameter describing the emission trajectory of the rest of the world and analyse five alternative trajectories. Table 11 shows the results of this analysis: Regardless of the emissions produced by the rest of the world, the best policy mix of the baseline scenario beats any carbon tax regime. Without redistribution, higher carbon tax rates cause lower public support (due to an increase in the rate of unemployment).

policy scenario	ranked first	ranked second	ranked third	ranked fourth
start = 2020, slope = 1e-04, red = 1, sub = 0.8	5	0	0	0
start = 2020, slope = 1e-06, red = 0, sub = 0	0	5	0	0
start = 2020, slope = 1e-05, red = 0, sub = 0	0	0	5	0
start = 2020, slope = 1e-04, red = 0, sub = 0	0	0	0	5

Table 11: Ranking of the policy scenarios in five alternative global emission scenarios. Policy scenarios are described by the combination of the i) introduction year when the carbon tax scheme is introduced (i.e., start which we denoted formally as t_0^{clim} in the main analysis; ii) the slope of the carbon tax $g^{\tau,Em}$; iii) share of earmarked carbon tax revenues red (i.e., ρ^{ctax}); and (iv) green subsidy sub (i.e., ρ^{gsubs}).

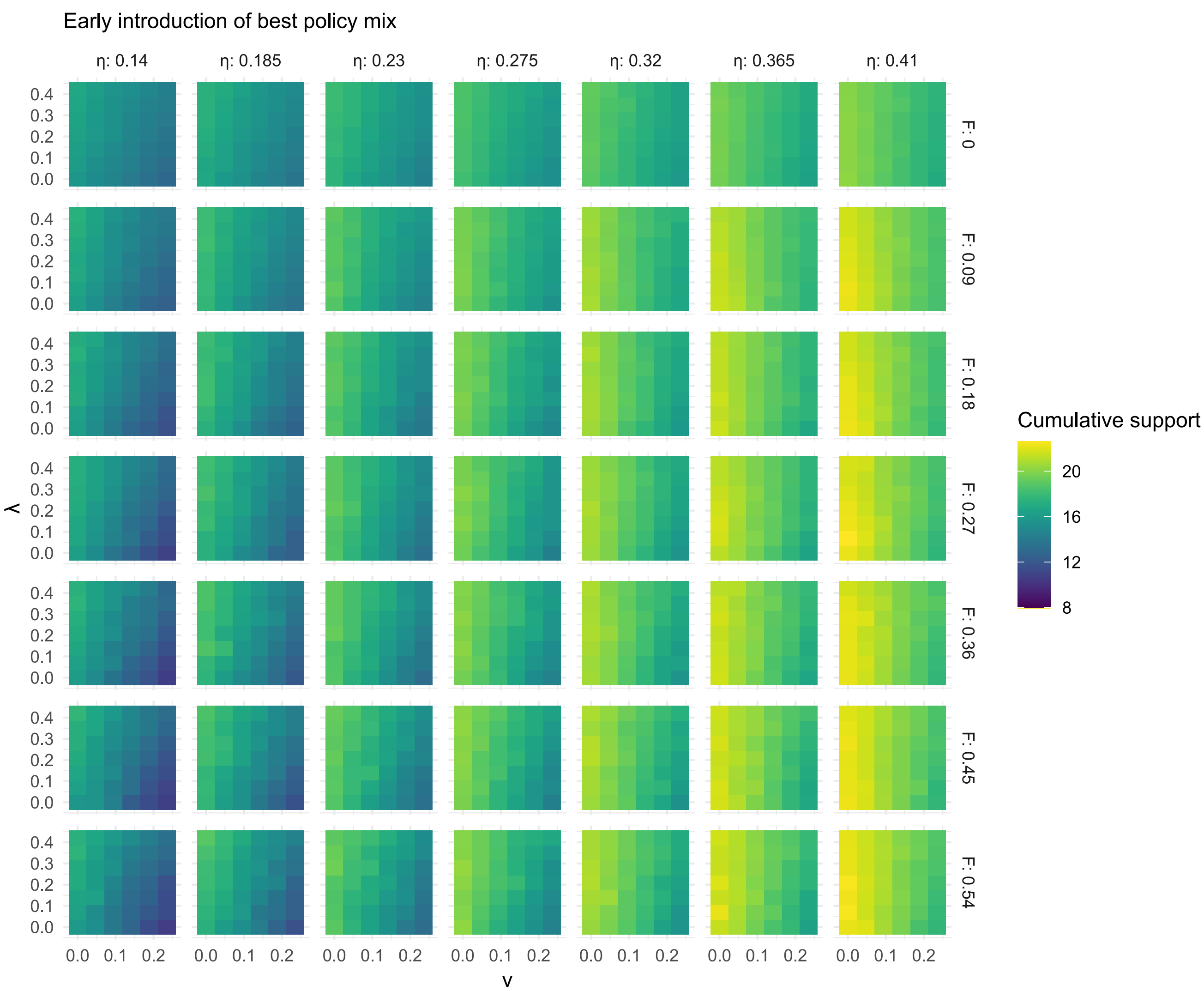

Figure 10: Sensitivity of cumulative public support during the transition period (2020-2050) across the estimated confidence interval for the evidence-effectiveness η, persuasive force F, unemployment impact ν and lobbying impact λ (average of 100 Monte Carlo experiments).

E Biased Assimilation

As known from the baseline calibration, we again run a full calibration excerise using the 'freelunch' package for R (Carrella, 2021). Again, we run 100,000 simulations in which we draw our parameters (whose number has now grown to five) from uniform distributions from 0 to 1, and then try to produce point estimates and confidence bounds using six different methods/algorithms.

A cross-validation exercise reveals that five out of six algorithms are able to identify all parameters (i.e., the performance of the estimated parameter is larger than 0.3), but rejection ABC is unable to identify the new parameter (see Table 12). In terms of coverage, OLS again performs best, and loclinear ABC again performs (by far) the worst (see Table 13).

Finally, we test which of the six point estimates produced by the various methods produces the lowest RMSE when used to predict the empirical data (see Table 14). In the case of biased assimilation, these are the quantile random forest regression and the random forest regression. However, it should be noted that the best parameter estimation of the model including biased assimilation performs worse than the best parameter estimation of the model without biased assimilation. This result is counterintuitive, as adding a parameter should, in principle, only be able to increase the fit (as, in the worst case, the new parameter is zero). However, linear regression is the only algorithm that produces a better fit with the model incorporating biased assimilation as an additional parameter. This might have something to do with the fact that adding a new parameter that is not highly relevant calls for a larger number of simulations that are used to calibrate the model. Since the calibration process is already extremely computationally expensive, we refrained from experimenting with a number of simulations that exceeds 100,000. We take this result as a hint, however, that adding biased assimilation would make the model not more valid, at least at the macro level.

algorithm	persuasive force	evidence effect	unemployment effect	lobbying effect	biased assimilation
loclinear ABC	0.76	0.91	0.84	0.79	0.54
linear regression	0.75	0.87	0.83	0.78	0.47
quantile random forest	0.76	0.87	0.84	0.74	0.43
random forest	0.75	0.87	0.84	0.74	0.42
semiautomatic ABC	0.65	0.67	0.63	0.62	0.46
rejection ABC	0.46	0.68	0.42	0.34	0.08

Table 12: Performance of the model parameters including biased assimilation in cross-validation exercises (algorithms ranked from the highest to the lowest mean performance)

algorithm	persuasive force	evidence effect	unemployment effect	lobbying effect	biased assimilation
linear regression	0.94	0.94	0.95	0.94	0.94
loclinear ABC	0.77	0.84	0.85	0.84	0.90
quantile random forest	0.99	0.99	0.99	0.99	0.98
random forest	0.98	0.98	0.99	0.98	0.97
rejection ABC	0.98	0.98	0.97	0.97	0.95
semiautomatic ABC	0.98	0.98	0.98	0.98	0.97

