Environmental and Resource Economics
https://doi.org/10.1007/s10640-025-01048-z

The Cultural Multiplier of Climate Policy

Daniel Torren-Peraire[1,2] · Jeroen C. J. M. van den Bergh[1,3,4] · Ivan Savin[5,1,6]

Received: 1 November 2024 / Revised: 15 September 2025 / Accepted: 16 October 2025

Abstract
To achieve deep decarbonisation, the design of climate policy needs to account for consumption choices being influenced not only by pricing but also by social learning. This involves changes that pertain to the whole spectrum of consumption, likely involving shifts in lifestyles. In this regard, it is crucial to consider social learning not only in the short term but also slower and longer-term cultural change. Against this background, we analyse the interaction between climate policy and cultural change, focusing on carbon pricing. We extend the notion of "social multiplier" of environmental policy derived in an earlier study to the context of multiple consumer needs while allowing for behavioural spillovers between these, giving rise to a "cultural multiplier". We develop a model to assess how this multiplier contributes to the effectiveness of carbon pricing. Our results show that the cultural multiplier stimulates a greater reduction in emissions compared to fixed preferences and the social multiplier. These findings are also good news for policy acceptance since the cultural multiplier greatly increases the effectiveness of a carbon price, meaning a lower price suffices for a given emissions-reduction goal. At high carbon prices, the distinction between social and cultural multiplier effects diminishes, as the strong price signal drives even resistant individuals toward low-carbon consumption. By varying economic and social conditions, such as substitutability between low- and high-carbon goods, social network structure, proximity of like-minded individuals, diversity of consumption lifestyles, and heterogeneity of preferences, the model provides insight into how cultural change can be leveraged to secure maximum effectiveness of climate policy.

Keywords Carbon pricing · Endogenous preferences · Social networks · Agent-based modelling

1 Introduction

To achieve the deep decarbonisation required to meet emissions targets, consumption changes are needed across the board, i.e. applying to all goods, services and hence production sectors. This may involve a shift in lifestyles (Girod et al. 2014). As part of this, there

Extended author information available on the last page of the article

Published online: 08 December 2025

can be spillovers (Lanzini and Thøgersen 2014; Truelove et al. 2014) between distinct consumption categories, such as following a vegetarian diet having positive spillovers on travel and housing consumption choices in individuals who hold strong pro-environmental values (Andersson and Nässén 2022). To better understand the mechanism and implications, we develop a model that connects a multiple consumption category module to a social network module and assess how a carbon price induces decarbonisation. We focus on carbon pricing because of its widespread implementation in countries – think of the EU-ETS (covering 31 countries) and carbon taxes in the UK and Sweden – its prominence in the literature on climate policy (Köppl and Schratzenstaller 2023; Döbbeling-Hildebrandt et al. 2024), and its flexibility in addressing heterogeneity in emissions intensity and reduction options through a systems-based approach (Baranzini et al. 2015).

Low-carbon consumption choices are influenced by a multitude of factors, not just pricing (Wang et al. 2021). Social norms (Davis et al. 2018), the framing of a carbon tax (Hartmann et al. 2023) or similarities in low- and high-carbon alternatives, can play significant roles. For example, individuals may perceive low-carbon goods such as electric vehicles (EVs) to be less substitutable because of different technological characteristics, seen in phenomena such as range anxiety where individuals are concerned their vehicle will run out of power before their destination (Pevec et al. 2020). More broadly, a growing body of empirical literature analyses the role of social learning in shaping environmentally relevant behaviours, such as electric vehicle adoption (Cui et al. 2021; Yang and Chen 2021; Bhat et al. 2022), rooftop solar panel uptake (Bollinger and Gillingham 2012; Liu et al. 2023), use of public transport and bicycles (Clark and Scott 2013; Kim et al. 2018) and vegetarian or plant-based diets (Nezlek and Forestell 2020). A takeaway from this literature is the need to include social influence processes when analysing the effectiveness of climate policy in driving shifts towards relevant low-carbon behaviours.

This paper contributes to the limited literature on carbon pricing with endogenous preference changes. The model proposed in Mattauch et al. (2022) studies the impact of carbon pricing which directly affects preferences for clean goods. This is described as a crowding-in (greater consumption of clean good) or -out (greater consumption of dirty good) effect of carbon pricing. Konc et al. (2021) study the role of direct and indirect effects of carbon pricing, through price and social influence mechanisms. Their focus centres on the impact of the social interactions on climate policy effectiveness, defined as a "social multiplier" (Glaeser et al. 2003; Konc et al. 2021). The social multiplier leads to additional decarbonisation, for the same carbon price. One interpretation is that individuals misinterpret observed changes in consumption as shifts in preferences rather than responses to price changes. It specifically captures how individuals adjust their consumption in a specific category (e.g., transport) by observing neighbours' behaviour in that same category.

To study large-scale shifts in consumption behaviours due to repeated and cumulative social interactions, we conduct our analysis through the lens of cultural change (Davis et al. 2018, Kaaronen and Strelkovskii 2020, Sovacool and Griffiths 2020). Building on computational models of cultural change (Epstein and Axtell 1996; Axelrod 1997; Kuperman 2006; Torren-Peraire et al. 2024), we study how long-term preference dynamics may affect decarbonisation. This involves a focus on long-term change as decarbonisation of lifestyles requires coordinated shifts across multiple areas of consumption, rather than a simple one-off behavioural switch such as buying an electric vehicle. This systemic change may develop gradually over multiple decades. Therefore, we consider model dynamics over a multi-decade period, which is in line with many national net-zero targets.

In this article, we extend the social multiplier concept to the case of social learning across multiple consumption categories (e.g. transport, food, tourism), leading to a "cultural multiplier". Individuals evaluate the overall pro-environmental orientation of their peers. Thus, rather than focusing on isolated behaviours, individuals influence each other through imitation of lifestyles, composed of multiple consumption choices. As such, the cultural multiplier describes an identity-based process of preference change across consumption categories. In contrast to previous economics literature on the interaction of culture and the environment (Schumacher 2015; Bezin 2019), we choose not to take a generation-based modelling approach due to the limited timeframe over which decarbonisation must occur, e.g. EU net-zero by 2050 target. However, in a similar fashion to Schumacher (2015) we model how the emergence of pro-environmental culture can stimulate greater decarbonisation in a positive feedback loop.

A key component in determining the dynamics of socially informed preferences is the structure of the network within which social interactions occur. This structure not only affect social learning but also shapes how external shocks, such as governments implementing carbon pricing, propagate through the network, potentially inducing contagion and tipping dynamics (Granovetter 1978; Orléan 1995; Watts 2002; Banerjee et al. 2013). Individuals with a high socioeconomic status (Nielsen et al. 2021), who tend to occupy central positions in social networks, can generate social tipping points for decarbonisation, for example as seen in the diffusion of solar energy (Bollinger and Gillingham 2012; Bollinger et al. 2020). However, if their preferences are not consistently aligned with decarbonisation goals they may also inhibit a rapid transition to low-carbon alternatives through their sustained high-carbon consumption (Mattioli et al. 2023).