Table 13: Coverage for the different algorithms with biased assimilation (in alphabetical order)

algorithm	persuasive force	evidence effect	unemployment effect	lobbying effect	biased assimilation	RMSE
quantile random forest	0.257	0.247	0.108	0.109	0.256	5.61
	(0.051 – 0.611)	(0.114 – 0.389)	(0.011 – 0.248)	(0.005 – 0.552)	(0.01 – 0.868)	
random forest	0.215	0.273	0.106	0.13	0.313	5.81
	(-0.072 – 0.504)	(-0.075 – 0.594)	(-0.074 – 0.298)	(-0.072 – 0.338)	(-0.381 – 1.074)	
loclinear abc	0.045	0.115	0.232	-0.186	0.011	5.86
	(0.004 – 0.1)	(0.095 – 0.15)	(0.176 – 0.292)	(-0.428 – 0.094)	(-1.296 – 1.579)	
semiautomatic abc	0.196	0.299	0.307	0.2	0.279	6.22
	0.01 – 0.669)	(0.013 – 0.82)	(0.014 – 0.842)	(0.009 – 0.601)	(0.012 – 0.904)	
rejection abc	0.42	0.353	0.292	0.373	0.401	6.33
	(0.036 – 0.971)	(0.069 – 0.639)	(0.014 – 0.841)	(0.019 – 0.945)	(0.017 – 0.96)	
linear regression	-0.093	0.016	0.133	-0.111	0.092	9.08
	(-0.244 – 0.037)	(-0.048 – 0.119)	(0.041 – 0.256)	(-0.233 – 0.018)	(-0.259 – 0.436)	

Table 14: Point estimates (confidence intervals) for different algorithms with biased assimilation

We then use the point estimates from the quantile random forest estimation to run the model 1,000 times and check whether our main policy conclusions still hold in the more complex model. As we can see in Figure 11, the hybrid redistribution scheme that we propose again fares best in terms of public acceptance, supporting our main result. The decomposition of effects shown in Figure 12 again highlight the importance of social influence in this model.

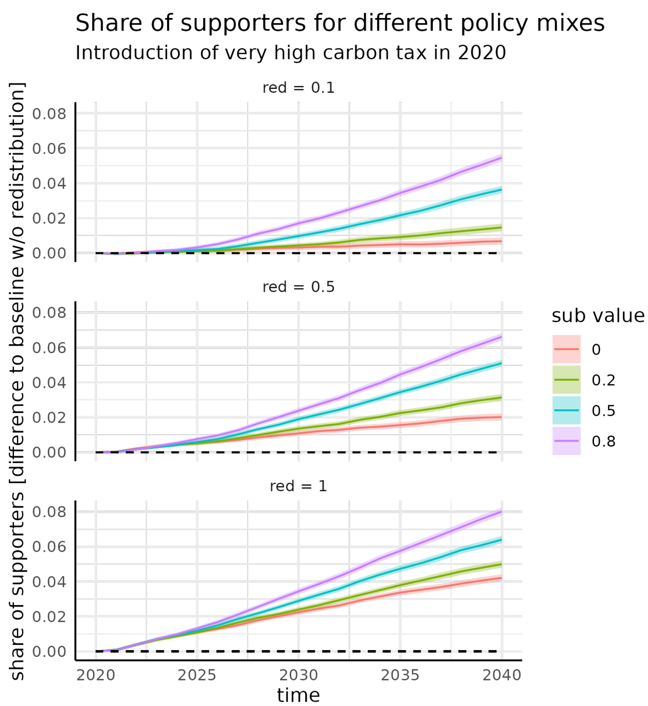

Figure 11: Share of supporters across revenue recycling configurations defined by a combination of earmarked carbon tax revenues for redistribution to society ρ^{ctax} and green investment subsidy ρ^{gsubs}

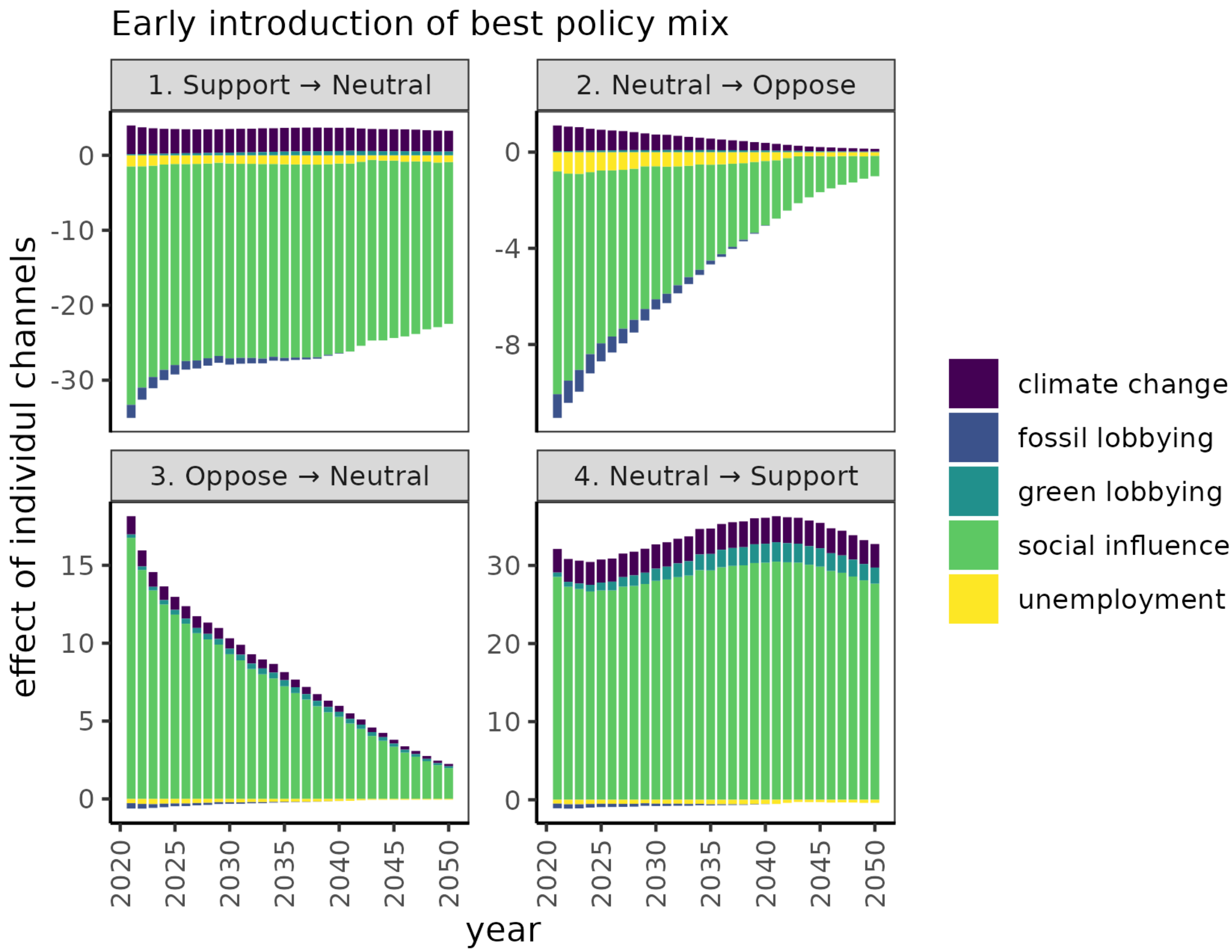

Figure 12: Relative importance of different channels to update opinion in the model including biased assimilation (average of 100 Monte Carlo experiments).

F Social desirability bias

Like the model including biased assimilation, we again fully calibrate the model including a social desirability bias using the 'freelunch' package Carrella (2021).

As shown in Table 15, the new parameter can be identified by any of the six algorithms. However, adding the new parameter also produces identification failures (albeit not critical ones, i.e., $0.1 <$ performance < 0.3) for two parameters using the rejection ABC algorithm. As known from the other models, OLS performs best in terms of coverage and loclinear the worst (albeit the coverage of the bounds produced by loclinear ABC are much closer to 0.95 than the bounds produced by loclinear ABC for the other two models (see Table 16).