Our central research question is: How does cultural change moderate the effectiveness of carbon pricing. In pursuit of this goal, we explore the following sub-questions: Is the cultural multiplier similar in size to the social multiplier? And what are the socioeconomic characteristics affecting the magnitude of the cultural multiplier? Regarding the latter, we will consider substitutability between low- and high-carbon goods, social network structure, proximity of like-minded individuals in a social network, and diversity of lifestyles.

Our results show that the cultural multiplier enhances the effectiveness of carbon pricing, especially at low price levels relative to the social multiplier and fixed preferences as it leverages faster consensus formation. However, this effect diminishes at high carbon price levels, where the strength of the price signal overrides social interactions and cultural change. We further find that the cultural multiplier becomes stronger when low- and high-carbon goods are more substitutable, when lifestyles involve a greater number of consumption categories, and when individuals are embedded in diverse networks with low homophily. Additionally, greater expenditure inequality leads to higher emissions while the progressive redistribution of carbon pricing revenues can mitigate this effect. Overall, these findings suggest that policymakers can increase emissions reduction by carbon pricing through complementing it with interventions that foster pro-environmental identities cultivating a broader vision of low-carbon lifestyles, in turn leveraging the cultural multiplier.

The remainder of the paper is organised as follows. In Sect. 2, we formulate the model of market processes, social network interactions, cultural change, and climate policy. In Sect.

3, we analyse the strength of the cultural multiplier, compare it to the social multiplier, and explore which socioeconomic factors shape its size. Section 4 concludes.

2 The Model

2.1 Conceptual Approach

We construct a model of individuals' consumption behaviour subject to a carbon price. To capture the interaction of endogenous preference driven by social interactions and climate policy we use an agent-based model (ABM). Individuals act as utility-maximising agents with heterogeneous preferences for low-carbon goods that evolve through social imitation.

Figure 1 provides a schematic overview of the model. The yellow boxes represent the market modules that include the expenditure, low-carbon preferences the consumption choices of individuals. These choices are constructed from the utility function subject to a budget constraint. Stacked boxes indicate that consumption and emissions occur in multiple sectors, such as energy, transport or food. The blue boxes represent the social imitation module of the model which produces dynamic preferences for low-carbon consumption via social interactions. The grey stacked box indicates the multiple individuals that compose the social network. Individuals' consumption choices produce emissions each time step which contribute to network-wide cumulative emissions, shown in the red boxes. Lastly, the green boxes represent the climate policy module, capturing the role of carbon pricing in guiding the social network towards low-carbon consumption. Specifically, a carbon price applied

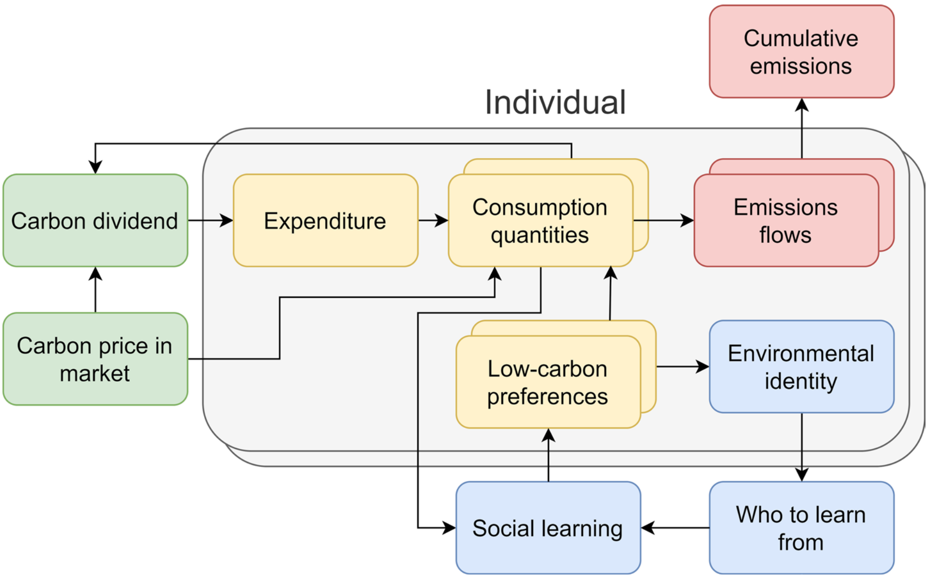


Fig. 1 Model structure. Blue boxes capture the social interactions; yellow the preference dynamics and consumption choices; green the climate policy; and red the carbon emissions. Arrows indicate the direction of influence. Grey stacked boxes indicate multiple individuals whilst coloured stacked boxes show multiple consumption categories

to consumption across all the different categories influences high-carbon good prices and produces revenues which are redistributed as a lump sum.

2.2 Market Module

The model employs a constant elasticity of substitution (CES) utility function where individuals have preferences for low- and high-carbon alternatives. Highly substitutable goods such as energy, where the source has little impact on utility, have strongly non-linear responses to price changes or a given preference between alternatives. However, to answer the main research question of how carbon pricing is affected by cultural change requires representing consumption habits across multiple human needs, i.e. lifestyle (Foramitti et al. 2024). To capture this, we extend the CES function to multiple consumption categories which results in a nested CES or NCES utility function. Individuals' make choices of consumption quantities between low- L and high-carbon H goods across multiple consumption categories m, for a total of M categories. In the model at each discrete time step t, individuals, denoted by index i, maximize their utility based on their preference for low-carbon goods, $A_{t,i,m}$, subject to a budget constraint imposed by individuals' expenditure B. The utility is given by a NCES function with two levels (Sato 1967) as in Eq. 2. At the top level, we represent different consumption categories, while on the second level (within each category) are low- and high-carbon goods alternatives (Konc et al. 2021; Mattauch et al. 2022), $L_{t,i,m}$ and $H_{t,i,m}$ with substitutability between each of the two alternatives denoted by σ. Between categories, there is a further preference parameter for consumption a_m where $\sum_{m=1}^{M} a_m = 1$ and substitutability across categories ν.

$$\max_{L_1,...,L_M,H_1,...,H_M} U(L_1,...,L_M,H_1,...,H_M,a_1,...,a_M,A_1,...,A_M,\sigma_1,...,\sigma,\nu) \tag{1}$$

$$U_{t,i} = \left(\sum_{m=1}^{M} a_m \left(A_{t,i,m} L_{t,i,m}^{\frac{\sigma-1}{\sigma}} + (1-A_{t,i,m}) H_{t,i,m}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma(\nu-1)}{(\sigma-1)\nu}} \right)^{\frac{\nu}{\nu-1}}, \tag{2}$$

To reduce model complexity, for each individual i we assume the preference parameter between categories a_m, e.g. the preference for transport over energy consumption, is fixed and there is equal weighting of consumption categories $\sum_{m=1}^{M} a_m = 1$. Utility maximisation is subject to a budget constraint, where individuals buy low- and high-carbon goods with prices $P_{L,m}$ and $P_{H,m}$ respectively. These prices do not change over time and consist of a base price and an additional carbon price, see Sect. 2.4. It is assumed that low-carbon goods are not subject to the carbon price. The base price of low- and high-carbon goods are $P_{L,m}, P_{B,H,m} = 1$. This assumption of price parity for low and high-carbon goods may not hold for all sectors, such as internal-combustion engine versus electric vehicles, but for other choices, such as vegetarian versus meat-based diet low-carbon alternatives can be cheaper. If a higher price for low carbon goods is assumed, then the required carbon price for the same emissions reduction would be higher. Additionally, the social and cultural multipliers would act as a lock-in mechanism of high-carbon preferences for those carbon tax values that are below price parity.

$$B = \sum_{m=1}^{M} L_{t,i,m} P_{L,m} + H_{t,i,m} P_{H,m}. \tag{3}$$

From the Lagrangian first-order conditions for the system we derive demand relationships for the low- and high-carbon alternatives for all consumption categories as functions of preferences, prices and degrees of substitution (see Appendix A). The demands for high- and low-carbon goods are given by,

$$H_{t,i,m} = \frac{B\chi_{t,i,m}}{Z_{t,i}} \tag{4}$$

$$L_{t,i,m} = \frac{B\Omega_{t,i,m}\chi_{t,i,m}}{Z_{t,i}} \tag{5}$$

Here $\Omega_{t,i,m}$ is the ratio between low- and high-carbon good quantities, $\chi_{t,i,m}$ captures the relative weighting of consumption between different categories, and $Z_{t,i}$ is a normalisation term. They are defined as:

$$\Omega_{t,i,m} = \frac{L_{t,i,m}}{H_{t,i,m}} = \left(\frac{P_{H,m}A_{t,i,m}}{P_{L,m}(1 - A_{t,i,m})}\right)^{\sigma} \tag{6}$$

$$\chi_{t,i,m} = \left(\frac{a_m A_{t,i,m}}{P_{L,m}\Omega_{t,i,m}^{\frac{1}{\sigma}}}\right)^{\nu} \left(A_{t,i,m}\Omega_m^{\frac{\sigma-1}{\sigma}} + 1 - A_{t,i,m}\right)^{\frac{\nu-\sigma}{(\sigma-1)}} \tag{7}$$

$$Z_{t,i} = \sum_{p=1}^{M} \chi_{t,i,p}(\Omega_{t,i,p}P_{L,t,p} + P_{H,t,p}) \tag{8}$$

2.3 Social-Imitation Module

This module is closely adapted from the one proposed in Torren-Peraire et al. (2024), which in turn is derived from DeGroot (1974). Individual preferences for low-carbon consumption evolve due to social imitation of neighbours' consumption behaviour. A social network is introduced to represent the context within which this process occurs. The network is composed of N individuals i, each with ego networks N_i, which interact with each other each time-step t. Future preferences are a weighted average of current preferences $A_{t,i,m}$ and an external social imitation influence of others' low-carbon consumption behaviour $C_{t,i,m}$:

$$A_{t+1,i,m} = (1 - \phi_m)A_{t,i,m} + \phi_m \sum_{j=1}^{N_i} \alpha_{t,i,j} C_{t,j,m}, \tag{9}$$

How sensitive an individual's preferences are to social influence is mediated by the social susceptibility parameter $\phi \in [0, 1]$. The parameter $\alpha_{i,j}$ captures how much individual i values the opinion of neighbouring individual j. The initial preferences for low-carbon consumption across multiple consumption categories $A_{0,i,m}$ are generated using a Beta distribution in the interval $[0, 1]$. This distribution is defined by two shape parameters (a, b) that dictate skewness and polarisation among sampled values. Of particular interest is its flexibility to approximate very different distributions, such as uniform and pseudo-normal. We set the similarity between an individual's initial preferences for low-carbon consumption across different categories using an initial coherence parameter, $c \in [0, 1]$, where the case of $c = 0$ represents an individual whose preferences do not align with each other. Following Konc et al. (2021), individuals copy the proportion of neighbours' consumption that is low-carbon:

$$C_{t,j,m} = \frac{L_{t,j,m}}{L_{t,j,m} + H_{t,j,m}}. \tag{10}$$

In the model, the consumption behaviours of neighbours in the social network are not taken into consideration equally leading to a lack of global preference convergence (Dandekar et al. 2013). Instead, individuals strive for greater homophily through weighted social imitation. To model this we follow Axelrod (1997), where past interactions between pairs of individuals leads to stronger future interactions. The intensity of these interactions between individuals, $\alpha_{t,i,j}$, is the channel through which the social and cultural multiplier are distinguished.

To highlight the role of environmental identity as a mechanism for behavioural spillovers in consumption, consider two individuals: Alice and Bob. Each evaluates the others' consumption behaviour across three consumption categories: food, transport, and energy. Alice is a vegetarian and thus has a strong low-carbon preference for the consumption category food ($A_1 = 1$) but is relatively indifferent towards low-carbon consumption of other categories (e.g., $A_2 = A_3 = 0.5$). Bob has mild low carbon preferences regarding all consumption categories (e.g., $A_1 = A_2 = A_3 = 0.45$). In the case of the social multiplier, influence is category specific, thus Bob may pay attention to Alice's behaviour in transport and energy consumption. However, in the case of food consumption, Bob ignores Alice's behaviour. In the case of the cultural multiplier, things work differently. Here Bob considers the similarity in environmental identity between themselves and Alice, considering their proximity in preferences across multiple consumption categories (see Eq. 13). Bob pays less attention to Alice in transport and energy categories but considers their food choices. Over repeated social interactions, Alice influences Bob towards a more low-carbon preference in food which would have been ignored under the social multiplier scenario. In this fashion, selective imitation based on environmental identity at the individual level acts as a mechanism for generating cohesion in consumption across the entire social network.

For our model of the cultural multiplier, we assume that the preferences of individuals for low-carbon goods are not observable, instead, these must be inferred through observing actual consumption choices. The social multiplier of climate policy may be characterised as a misinterpretation of consumption change (from increased price) as a preference change. The result of this misinterpretation is that for a given carbon emission target a lower carbon price is required. Alternatively, the actual decarbonisation effect exceeds the one predicted by fixed preference models of Pigouvian taxes, as the policy induces preference change (Koessler et al. 2021). Given the importance of imitation, in Appendix B we study how greater substitutability between goods leads to a more non-linear relationship between preferences and consumption shares.