When turning to descriptive output validation shown in Table 17, we again see (as in the case of 'biased assimilation') that adding the new parameter counter-intuitively does not improve the fit to the empirical data for most of the algorithms. Unexpectedly, we see that rejection ABC performs by far the best in terms of the RMSE of the simulated vs. empirical distributions. Since this method is the only one that produces RMSE values that are comparable to the other two models, we use these estimates in spite of the parameter identification issues in the cross validation exercises.

algorithm	persuasive force	evidence effect	unemployment effect	lobbying effect	social desirability
loclinear ABC	0.80	0.76	0.70	0.64	0.80
quantile random forest	0.72	0.74	0.70	0.57	0.76
random forest	0.73	0.73	0.70	0.56	0.76
linear regression	0.75	0.64	0.59	0.53	0.72
semiautomatic ABC	0.62	0.57	0.55	0.51	0.59
rejection ABC	0.31	0.45	0.20	0.12	0.48

Table 15: Performance of the model parameters including social desirability in cross-validation exercises (algorithms ranked from the highest to the lowest mean performance)

algorithm	persuasive force	evidence effect	unemployment effect	lobbying effect	social desirability
linear regression	0.94	0.94	0.95	0.94	0.95
loclinear ABC	0.87	0.90	0.89	0.89	0.88
quantile random forest	0.99	0.99	0.99	0.98	0.99
random forest	0.98	0.98	0.98	0.97	0.98
rejection ABC	0.97	0.97	0.96	0.96	0.97
semiautomatic ABC	0.98	0.98	0.98	0.98	0.98

Table 16: Coverage for the different algorithms with social desirability bias

algorithm	persuasive force	evidence effect	unemployment effect	lobbying effect	social desirability	RMSE
rejection abc	0.122	0.439	0.501	0.54	0.406	5.85
	(0.005 – 0.625)	(0.088 – 0.839)	(0.032 – 0.97)	(0.036 – 0.977)	(0.026 – 0.892)	
quantile random forest	0.18	0.48	0.186	0.372	0.488	6.88
	(0.014 – 0.801)	(0.26 – 0.803)	(0.01 – 0.756)	(0.016 – 0.918)	(0.039 – 0.847)	
random forest	0.191	0.496	0.239	0.387	0.482	6.89
	(-0.234 – 0.642)	(0.3 – 0.656)	(-0.321 – 0.787)	(-0.037 – 0.815)	(-0.011 – 0.886)	
loclinear abc	-0.183	0.104	0.606	0.168	0.703	7.67
	(-0.209 – -0.145)	(0.015 – 0.2)	(0.544 – 0.687)	(-0.42 – 0.79)	(0.3 – 0.99)	
linear regression	-0.338	-0.369	0.599	0.492	0.829	8.72
	(-0.469 – -0.186)	(-0.537 – -0.171)	(0.364 – 0.844)	(0.261 – 0.778)	(0.674 – 1.033)	
semiautomatic abc	0.159	0.154	0.545	0.49	0.702	11.09
	(0.006 – 0.46)	(0.006 – 0.515)	(0.06 – 0.977)	(0.037 – 0.969)	(0.129 – 0.985)	

Table 17: Point estimates (confidence intervals) for different algorithms with a social desirability bias

Again, we run the model 1,000 times using the point estimates of the parameter set which performs best in terms of the RMSE. As we can see in Figure 13, our main result, namely that the hybrid redistribution scheme that we propose fares best in terms of public acceptance, also holds in this model. However, the decomposition of effects shown in Figure 14 looks markedly different than in the baseline model and the model with biased assimilation, as social influence plays a much smaller role as explicit channel to shape the opinion of agents. However, '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, while the influence of the society as a whole is larger.

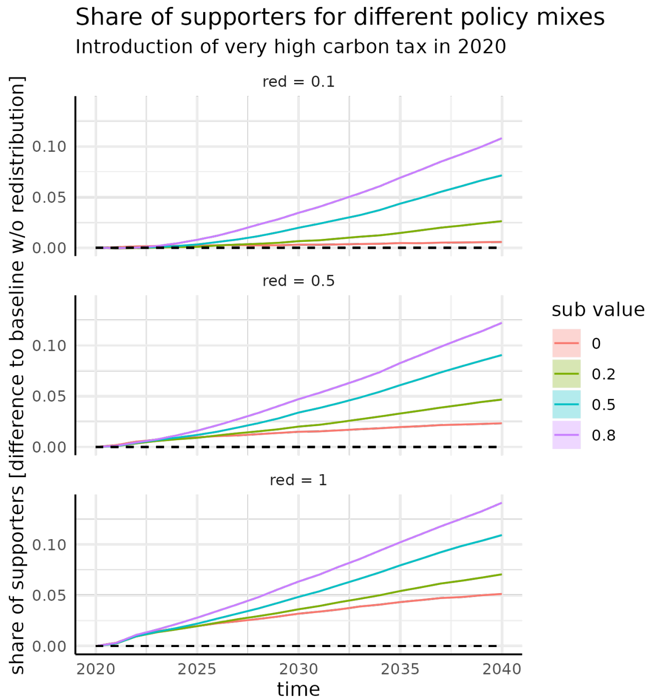

Figure 13: Share of supporters across revenue recycling configurations defined by a combination of earmarked carbon tax revenues for redistribution to society ρ^{ctax} and green investment subsidy ρ^{gsubs} in the model including a social desirability bias

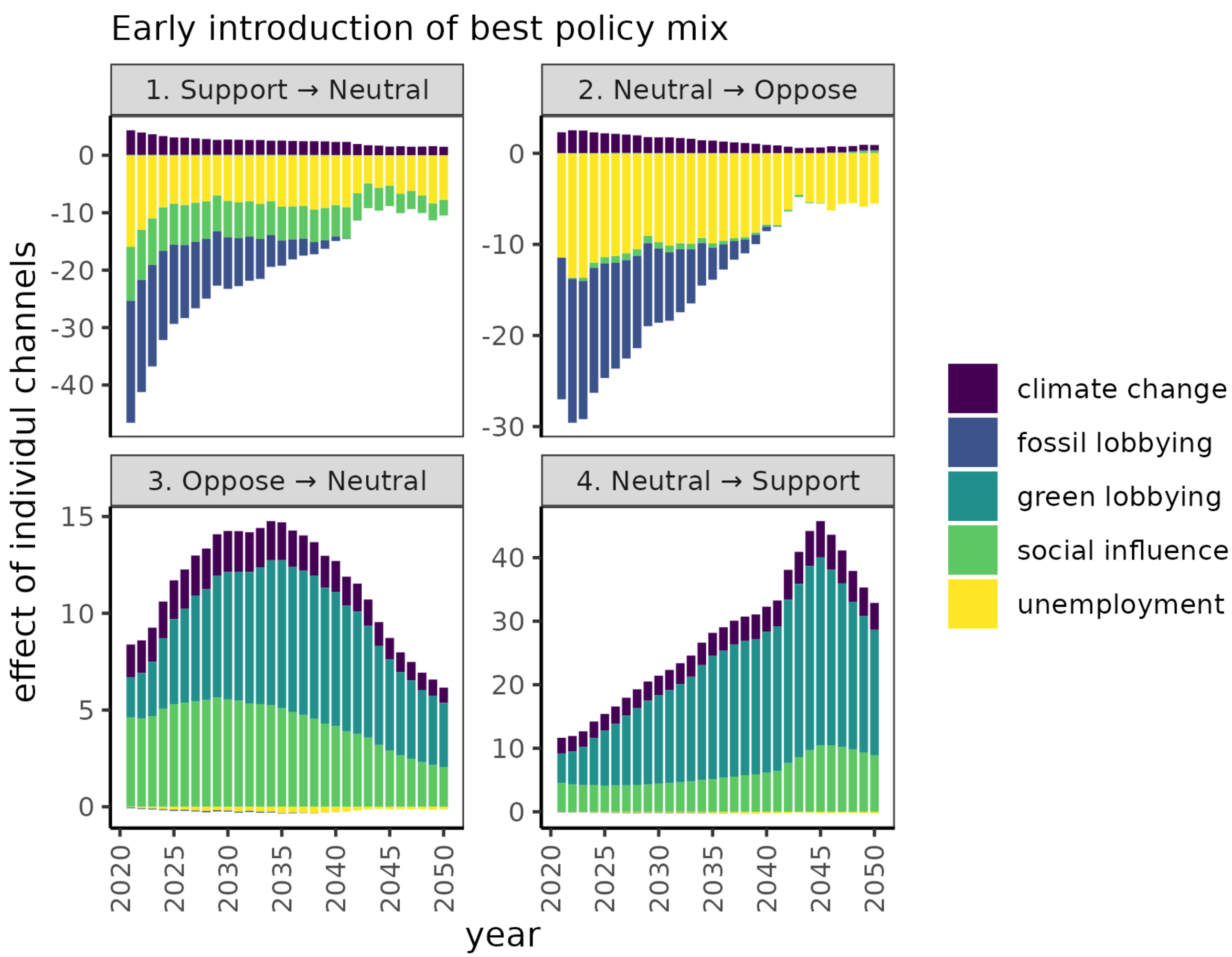

Figure 14: Relative importance of different channels to update opinion in the model including a social desirability bias (average of 100 Monte Carlo experiments).