We now formulate the social and cultural multipliers in the model by specifying the weighting matrices that determine how strongly an individual imitates each neighbour. Both are modelled using a softmax function (Konc and Savin 2019) such that the interaction strength of individuals with all their neighbours is normalised, with greater similarity in preferences or environmental identity resulting in stronger interactions. A confirmation bias θ modulates how open individuals are to imitating the behaviour of neighbours with different preferences or environmental identity. The social multiplier is represented via a weighting matrix $\alpha^{SM}_{t,i,j,m}$ where individuals evaluate their similarities with neighbours separately for each of their m consumption categories, making its structure one-dimensional in line with Konc et al. (2021),

$$\alpha^{SM}_{t,i,j,m} = \frac{e^{-\theta|A_{t,i,m}-A_{t,j,m}|}}{\sum_{j\neq i}^{N_i} e^{-\theta|A_{t,i,m}-A_{t,j,m}|}}. \tag{11}$$

This can result in individuals paying varying amounts of attention to a neighbour's consumption behaviour depending on the consumption category. By contrast, interaction strength in the cultural multiplier takes a multiple consumption category approach, where similarity in environmental identity is used. A simplified version of the identity model developed in Torren-Peraire et al. (2024) is implemented here. It defines the environmental identity of an individual as the average of their preferences for different categories of low-carbon goods. This model provides an indirect mechanism for spillovers, through which a greater pro-environmental identity can make green behaviours more likely (Van der Werff et al. 2014). The social network weighting matrix in the cultural multiplier case, $\alpha^{CM}_{t,i,j}$, is given by,

$$\alpha^{CM}_{t,i,j} = \frac{e^{-\theta|I_{t,i}-I_{t,j}|}}{\sum_{j\neq i}^{N_i} e^{-\theta|I_{t,i}-I_{t,j}|}}, \tag{12}$$

Based on the environmental identity distance of N_i neighbours,

$$I_{t,i} = \frac{1}{M}\sum_{m=1}^{M} A_{t,i,m}. \tag{13}$$

A shift towards pro-environmental identities not only requires a change in one category of consumption, such as the growing popularity of a vegan diet, but coordination across multiple consumption categories in a low-carbon direction. This results in preference change producing a slower, longer-term cultural change.

Social influence between individuals is facilitated in the model via a social network. The specification of the network can be adapted to capture the relevant context in terms of consumption category (e.g., more or less conspicuous) and medium of social interaction (e.g., face-to-face, word of mouth, online, or geographical). We consider three unique network structures, each with differing degree distribution: Small-world, SW (Watts and Strogatz 1998), Stochastic block model, SBM (Holland et al. 1983), and Scale-free, SF (Albert and Barabási 2002), see Fig. 2.

The SW model represents physical (offline) social networks where people form densely connected clusters of friends with short paths between these clusters, representing social mobility (studies abroad, relocation for a new job) or people occasionally migrating. This results in a network with simultaneously high clustering and short mean path length producing the small world property. The SBM allows for the representation of clustered groups of nodes that have higher connection density within blocks than between them. In the model, we consider how the dichotomous relationship between two blocks can affect decarbonisation across the entire network. This network structure facilitates the study of consumption decarbonisation in loosely linked communities, such as rural versus urban settings. For the SF network, the use of a growing network with preferential attachment generates a degree distribution that follows a power law. This results in a handful of nodes having a high number of connections whilst most have few, such as in online social networks. This network structure may be used to study the role of individuals with high socioeconomic status (Nielsen et al. 2021). Specifically of interest is how a central hegemony of low- or high-carbon consumption in the highest degree nodes may tip the rest of the system due to their far-reaching social influence.

We assume that network structures remain fixed over time but allow for dynamic strength of connections enabling agents to ignore individuals with very different preferences within their neighbour network. This choice allows to reduce model complexity as we do not have to include a mechanism for deciding the process of re-wiring social connections. This simplification has the benefit of preserving the properties of the network types considered; Watts-Strogatz (small-world), Barabasi-Albert (scale free) and stochastic block model networks (multiple but separate communities). The structure of the social network indirectly influences preference dynamics by dictating whom an individual can imitate and the ease with which different lifestyles can diffuse through the population. For example, in the SF network hubs can accelerate diffusion by broadcasting to a large population, or in the SBM network the nodes between communities can act as bridges for preference diffusion.

Lastly, we introduce a measure of homophily $h \in [0, 1]$, which indicates the distribution of initial environmental identities among neighbours. For $h = 0$, individuals are randomly

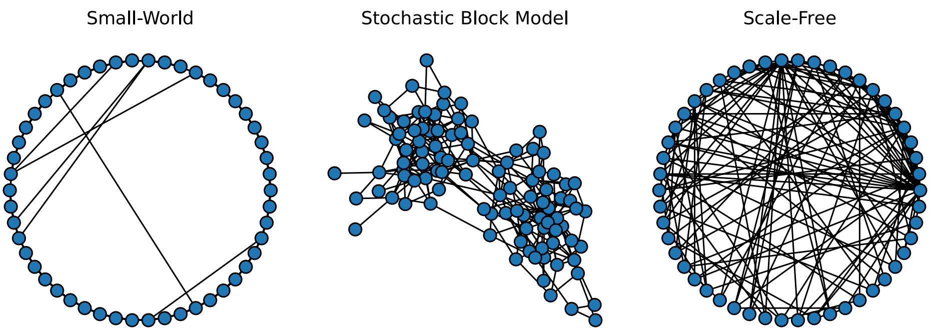


Fig. 2 Illustrative example of different social network structures tested (left - SW, middle – SBM, right - SF)

positioned within the network, while for $h = 1$ individuals connected have the smallest possible distance in environmental identities.

2.4 Climate-Policy Module

Without loss of generality, we assume that high-carbon goods and services have emissions of one and the low-carbon goods have zero emissions. The consumption of high-carbon goods by individuals produces emissions which contribute to a global cumulative quantity E, according to

$$E = \sum_{t=0}^{t_{max}} \sum_{i=1}^{N} \sum_{m=1}^{M} H_{t,i,m}. \tag{14}$$

where there are t_{max} time steps in each experiment. The carbon price is implemented as a tax, τ, on high-carbon goods

$$P_{H,m} = P_{B,H,m} + \tau \tag{15}$$

The revenues of the carbon price are recycled to consumers in a lump-sum.

3 Results

3.1 Overview of Numerical Experiments

Each experimental run consists of 3000 individuals interacting over 360 time steps. This can be considered to represent 30 years with each time step being a month. Unless stated otherwise in the following results each sub-figure is composed of 30,000 experimental runs. Individual initial preferences are drawn from a Beta distribution symmetrical about indifference towards the carbon content of goods ($\bar{A}_m = 0.5$). In the initial results, individuals are assumed to have the same budget, B, and this assumption is later relaxed to test the effects of heterogeneous budgets. Appendix Fig. 11 gives an illustrative example of a typical model run showing the environmental identity trajectories for zero and low carbon price of $\tau = 0.15$. The parameters used in models are shown in Table 1.

Evaluating the ultural multiplier

To assess the impact of cultural change on the effectiveness of climate policy we measure cumulative carbon emissions E under three conditions:

(1) Fixed preferences – no social influence of preferences and consumption decisions.
(2) Social multiplier - dynamic preferences due to social imitation through preference similarity for each consumption category separately, as captured by Eq. 11
(3) Cultural multiplier - dynamic preferences due to social imitation through identity similarity, as captured by Eq. 12

Table 1 Model parameters

Parameter Name	Symbol	Description	Default Value	Range Tested
Initial preference Beta	a, b	Beta distribution parameters used to generate initial preferences	(2,2)	([0.1, 8],[0.1, 8])
Low- and high-carbon substitutability	σ	Elasticity of substitution between low- and high-carbon goods	4	[1.1, 8]
Between category substitutability	ν	Elasticity of substitution across consumption categories	2	[1.1, 8]
Social susceptibility	ϕ	Influence of social imitation on preference for low-carbon consumption	0.02	[0,1]
Confirmation bias	θ	Confirmation bias towards individuals with similar environmental identities	5	[0, 50]
Carbon price	τ	Additional price imposed on high-carbon goods	[0,1]	[0, 5]
Consumption categories	M	Number of categories of goods	2	[1, 50]
Total individuals	N	Total number of individuals in the model	3000	[500,3000]
Homophily state	h	Degree of initial similarity between neighbours in terms of environmental identity	0	[0, 1]
Coherence state	c	Similarity individual's low-carbon preferences across consumption categories.	0.9	[0, 1]
Maximum time steps	t_{max}	Total time-steps in experimental runs	360	
Price of low-carbon goods	$P_{L,m}$	Price of low-carbon goods in category m	1	
Base price of high-carbon goods	$P_{B,H,m}$	Base price of high-carbon goods in category m	1	
SF density		Density of connections between individuals	0.1	
SBM block number		Number of blocks in stochastic block model	2	
SBM intra-block density		Density of connection between individuals within block	0.02	
SBM inter-block density		Density of connection between individuals between blocks	0.005	
SW density		Density of connections between individuals	0.1	
SW probability rewire		Probability of rewiring to produce long distance ties	0.1	
Stochastic Seed Repetitions		Variations of initials seed for preferences, network structure, homophily and coherence	100	

In the model, social influence occurs through the imitation of consumption behaviours which depend on both preferences and the carbon price level. To test whether the cultural multiplier is a function of the strength of the carbon price we consider a range of values $\tau = [0, 1]$. Figure 3 shows the cumulative emissions for the three different cases in a small-world network. For each carbon price and network structure, we ran 100 experiments with different stochastic seeds for the initial preference distribution, network structure, distribution of individuals in the network and coherence in preferences. In the figure the solid line shows the mean and shaded region showing the 95% confidence interval over stochastic seed runs.

In the case of the cultural multiplier (green) we see a large and instant decrease in cumulative emissions with the introduction of a carbon price, relative to the fixed preferences

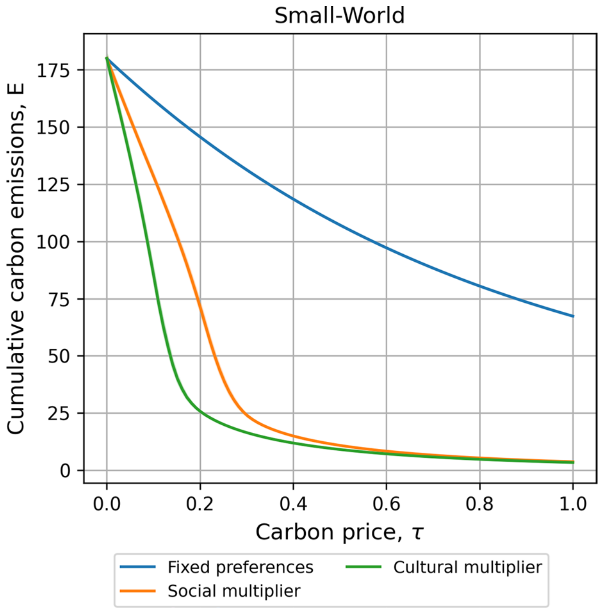


Fig. 3 Cumulative emissions for the case of fixed preferences (blue), cultural multiplier (green) and social multiplier (orange) using a small-world network. The shaded region indicates 95% confidence interval for 100 stochastic runs (small due to high number of runs). The stochastic block model and scale-free graphs are shown in Appendix Fig. 12

scenario. The imitation of consumption choices results in additional decarbonisation across multiple consumption categories. When comparing the social (orange) and cultural multiplier cases (green) we find that the latter has much lower emissions for low carbon prices (approximately $\tau < 0.5$). This greater strength of the cultural multiplier over the social multiplier can be explained by the consensus-forming effect of environmental identity. When evaluating individuals across multiple preferences collectively it becomes harder for outliers in the preference space to isolate themselves into communities with a high degree of preference homophily. This results in individuals imitating a wider range of consumption behaviours, and reach faster consensus formation, translating into greater emissions reduction of carbon pricing.

In the model, we assume price parity between low- and high-carbon goods, meaning their base prices are equal and only high-carbon goods are subject to the carbon price. However, for specific consumption categories such as EVs this is not the case as internal combustion engine vehicles are cheaper. If generally low-carbon goods are assumed to have a higher base price than high-carbon goods, then a higher carbon price would be required to achieve the same level of emissions reduction. Additionally, the social and cultural multipliers would act as a lock-in mechanism of high-carbon preferences for those carbon prices that are below price parity. This lock-in leads to higher emission than those of the fixed preferences case for both social and cultural multipliers.

Changes and especially a gradual increase in the carbon price the EU-ETS over time suggests that next to a constant carbon price, as considered in Fig. 3, it is worthwhile to assess the implications of a dynamic carbon price, to see if effects simply scale up or some nonlinear effects result. To evaluate this, we consider the impact of a linearly increasing carbon price under fixed preferences and social and cultural multipliers. The results are shown in Appendix Fig. 13. The horizontal axis indicates the final carbon price after 360 periods. The general finding is that the results stay robust. For example, the ordering of the emission curves is unchanged, and both the fixed preferences and cultural multiplier behave consistently across the fixed and linear cases. The key difference between the two carbon price implementations is that for small values the social multiplier follows the emission path of the fixed preferences, unlike in Fig. 3. At low carbon price values, $\tau < 1$, individuals can lock-in high-carbon preferences due to social imitation early in the simulation, before the penalty from the carbon price becomes too large later on. It is only for values above a final tax of 1 that the social multiplier emissions falls rapidly as the strength of the carbon price tips the network out of its locked-in preferences and towards low-carbon consumption.