G DSK-SFC: model description

G.1 Households

Households' disposable income is given by:

$$YD_t = W_t + Div_{t-1} + UB_t + TR^H_t + iD_{h,t} - Tax^H_t \tag{34}$$

Where:

- $W_t \equiv$ wage bill, defined as $W_t = w_t L_t$, where:
  - $w_t \equiv$ wage rate
  - $L_t \equiv \#$ employed workers
- $Div_{t-1} \equiv$ dividends paid by firms, energy sector, and banks
- $UB_t \equiv$ unemployment benefits, defined as: $\zeta w_t(LS_t - L_t)$, where:

- $\zeta \equiv$ unemployment benefit rate (exogenous parameter)
- $LS_t \equiv$ total labor supply
- $(LS_t - L_t) \equiv$ # unemployed workers

- $iD_{h,t} \equiv$ interest payments on deposits, defined as: $iD_{h,t} = r_{d,t-1}D_{h,t-1}$, where:
  - $r_{d,t-1} \equiv$ interest rate on deposits
  - $D_{h,t-1} \equiv$ households deposit stock

- $Tax_t^H \equiv$ taxes on wage income, defined as: $Tax_t^H = \tau^H W_t$, where:
  - $\tau_t^H \equiv$ tax rate on labor income

- $TR_t^H \equiv$ government transfers (see section 3.4.2)

The wage rate dynamics can be broken down into a trend component and a cyclical component. Wages are pegged to the aggregate productivity trend and fluctuate around it in a Phillips curve fashion:

$$w_{t+1} = (1 + \mathfrak{w}_t)w_t \tag{35}$$

Where $\mathfrak{w}_t$ is the period-by-period nominal wage growth rate, defined as:

$$\mathfrak{w}_t = min\left(\overline{\mathfrak{w}},\ \ max\left(-\overline{\mathfrak{w}},\ \ \pi^* + \psi_1\widehat{\pi}_t + \psi_2\widehat{Pr}_t - \psi_3\widehat{U}_t\right)\right) \tag{36}$$

Where:

- $\overline{\mathfrak{w}} \equiv$ exogenous parameter specifying the range for wage variation between periods
- $\pi^* \equiv$ central bank inflation target
- $\widehat{\pi}_t \equiv$ actual inflation deviation from target
- $\widehat{Pr}_t \equiv$ smoothed aggregate productivity growth
- $\widehat{U}_t \equiv$ change in the unemployment rate

G.2 Capital good sector

The capital goods sector is disaggregated in $N1$ firms, where K-Firms are indexed by k, with $k = 1, ..., N1$. K-Firms produce and sell heterogeneous capital goods employing heterogeneous production techniques. A production technique is a blueprint dictating how much labor and energy are required to produce a given amount of capital items in a unit of time. K-Firms innovate both the capital vintage that they produce and their own production technique.

G.2.1 Production and labor demand

A vintage is characterized by the triple $\Sigma_\kappa = (Pr_\kappa, EE_\kappa, EF_\kappa)$, which indicates respectively labour productivity, energy efficiency, and environmental friendliness. The unit cost of production associated to the vintage κ is therefore given by:

$$uc_{\kappa,t} = \frac{w_t}{Pr_\kappa} + \frac{p_{e,t}}{EE_\kappa} \tag{37}$$

Where $p_{e,t}$ is the price of energy. A K-Firm produces only one vintage in a given period t. Similarly, the production technique of firm k in time t is defined over the triple $\Sigma_k = (Pr_{k,t}, EE_{k,t}, EF_{k,t})$, indicating, respectively, the labour productivity, energy efficiency, and environmental friendliness of firm k. Firm k's unit cost of production is therefore given by:

$$uc_{k,t} = \frac{w_t}{Pr_{k,t}} + \frac{p_{e,t}}{EE_{k,t}} \tag{38}$$

Note that firm k produces only one vintage at a time.

Given the k's production technique and individual demand $(Q_{k,t})$[24], its labor demand $(L^d_{k,t})$ and energy demand $(En^d_{k,t})$ are given by:

$$\begin{cases} L^d_{k,t} = \frac{Q_{k,t}}{Pr_{k,t}} \\ \\ En^d_{k,t} = \frac{Q_{k,t}}{EE_{k,t}} \end{cases} \tag{39}$$

G.2.2 Pricing and competition

K-firms set prices by applying a fixed and homogeneous markup (μ^K) over the unit cost of production:

$$p_{k,t} = (1 + \mu^K) uc_{k,t} \tag{40}$$

To attract new clients each K-Firm sends brochures to a number of C-Firms $(BROCH_{k,t})$. Each brochure contains the triple Σ_κ characterising the vintage κ supplied by firm k and the price charged $(p_{k,t})$. The number of brochures sent by each firm k is increasing in k's size:

$$BROCH_{k,t} = max\,(1, \lfloor \Gamma CLNT_{k,t-1} \rceil) \tag{41}$$

Where $CLNT_{k,t-1}$ is the number of k's clients in the previous period and Γ is an exogenous parameter. The C-Firms to which brochures are actually sent are randomly drawn from the entire C-Firms population.

G.2.3 Innovation

K-Firms invest in R&D to improve the technology embedded in the machines they produce Σ_κ as well as their production technologies Σ_k. We model innovation as a two-step process: in the first step, K-Firms invest a certain monetary amount in innovation and imitation, whose probability of success is increasing in the R&D investment size. In the second step, if innovation/imitation has been successful, a new/imitated technology is randomly drawn. Note that the second step is not influenced by the amount of resources invested in R&D. Finally, K-Firms compare their old technologies with the innovated and imitated ones and choose to adopt the most efficient one. Note that Σ_κ and Σ_k are bundled together, this implies that (i) innovation/imitation brings about technologies defined over the pair $(\Sigma_\kappa, \Sigma_k)$, (ii) a K-Firm can decide to adopt the whole bundle $(\Sigma_\kappa, \Sigma_k)$ and not, for example, adopt the innovated/imitated production technology Σ_k, while keeping producing the old capital vintage.

R&D investment is set to:

$$RD_{k,t} = \begin{cases} \mathfrak{o} Sales_{k,t} & \text{If} \quad Sales_{k,t} > 0 \\ RD_{k,t-1} & \text{Otherwise} \end{cases} \tag{42}$$

Where:

- $\mathfrak{o} \equiv$ share of past sales devoted to $R\&D$ (exogenous and homogeneous across K-Firms)

[24] Unlike C-Firms, K-firms produce on demand. They labor demand is therefore not based on demand expectations, but on received orders.

- $Sales_{k,t} \equiv$ nominal sales

Note that $RD_{k,t}$ is used to hire researchers who perform R&D. The labour demand generated by R&D is therefore defined as:

$$L_{k,t}^{rd} = \frac{RD_{k,t}}{w_t} \tag{43}$$

Resources invested in R&D are further divided between innovation and imitation investment:

$$\begin{aligned} RD_{k,t}^{in} &= \mathfrak{r}^K L_{k,t}^{rd} \\ RD_{k,t}^{im} &= \left(1 - \mathfrak{r}^K\right) L_{k,t}^{rd} \end{aligned} \tag{44}$$

Where $\mathfrak{r}^K \in (0, 1)$ is the fixed and homogeneous across K-Firms share of R&D allocated to innovation.