To compare the findings with previous work by Konc et al. (2021) we study the tax reduction M_{tax}, induced by the social and cultural multipliers, defined as

$$M_{tax} = 1 - \frac{\tau_s}{\tau_f} \tag{16}$$

where τ_f is the carbon price required in the fixed preferences case to match the emissions reduction caused by a carbon price τ_s in the social and cultural multiplier cases. Using data from Fig. 4 on cumulative emissions we can map the required τ_f value onto a τ_s value i.e. for a given emissions target what is the carbon price required in the fixed preferences, social and cultural multiplier cases. However, given that cumulative emissions are much lower with the social and cultural multipliers than in the fixed preferences case, additional simulations are needed to determine the carbon price required for the fixed preferences case to match the emissions of the other two across all carbon price levels. With this aim, we first calculate what the maximum and minimum cumulative emission produced by the social and cultural multiplier cases are for carbon prices $\tau_s = [0, 1]$. Secondly, we use these extreme emission values as targets and calculate what the required carbon price τ_f would be to achieve this in the fixed preferences case.

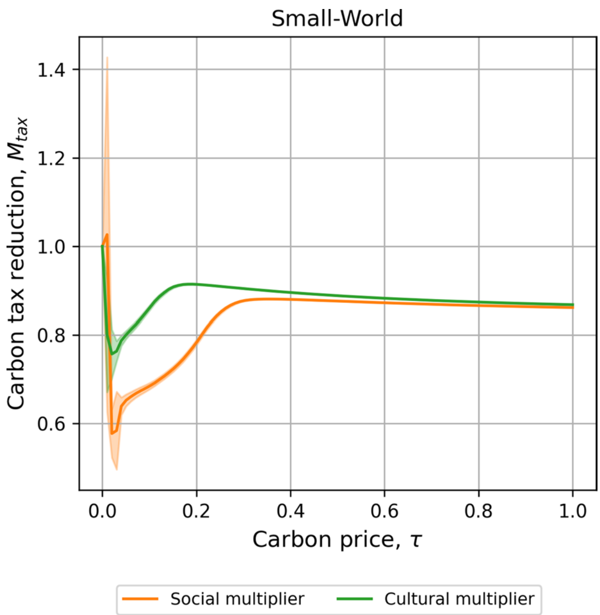


Fig. 4 Carbon price reduction for social multiplier (orange) and cultural multiplier (green). A small-world network is used; results for alternative networks are shown in Appendix Fig. 14. The shaded region indicates 95% confidence interval for 100 stochastic seed runs

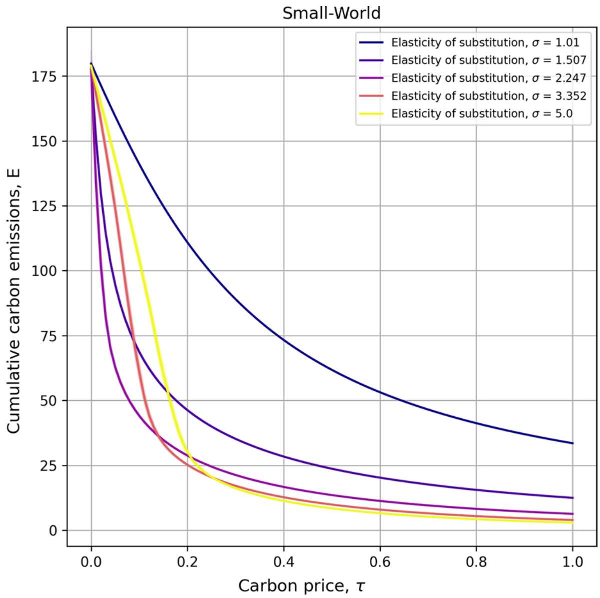
Figure 4 shows that the cultural multiplier has a greater tax reduction effect than the social multiplier. Additionally, due to the repeated nature of the interactions in the model, the mean magnitude of the emissions reduction ($M_{tax} > 0.5$) of both multipliers is much stronger than that identified in Konc et al. (2021) ($M_{tax} = 0.38$). With each time step, a growing share of an individual's current preferences are shaped cumulatively by the behaviour of their neighbours, potentially away from their initial preferences. For high carbon prices, $\tau > 0.5$ the difference between the social and cultural multiplier cases almost vanishes. At these values, the strength of the carbon price signal overwhelms any nuances in how the preference change due to social influence occurs. Even the most resistant of individuals with strong high-carbon preferences choose to pursue low-carbon consumption in all categories, with social imitation accelerating this change in lifestyles. In other words, if high-carbon goods are sufficiently expensive relative to the low-carbon alternative, then the specifics of who individuals choose to imitate no longer matter; the network tips collectively towards low-carbon consumption. In the case of very small carbon prices ($\tau < 0.05$), there is a much greater variance in the tax reduction M_{tax} due to the strong path dependency of the model. Small differences in social interactions can lead to radically different preference outcomes and, consequently, emissions due to the polarizing effect of consumption imitation. As opposed, the presence of a higher carbon price steers the system towards a narrower set of equilibrium states.

3.2 Impact of Key Parameters on the Cultural Multiplier

3.2.1 Impact of Substitutability Between Low- and High-Carbon Goods on the Cultural Multiplier

To better understand how sensitive the cultural multiplier is to different socio-economic conditions, we vary the latter and assess how these influence the effectiveness of the carbon price in reducing carbon emissions. Improvements in low-carbon technologies such as plant-based alternatives, better EV charging facilities or investment in public transport may increase the substitutability between low- and high-carbon goods. Therefore, different levels of low- and high-carbon good substitutability σ can represent degrees of low-carbon technological progress or infrastructure availability. We now consider the strength of the cultural multiplier under these varying scenarios. In Fig. 5 we plot cumulative emissions for the cultural multiplier case (preference spillovers) for different substitutability σ in the SW network (see Appendix Fig. 15 for SBM and SF networks). For high-carbon prices, the greater the substitutability, the greater the decarbonisation. This occurs because individuals receive a much lower penalty in the utility function for concentrating their consumption in one good, allowing them to better exploit the price asymmetry between low- and high-carbon alternatives. However, this same concentration of consumption results in polarised consumption proportions $C_{t,i,m}$. Individuals then imitate these consumption proportions, gradually leading to polarisation in low-carbon preferences. This can inhibit the spread of low-carbon consumption as individuals who have high-carbon preferences are able to express this preference in their consumption. Consequently, high-carbon groups of individuals isolate themselves by avoiding interactions with "greener" neighbours. This effect hinders decarbonisation at low carbon prices, reversing the emissions pattern across substitutability scenarios. In contrast to these dynamics in the extreme case of $\sigma = 1.01$, the emis-

Fig. 5 Impact of substitutability between low- and high-carbon alternatives on cumulative emissions



sions curves detach from that of larger substitutability values. Here, individuals are unable to fully express their preferences in their consumption, and thus, social imitation becomes less representative of true beliefs, resulting in a lower effectiveness of carbon pricing.