The probabilities to innovate and imitate are given by:

$$\begin{aligned} P(Innovate)_{k,t} &= 1 - exp\left(-\mathfrak{b}_1^K RD_{k,t}^{in}\right) \\ P(Imitate)_{k,t} &= 1 - exp\left(-\mathfrak{b}_2^K RD_{k,t}^{im}\right) \end{aligned} \tag{45}$$

Where $(\mathfrak{b}_1^K, \mathfrak{b}_2^K)$ are fixed and homogeneous across K-Firms parameters[25].

In case of successful innovation, a K-Firm draws a technology $(\Sigma_{\kappa_{in}}, \Sigma_{in,k,t})$ defined as:

$$\begin{aligned} Pr_{\kappa_{in}} &= \left(1 + \mathfrak{I}_{1,k,t}\right) Pr_{\kappa} \\ EE_{\kappa_{in}} &= \left(1 + \mathfrak{I}_{2,k,t}\right) EE_{\kappa} \\ EF_{\kappa_{in}} &= \left(1 - \mathfrak{I}_{3,k,t}\right) EF_{\kappa} \\ Pr_{in,k,t} &= \left(1 + \mathfrak{I}_{4,k,t}\right) Pr_{k,t} \\ EE_{in,k,t} &= \left(1 + \mathfrak{I}_{5,k,t}\right) EE_{k,t} \\ EF_{in,k,t} &= \left(1 - \mathfrak{I}_{6,k,t}\right) EF_{k,t} \end{aligned} \tag{46}$$

Where:

- $\mathfrak{I}_{1,k,t}$ is a draw from a beta distribution with shape parameters $\mathfrak{b}_3^K$ and $\mathfrak{b}_4^K$, rescaled on the interval $\left(\mathfrak{b}_5^K, \mathfrak{b}_6^K\right)$.
- $\mathfrak{I}_{2,k,t}$ is a draw from a beta distribution with shape parameters $\mathfrak{b}_7^K$ and $\mathfrak{b}_8^K$, rescaled on the interval $\left(\mathfrak{b}_9^K, \mathfrak{b}_{10}^K\right)$.
- $\mathfrak{I}_{3,k,t}$ is a draw from a beta distribution with shape parameters $\mathfrak{b}_{11}^K$ and $\mathfrak{b}_{12}^K$, rescaled on the interval $\left(\mathfrak{b}_{13}^K, \mathfrak{b}_{14}^K\right)$.
- $\mathfrak{I}_{4,k,t}$ is a draw from a beta distribution with shape parameters $\mathfrak{b}_{15}^K$ and $\mathfrak{b}_{16}^K$, rescaled on the interval $\left(\mathfrak{b}_{17}^K, \mathfrak{b}_{18}^K\right)$.
- $\mathfrak{I}_{5,k,t}$ is a draw from a beta distribution with shape parameters $\mathfrak{b}_{19}^K$ and $\mathfrak{b}_{20}^K$, rescaled on the interval $\left(\mathfrak{b}_{21}^K, \mathfrak{b}_{22}^K\right)$.
- $\mathfrak{I}_{6,k,t}$ is a draw from a beta distribution with shape parameters $\mathfrak{b}_{23}^K$ and $\mathfrak{b}_{24}^K$, rescaled on the interval $\left(\mathfrak{b}_{25}^K, \mathfrak{b}_{26}^K\right)$.

[25] Note that a K-Firm can innovate and imitate in the same period. If this is the case, the best technology is chosen and the other one discarded.

If a K-Firm imitates successfully, it is allowed to copy the technology $(\Sigma_{\kappa_{im}}, \Sigma_{im,k,t})$ of a randomly chosen competitor[26]. At the second step of innovation, K-Firms compute an attractiveness measure for their old technology, the imitated one and the innovated one:

$$\begin{aligned} A_{\kappa,t} &= p_{k,t} + uc_{\kappa,t}b \\ A_{\kappa_{in},t} &= p_{in,k,t} + uc_{\kappa_{in},t}b \\ A_{\kappa_{im},t} &= p_{im,k,t} + uc_{\kappa_{im},t}b \end{aligned} \tag{47}$$

Where:

- $p_{k,t} \equiv$ price charged given production technology $\Sigma_{k,t}$ and pricing Equation (40)
- $p_{in,k,t} \equiv$ price charged given production technology $\Sigma_{in,k,t}$ and pricing Equation (40)
- $p_{im,k,t} \equiv$ price charged given production technology $\Sigma_{im,k,t}$ and pricing Equation (40)
- $uc_{\kappa,t} \equiv$ cost of producing one unit of consumption good, given technology Σ_{κ} and the vintage-specific unit production cost (Equation 19)
- $uc_{\kappa_{in},t} \equiv$ cost of producing one unit of consumption good, given technology $\Sigma_{\kappa_{in}}$ and the vintage-specific unit production cost (Equation 19)
- $uc_{\kappa_{im},t} \equiv$ cost of producing one unit of consumption good, given technology $\Sigma_{\kappa_{im}}$ and the vintage-specific unit production cost (Equation 19)
- $b \equiv$ fixed and homogeneous payback parameter

The K-Firm will choose the technology associated to the $min(A_{\kappa,t}, A_{\kappa_{in},t}, A_{\kappa_{im},t})$ value, that is the technology which ensures the best competitive advantage in terms of price and embedded efficiency from the C-Firms' point of view.

G.2.4 Profits and dividends

K-Firms' gross profits are calculated as:

$$\Pi^{gross}_{k,t} = Sales_{k,t} + iD_{k,t} - W_{k,t} - En_{k,t} \tag{48}$$

Where:

- $Sales_{k,t} \equiv$ nominal sales, defined as $Sales_{k,t} = p_{k,t}Q_{k,t}$, where:
  - $p_{k,t} \equiv$ price
  - $Q_{k,t} \equiv$ (real) quantity sold
- $iD_{k,t} \equiv$ interest payment on deposits, defined as $iD_{k,t} = r^d_{t-1}Dep_{k,t-1}$, where:
  - $r^d_{t-1} \equiv$ interest rate on deposits
  - $Dep_{k,t-1} \equiv k$'s deposit stock
- $W_{k,t} \equiv$ wage bill, defined as: $W_{k,t} = w_tL_{k,t} + w_{t-1}L^{rd}_{k,t-1}$, where:

[26] We assume a technological proximity bias, that is competitors who are closer in a technological sense are more likely to be drawn for imitation.

- $L_{k,t} \equiv k$'s # workers employed in production
- $L^{rd}_{k,t} \equiv k$'s # workers employed in R&D
- $w_t \equiv$ wage rate

- $En_{k,t} \equiv$ energy bill, defined as $En_{k,t} = p_{e,t} En^d_{k,t}$, where:
  - $En^d_{k,t} \equiv k$'s energy demand
  - $p_{e,t} \equiv$ energy price

K-Firms pay a profit tax whenever gross profits are positive. Net profits are therefore given by:

$$\Pi^{net}_{k,t} = \left(1 - \mathbf{1}^{[\Pi^{gross}_{k,t} > 0]} \tau^K\right) \Pi^{gross}_{k,t} \tag{49}$$

Where:

- $\mathbf{1}^{[\Pi^{gross}_{k,t} > 0]}$ is an indicator function taking the value 1 if $\Pi^{gross}_{k,t} > 0$ and 0 otherwise.
- $\tau^K \equiv$ K-sector profit (flat) tax rate

If profits are positive, K-Firms pay out a fixed share of profits (δ^K) as dividends:

$$Div_{k,t} = \mathbf{1}^{[\Pi^{net}_{k,t} > 0]} \delta^K \Pi^{net}_{k,t} \tag{50}$$

G.3 Consumption good sector

The consumption good sector is disaggregated in $N2$ firms, where C-Firms are indexed by c, with $c = 1, ..., N2$. C-Firms produce and sell a homogeneous good using labor, capital and energy. C-Firms compete in the good market to acquire the largest market share possible, and as they offer a homogeneous good, the competition is solely based on prices.

G.3.1 Desired production

C-Firms' production plans are set to match expected demand plus a stock of target inventories:

$$Q^d_{c,t} = Dem^e_{c,t} - N_{c,t-1} \tag{51}$$

Where:

- $Q^d_{c,t} \equiv$ desired production
- $Dem^e_{c,t} \equiv$ expected demand, defined as: $Dem^e_{c,t} = \sigma Dem_{c,t-1} + (1-\sigma) Dem^e_{c,t-1}$, where:
  - $Dem_{c,t-1} \equiv$ realized demand in the previous period
  - $\sigma \equiv$ adaptive parameter, fixed and homogeneous across C-Firms
- $N_{c,t-1} \equiv$ inventory stock accumulated up to the previous period[27]

[27] Note that since we assume no planned inventories, accumulated inventories simply reflect mistakes in demand expectations.

G.3.2 Investment

C-Firms receive a certain number of brochures from K-Firms (see section G.2.2) containing the technical characteristics of the offered vintage (Σ_{κ}) and the price charged. C-Firms compare the different vintages offered and choose the most convenient one (κ^*)[28].

C-Firms perform two types of investment: (i) *capacity expansion*, which is aimed at reaching a pre-defined productive capacity target and (ii) *replacement investment*, which is aimed at replacing capital which is deemed to be technologically obsolete, although not yet physically depreciated.

C-Firms aim to attain a given capacity utilization target (u), thus the desired productive capacity is given by:

$$\mathfrak{K}^d_{c,t} = \frac{Q^d_{c,t}}{u} \tag{52}$$

Capacity investment is therefore set so that productive capacity matches $K^d_{c,t}$:

$$EI^d_{c,t} = max\left(0, \left\lfloor \frac{min(\overline{EI}_{c,t},\ \ \mathfrak{K}^d_{c,t} - \mathfrak{K}_{c,t})}{\mathfrak{Q}} \right\rfloor \mathfrak{Q}\right) \tag{53}$$

Where:

- $\mathfrak{Q} \equiv$ maximum unit of output producible with one unit of capital, fixed and homogeneous across capital vintages
- $\mathfrak{K}_{c,t} \equiv k$'s productive capacity
- $\overline{EI}_{c,t} \equiv$ maximum capacity expansion, defined as; $\overline{EI}_{c,t} = \left\lceil \frac{(1+\overline{\lambda})\mathfrak{K}_{c,t}}{\mathfrak{Q}} \right\rceil \mathfrak{Q} - \mathfrak{K}_{c,t}$, where:
  - $\overline{\lambda} \equiv$ exogenous parameter

C-Firms replace the whole capital stock which is deemed to be obsolete. A vintage κ is considered obsolete if the following condition holds:

$$\frac{p_{\kappa^*,t}}{uc_{\kappa,t} - uc_{\kappa^*,t}} \leq b \tag{54}$$

Where:

- $p_{\kappa^*,t} \equiv$ price of the offered vintage κ^*
- $uc_{\kappa,t} \equiv$ unit cost of production of vintage κ
- $uc_{\kappa^*,t} \equiv$ unit cost of production of vintage κ^*
- $b \equiv$ payback parameter

G.3.3 Markup setting, productive inputs demand, and emissions

C-Firms adjust their markups to market conditions. In particular, firm c revises its markup (downward) upward when c's market share (decreases) grows:

$$\mu_{c,t} = \begin{cases} \mu_{c,t-1}\left[1 + \Delta^{\mu}\widehat{f}_{c,t-1}\right] & \text{if } f_{c,t-2} > 0 \\ \mu_{c,t-1} & \text{Otherwise} \end{cases} \tag{55}$$

Where:

[28] C-Firms compare different vintages in the same way K-Firms do, see Equation (47)

- $\mu_{c,t} \equiv c$'s markup
- $f_{c,t}$ c's market share
- $\Delta^{\mu} \equiv$ exogenous parameter
- $\widehat{f}_{c,t} \equiv$ changes in the market share from period to period, defined as: $\widehat{f}_{c,t} = \frac{f_{c,t}-f_{c,t-1}}{f_{c,t-1}}$

In order to calculate the demand for productive inputs and total emissions, we need to define c's effective labor productivity ($Pr^e_{c,t}$), effective energy efficiency ($EF^e_{c,t}$), and effective environmental friendliness ($EF^e_{c,t}$):

$$\begin{aligned} Pr^e_{c,t} &= \sum_{\kappa \in \Phi^u_{\kappa,c,t}} Pr_{\kappa,t} \frac{\mathfrak{K}_{\kappa,c,t}}{\mathfrak{K}^u_{c,t}} \\ EE^e_{c,t} &= \sum_{\kappa \in \Phi^u_{\kappa,c,t}} EE_{\kappa,t} \frac{\mathfrak{K}_{\kappa,c,t}}{\mathfrak{K}^u_{c,t}} \\ EF^e_{c,t} &= \sum_{\kappa \in \Phi^u_{\kappa,c,t}} EF_{\kappa,t} \frac{\mathfrak{K}_{\kappa,c,t}}{\mathfrak{K}^u_{c,t}} \end{aligned} \tag{56}$$

Where:

- $\Phi^u_{\kappa,c,t} \equiv$ set of vintages employed in production by firm c at time t
- $Pr_{\kappa,t} \equiv$ labor productivity of vintage κ
- $EE_{\kappa,t} \equiv$ energy efficiency of vintage κ
- $EF_{\kappa,t} \equiv$ environmental friendliness of vintage κ
- $\mathfrak{K}_{\kappa,c,t} \equiv$ productive capacity of the capital stock of vintage κ belonging to c in time t
- $\mathfrak{K}^u_{c,t} \equiv k$'s utilized productive capacity

Therefore, labor demand ($L^D_{c,t}$), energy demand ($EN^d_{c,t}$), and emissions ($Em_{c,t}$) are defined as:

$$\begin{aligned} L^d_{c,t} &= \frac{Q^d_{c,t}}{Pr^e_{c,t}} \\ En^d_{c,t} &= \frac{Q^d_{c,t}}{EE^e_{c,t}} \\ Em_{c,t} &= \frac{EF^e_{c,t}}{EE^e_{c,t}} Q^d_{c,t} \end{aligned} \tag{57}$$

G.3.4 Credit demand

C-Firms have an internal constraint $\mathfrak{c}^{d,max}_{c,t}$ to the amount they are willing to borrow:

$$\mathfrak{c}^{d,max}_{c,t} = max(0, \;\; \phi NR_{c,t-1} - \mathfrak{l}_{c,t-1}) \tag{58}$$

Where:

- $NR_{c,t-1} \equiv$ previous revenue net of production costs

- $\phi \equiv$ exogenous parameter
- $\mathfrak{l}_{c,t-1} \equiv$ loan stock

Moreover, C-Firms compute a liquidity measure $IF_{c,t}$ defined as:

$$IF_{c,t} = max(0, \;\; D_{c,t} - \mathfrak{l}_{c,t-1} - uc^{e}_{c,t}Q^{d}_{c,t}) \tag{59}$$

Where:

- $D_{c,t} \equiv$ deposits stock
- $uc^{e}_{c,t}Q^{d}_{c,t} \equiv$ costs of desired production

C-Firms utilize internal funds to cover planned production costs and investments. In cases where internal funds fall short, firms resort to credit. However, if available credit proves insufficient, either due to exceeding firms' maximum demand or banks' willingness to lend (see section G.4), planned expenditures are reduced hierarchically: first, substitution investment is cut, followed by expansion investment, and, if necessary, production is scaled down.

G.3.5 Competition

As the household sector is aggregated into a single agent, decentralized interaction in the goods market is not modeled. However, to distribute the total demand for goods among firms, we assign each firm a market share, which evolves through a quasi-replicator dynamics.