To represent the varied constraints that individuals may face in the adoption of low-carbon goods other than preferences, for example high range-anxiety with EV adoption or dietary requirements for vegetarianism, we now consider a model extension of heterogeneous elasticity of substitution. Building on the results of Fig. 5, our analysis now considers a distribution of elasticity values σ_i, instead of a single elasticity of substitution between high- and low-carbon goods, σ. In Appendix Fig. 16, the mean elasticity of substitution is varied while keeping the values distributed in a pseudo-normal fashion, again using a Beta distribution, spanning a range of 1 between the minimum and maximum in the samples. As in Fig. 5, the greater the mean elasticity of substitution, the lower the decarbonisation achieved by low carbon prices and the greater decarbonisation at large carbon prices. Overall, the inclusion of a distribution of substitutability values for individuals has little effect on overall decarbonisation dynamics. However, due to the greater variance in elasticity of substitution values this leads to a wider 95% confidence interval, as indicated by the shaded region.

To further study the relationship between the social and cultural multiplier we compare the two for different levels of input substitutability between low- and high-carbon goods σ, see Fig. 6. Note that in this figure we only consider the small-world network case. For very low substitutability $\sigma = 1.01$, the social and cultural multiplier converge. As previously identified in Fig. 5, this low substitutability causes a breakdown in effective social learning through imitation. This results in less opportunity for behavioural spillovers to be leveraged, hence the small differences in emissions between the social and cultural multiplier. On the other hand, increasing substitutability enhances the cultural multiplier, whereas the effect of the social multiplier shows a comparatively smaller gain. This effect is especially pertinent at low tax values where the gap between the two multipliers is largest. The emissions

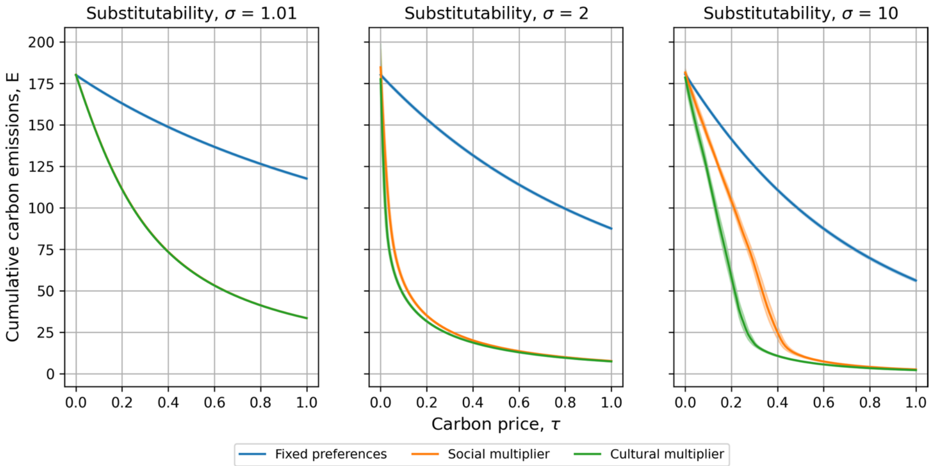


Fig. 6 Diffrences between social and cultural multiplier at diffrent values of input substitutability between low and high-carbon goods

curve for the social multiplier (orange) shifts towards the fixed preferences case (blue) for increasing substitutability (across sub-figures). As highlighted in Fig. 5, a greater σ parameter facilitates the concentration of consumption into either a low or high-carbon good. This polarisation enables the formation of social bubbles in which individuals who prefer high-carbon goods only communicate with like-minded individuals. These effects make preference change more challenging in the social multiplier case, as individuals become less responsive to the consumption habits of others outside their social bubble. Therefore, the absence of a behavioural spillover mechanism in the social multiplier case results in a lock-in of high-carbon consumption for individuals with a preference for high-carbon goods ($A < 0.5$). Consequently, in the social multiplier case at large values of the input substitutability, a larger part of consumption changes occur primarily due to carbon price increases across experiments. However, a much higher substitutability does not significantly increase the gap between the social and cultural multiplier. This can be seen in comparing Fig. 3, $\sigma = 4$, with the $\sigma = 10$ experiments in Fig. 5.

3.2.2 Homophily, Network Structure and Lifestyle Diversity

When comparing the social and cultural multiplier cumulative emissions curves over a range of carbon prices for the SW, SBM and SF networks, we see little variation in results (shown in Fig. 3 and Appendix Fig. 12). This can be explained by the fact that, in these experimental runs, we assume no homophily in the initial environmental identity of individuals within the network. However, ideological polarisation surrounding climate change is growing (Falkenberg et al. 2022). Therefore, a key avenue for study is how this polarisation of preferences within social networks, and the structure of networks themselves, can inhibit decarbonisation of consumption (von Flüe and Vogt 2024). In our model we represent this polarisation by considering initial homophily in environmental identity: The extent to which individuals are surrounded by like-minded neighbours. Across the SW, SBM and SF networks we find that greater homophily in initial preferences between neighbours increases the required effective carbon price to meet the same emissions reduction - see 8 for an in-depth study.

Given the importance of behavioural spillover shown in the cultural versus social multiplier, we now consider how a richer representation of lifestyles can affect decarbonisation by increasing the complexity of consumption decisions. In Appendix Fig. 18, we, therefore, vary the number of consumption categories modelled, M, for three different carbon prices. For the cultural multiplier, at low carbon prices, the addition of more consumption categories leads to lower emissions, relative to the social multiplier case. The greater M, the lower the impact of extreme preferences on the formation of environmental identity I. This results in greater consensus formation and thus a faster collective shift to low-carbon lifestyles. However, at high carbon prices, as in Fig. 3, there is no distinction between the cultural and social multiplier due to the constraining force of the price signal on consumption choices.

3.2.3 Expenditure Inequality and Revenue Recycling

With the current model formulation, inequality plays no role in decarbonisation. This is due to the homothetic nature of the constant elasticity of substitution function used, implying that if preferences are equal then individuals consume goods in the same proportions regardless of their expenditure. To test the role of inequality we therefore consider an adjustment to the NCES model implemented, namely requiring a minimum quantity of high-carbon goods, h_m, such as transport and heating as necessities. This can drive dynamics in which the consumption habits of poorer individuals are largely dictated by needs rather than preferences. We capture this through a CES function with Stone-Geary preferences (Jacobs and van der Ploeg 2019; Sancho 2024)

$$U_{t,i} = \left(\sum_{m=1}^{M} a_m \left(A_{t,i,m} L_{t,i,m}^{\frac{\sigma-1}{\sigma}} + (1 - A_{t,i,m})(H_{t,i,m} - h_m)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma(\nu-1)}{(\sigma-1)\nu}} \right)^{\frac{\nu}{\nu-1}}, \quad (17)$$

with the quantities of high- and low-carbon goods now given by,

$$H_{t,i,m} = \frac{(B_i - \sum_{p=1}^{M} P_{H,p} h_p)\chi_{t,i,m}}{Z_{t,i}} + h_m \quad (18)$$

$$L_{t,i,m} = \frac{(B_i - \sum_{p=1}^{M} P_{H,p} h_p)\Omega_{t,i,m}\chi_{t,i,m}}{Z_{t,i}} \quad (19)$$

These demand equations are identical to those in Eqs. 4 and 5, expect with that the consumed quantity of the high-carbon good now account for this minimum amount required. Additionally, both the low- and high-carbon goods have a lower disposable expenditure to assign based on preferences.