First, We compute an attractiveness measure ($E_{c,t}$) for each firm:

$$E_{c,t} = -\left(\frac{p_{c,t}}{\widehat{p}_t}\right)^{\omega_1} - \left(\frac{l_{c,t}}{\widehat{l}_t}\right)^{\omega_2} \tag{60}$$

Where:

- $p_{c,t} \equiv$ price charged by c
- $\widehat{p}_t \equiv$ average good price
- $l_{c,t} \equiv$ c's unsatisfied demand from last period
- $\widehat{l}_t \equiv$ average unsatisfied demand in the good market from last period
- $\omega_1 \equiv$ attractiveness sensitivity to price (exogenous)
- $\omega_2 \equiv$ attractiveness sensitivity to unsatisfied demand (exogenous)

The attractiveness measure $E_{c,t}$ is used to update the market share ($f_{c,t}$). Before that, we calculate a fictitious market share $\tilde{f}_{c,t}$, defined as:

$$\tilde{f}_{c,t} = f_{c,t-1}\left(\frac{2\omega_3}{1+e^{\left(-\chi\frac{E_{c,t}-\widehat{E}_t}{\widehat{E}_t}\right)}} + \big(1-\omega_3\big)\right) \tag{61}$$

Where:

- $\widehat{E}_t \equiv$ weighted $E_{c,t}$ average using past market shares as weights

- $\omega_3 \equiv$ corridor within which the market share is allowed to change from one period to another (exogenous)
- $\chi \equiv$ relative attractiveness sensitivity (exogenous)

Finally, we obtain $f_{c,t}$ by normalizing $\tilde{f}_{c,t}$ to ensure that market shares sum up to 1:

$$f_{c,t} = \frac{\tilde{f}_{c,t}}{\sum_{i=1}^{N2} \tilde{f}_{i,t}} \tag{62}$$

G.3.6 Profits and dividends

C-Firms compute profits before taxes as:

$$\Pi^{gross}_{c,t} = Sales_{c,t} + iD_{c,t} + \Delta Inv_{c,t} + \Delta K_{c,t} - I_{c,t} - W_{c,t} - En_{c,t} - iL_{c,t} \tag{63}$$

- $Sales_{c,t} \equiv$ nominal sales, defined as: $Sales_{c,t} = p_{c,t} Q^s_{c,t}$, where:
  - $p_{c,t} \equiv$ prices
  - $Q^s_{c,t} \equiv$ real sales
- $iD_{c,t} \equiv$ interest payments on deposits, defined as: $iD_{c,t} = r^d_{t-1} Dep_{c,t-1}$, where:
  - $r^d_{t-1} \equiv$ interest rate on deposits
  - $Dep_{c,t-1} \equiv$ deposit stock
- $\Delta Inv_{c,t} \equiv$ investment in inventories, defined as: $\Delta Inv_{c,t} = p_{c,t} N_{c,t} - p_{c,t-1} N_{c,t-1}$, where:
  - $N_{c,t} \equiv$ real inventory stock
- $\Delta K_{c,t} \equiv$ change in the nominal value of capital stock, defined as: $\Delta K_{c,t} = I_{c,t} - Scrap_{c,t}$, where:
  - $I_{c,t} \equiv$ nominal investment
  - $Scrap_{c,t} \equiv$ nominal value of scrapped capital
- $W_{c,t} \equiv$ wage bill, defined as: $W_{c,t} = w_t L_{c,t}$, where:
  - $w_t \equiv$ wage rate
  - $L_{c,t} \equiv$ # workers employed by c
- $En_{c,t} \equiv$ energy bill, defined as $En_{c,t} = p_{e,t} En^d_{c,t}$, where:
  - $p_{e,t} \equiv$ energy price
  - $En^d_{c,t} \equiv$ energy demand
- $iL_{c,t} \equiv$ debt servicing, defined as: $iL_{c,t} = r^l_{c,t} \mathfrak{l}_{c,t}$, where:
  - $r^l_{c,t} \equiv$ interest rate on loans charged to firm c (see section G.4)
  - $\mathfrak{l}_{c,t} \equiv$ loan stock

If profits are positive, C-Firms pay a profit tax and net profits are then defined as:

$$\Pi^{net}_{c,t} = \left(1 - \mathbf{1}^{[\Pi^{gross}_{c,t} > 0]} \tau^C\right) \Pi^{gross}_{c,t} \tag{64}$$

Where:

- $\mathbf{1}^{[\Pi^{gross}_{c,t}>0]}$ $\equiv$ indicator function taking the value 1 if $\Pi^{gross}_{c,t} > 0$ and 0 otherwise
- $\tau^C \equiv$ profit tax rate

If profits are positive, C-Firms pay out a fixed share of profits (δ^C) as dividends:

$$Div_{c,t} = \mathbf{1}^{[\Pi^{net}_{c,t}>0]}\delta^C\Pi^{net}_{c,t} \tag{65}$$

G.4 Banks

The banking sector is disaggregated in NB banks, where individual banks are indexed by b, with $b = 1, ..., NB$. Banks provide deposit facilities to households, firms, and the energy sector, grant credit to C-Firms, and buy government bonds. In this static financial network, economic agents are assigned to a specific bank at the beginning of the simulation and remain affiliated with it during the whole simulation. Deposits belonging to aggregated agents, namely households and the energy sector, are distributed across banks proportionally to their sizes.

G.4.1 Deposits and loans

Banks hold deposits to which they pay an interest rate. The interest rate on deposit (r^d_t) is homogeneous across banks and set as a markdown (υ_B) over the central bank deposit rate ($r^d_{CB,t}$):

$$r^d_{b,t} = (1 - \upsilon_B)r^d_{CB,t} \tag{66}$$

Each bank set a maximum credit supply as a multiple of its net worth ($NW_{b,t}$):

$$\mathfrak{C}^s_{b,t} = \frac{NW_{b,t}}{buffer_{b,t}} \tag{67}$$

Where $buffer_{b,t}$ is a function of the bank's financial soundness:

$$buffer_{b,t} = cm(1 + \mathfrak{v} fragility_{b,t}) \tag{68}$$

Where:

- $cm \equiv$ credit multiplier (exogenous)
- $\mathfrak{v} \equiv$ exogenous parameter
- $fragility_{b,t} \equiv$ measure of financial fragility defined as: $fragility_{b,t} = \frac{BD_{b,t-1}+LE_{b,t-1}}{NW_{b,t-1}}$, where:
  - $BD_{b,t} \equiv$ defaulted loans suffered by bank b
  - $LE_{b,t} \equiv$ losses due to firms entry-exit

Once the maximum credit supply is determined, banks gather credit applications and rank them according to the applicants' debt service-to-revenue ratio. Applicants with low ratios are considered more credit worthy and they are therefore charged a lower interest rate on loans:

$$r^l_{b,c,t} = r^l_{b,t}[(1 + (rank_{c,t} - 1)\mathfrak{M})] \tag{69}$$

Where:

- $r^l_{b,c,t} \equiv$ interest rate on loan charged by bank b to firm c at time t
- $r^l_{b,t} \equiv$ banks' baseline rate, defined as: $r^l_{b,t} = (1 + \mu^B)r^l_{CB,t-1}$, where:

- $\mu^b \equiv$ banks markup (exogenous)
- $r^l_{CB,t-1} \equiv$ central bank lending rate

- $rank_{c,t} \equiv$ quartile of the distribution of debt service-to-revenue ratios among b's customers to which c belongs
- $\mathfrak{M} \equiv$ penalizing factor (exogenous)

G.5 Fossil fuel sector

The fossil fuel sector sells fossils to the energy sector, which uses it as an input for dirty capital. The price of fossil fuel ($p_{f,t}$) is set as:

$$p_{f,t} = p_{f,t-1}\overline{\Delta}_{w,t} \tag{70}$$

Where $\overline{\Delta_{w,t}}$ is a weighted average of current and past nominal wages defined as:

$$\overline{\Delta}_{w,t} = \eta^w \overline{\Delta}_{w,t-1} + (1-\eta^w)\frac{w_t}{w_{t-1}} \tag{71}$$

Note that in this way we ensure that the fossil fuel price grows in line with the nominal growth of the economy.

Given the fossil fuel demand (ff^d_t) and assuming zero cost of production, the profit of the fossil fuel sector is given by:

$$FF_t = p_{f,t} ff^d_t \tag{72}$$

Finally, we assume that a small share (δ^F) of the fossil fuel sector's accumulated wealth is distributed as dividends to households:

$$Div_{f,t} = \delta^F(R_{f,t-1} + FF_t) \tag{73}$$

Where $R_{f,t}$ is the fossil fuel sector wealth, which is accumulated in the form of central bank reserves.

G.6 Government

The government collect taxes from households by applying a flat tax rate on labor income τ^H and on profits, applying a flat tax rate on C-Firms, K-Firms, and banks called τ^C, τ^K, and τ^B respectively. The government also collect charges a carbon tax on the energy sector applying a time-varying rate $\tau^{Em,E}_t$. The government provide unemployment benefits. whose total amount at each point in time is defined as;

$$UB_t = UB_t = \zeta w_t(LS_t - L_t) \tag{74}$$

Where:

- w_t wage rate
- $\zeta \equiv$ unemployment benefit rate
- $LS_t - L_t \equiv$ # unemployed workers

As discussed in section 3.4.2, the government can also redistribute the carbon tax revenues, by an amount TR_t, which is the sum of the transfers to households (TR_t^H) and the energy sector (TR_t^E). Public expenditures are also used to finance firms' entry and banks' bailouts. Finally, the government must service public debt:

$$iGB_t = r_{GB,t-1}GB_{t-1} \tag{75}$$

Where:

- $iGB_t \equiv$ interest payments on public debt
- $r_{GB,t} \equiv$ interest rate on bonds
- $GB_t \equiv$ stock of public debt

The government deficit/surplus at each point in time is given by:

$$Sav_{g,t} = Tax_t + T_{cb,t} - UB_t - TR_t - iGB_t - T_{g,t} - Bail_t \tag{76}$$

Where:

- $Tax_t \equiv$ collected taxes
- $T_{cb,t} \equiv$ transfers from the central bank[29]
- $T_{g,t} \equiv$ funds used for firms' entry
- $Bail_t \equiv$ funds used for banks' bailouts

The public sector borrowing requirement is given by:

$$PSBR_t = Sav_{g,t} + \xi_{GB}GB_{t-1} \tag{77}$$

Where ξ_{GB} is the repayment share of the outstanding public debt stock.

If $PSBR_t > 0$, the government issues new bonds. New bonds are initially offered to banks. Whatever amount of newly issued public debt which is not bought by banks is acquired by the central bank. If $PSBR_t < 0$, the government reduces the stock of public debt accordingly.

Finally, the interest rate on public bonds is set as a markdown (υ_{GB}) over the central bank lending rate:

$$r_{GB,t} = (1 - \upsilon_{GB})r^l_{CB,t} \tag{78}$$

G.7 Central bank

The central bank's main task is to set the base interest rate, which is done using a Taylor rule:

$$r^l_{CB,t} = max\Big\{\underline{r},\ \ \iota_1 r^l_{CB,t-1} + (1-\iota_1)(r + \iota_2(\pi^a_t - \pi^*) + \iota_3(U^* - U_t))\Big\} \tag{79}$$

Where:

- $\underline{r} \equiv$ policy rate lower bound
- $\iota_1 \equiv$ policy rate smoothing parameter

[29]The central banks transfer all its profits to the government

- $r \equiv$ fixed intercept
- $\pi_t^a \equiv$ year-to-year inflation rate
- $\pi^* \equiv$ central bank's year-to-year inflation target
- $\iota_2 \equiv$ inflation sensitivity parameter
- $U^* \equiv$ central bank's unemployment rate target
- $U_t \equiv$ current unemployment rate
- $\iota_2 \equiv$ unemployment rate sensitivity parameter

Finally, the central bank deposit rate is set as a markdown (υ_{CB}) over the policy rate and incidentally coincides with the interest rate on bonds:

$$r^d_{CB,t} = \big(1 - \upsilon_{CB}\big) r^l_{CB,t} \tag{80}$$

H Climate policy and opinion dynamics

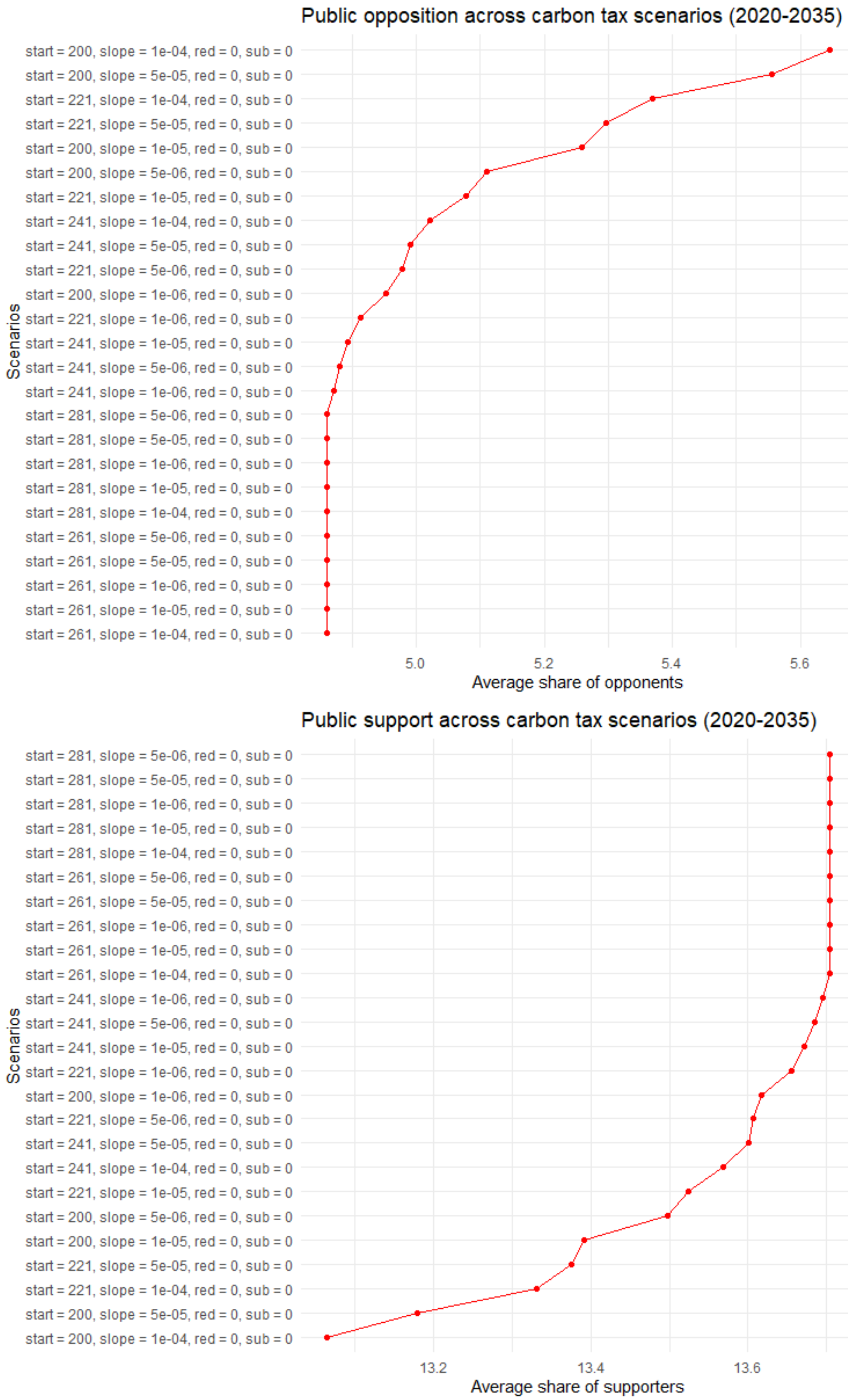

Figure 15: Average share of opponents and supporters over 2020-2035 across carbon tax pathways defined by the combination of the implementation year (start = 200, 221, 241, 261, 281 which corresponds to 2020, 225, 2030, 2035 and 2040, respectively), slope of the carbon tax (i.e. $g^{\tau,Em}$); share of earmarked revenues (i.e., ρ^{ctax}); and green subsidy (i.e., ρ^{gsubs}).