In Fig. 7 the quantity of the high-carbon good required is varied such that a larger share of individuals expenditure B is dedicated to fulfilling this need. Thus, the greater the minimum expenditure share the lower the influence of an individual's preferences on their consumption habits. The social imitation of these consumption habits reinforces this high-carbon

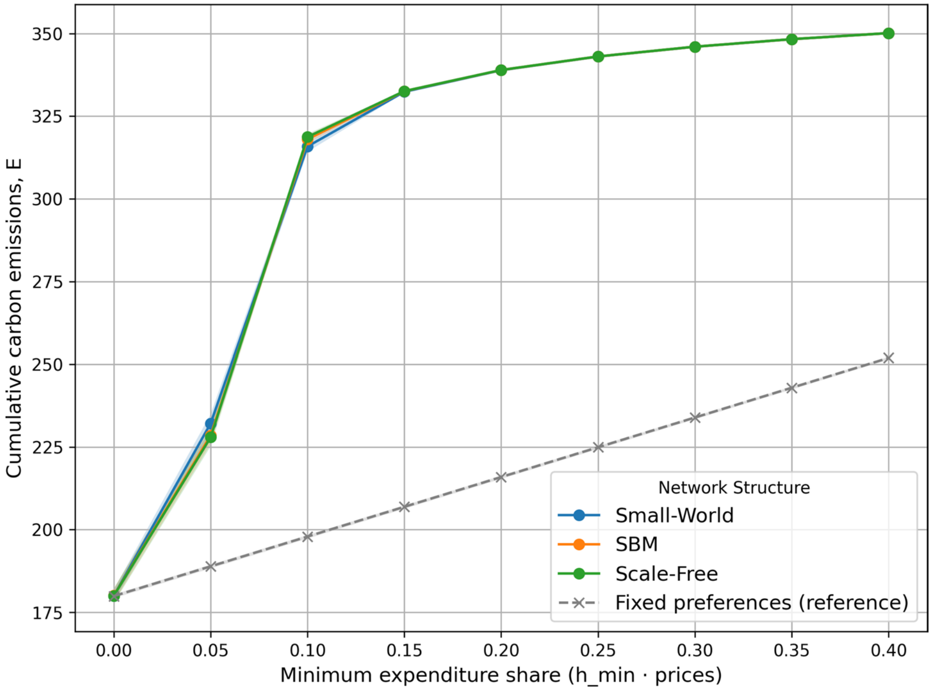


Fig. 7 Cumulative carbon emissions whilst varying the minimum proportion of expenditure dedicated to the high-carbon good. Social imitation leads to high-carbon emission relative to fixed preferences scenario

consumption as individuals cannot distinguish between consumption due to needs and preference. This lock-in due to social imitation can be seen in the concave nature of the curve at high proportion as the population collectively tips towards high-carbon consumption.

A key area of interest when modelling carbon pricing is the potential for "double dividend" wherein the revenue recycling can have additional benefits beyond carbon emission reduction. To study this we consider the role redistribution of carbon price revenues at different levels of inequality and carbon prices in Fig. 8D. Here the quantity of high-carbon goods required is kept constant and then the distribution of remaining expenditure is adjusted to generate different Gini coefficient values. We measure the cumulative carbon emission at different carbon prices with a progressive lump sum redistribution (dashed line) and without redistribution (dotted line) of revenues. Note that in the case of a zero carbon price there is no redistribution of revenues hence emissions are not affected. As a reference we also include the case where individuals all have the same expenditure. To be able to make comparisons between runs we maintain the total expenditure across all individuals, $\sum_{i=1}^{I} B_i = 1$, constant.

Lower inequality leads to lower emissions as individuals can better express their preferences given that a lower proportion of their consumption is determined by needs. Inequality in expenditures has the largest effect at lower carbon prices where social learning plays a more important role. This effect can be seen in the lower slope of those lines with higher

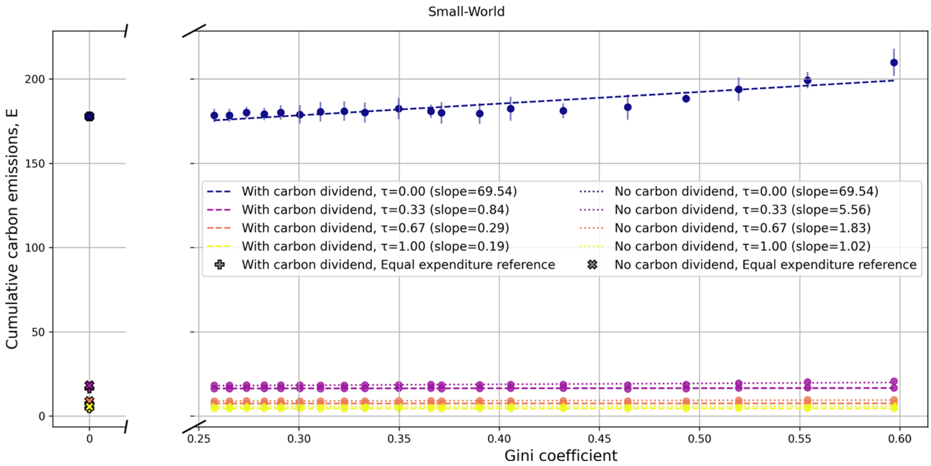


Fig. 8 The impact of varying inequality in individuals' expenditures on cumulative carbon emissions with a minimum consumption quantity of high-carbon goods. Dashed lines show cases with lump-sum redistribution of carbon pricing revenues and solid those without

carbon price. In the case of no redistribution of revenues the effect of inequality is stronger, as this acts as a mechanism to moderate inequality. A key takeaway from this simplified model is that higher income inequality in the face of minimum high-carbon consumption can increase overall emissions, while progressive redistribution of carbon price revenues can mitigate this effect. However, at high carbon prices the role played by both inequality and redistribution is much weaker as consumption is more strongly dictated by price differences.

3.2.4 Sensitivity to Other Model Parameters

The model is designed to explore how social dynamics, through long-term cultural change, influence decarbonisation outcomes under a wide range of plausible behavioural and policy conditions. Instead of pursuing the empirical calibration of highly abstract parameters such as confirmation bias or social susceptibility we instead test a wide range of values with sensitivity analysis. For example, in the case of substitutability we ensure that the range considered in Figs. 5 and 6 are guided by those found in related literature (Papageorgiou et al. 2017). On the other hand, for key parameters such as the Beta distribution for preference values we choose a default of $(a = 2, b = 2)$ to generate a distribution where most individuals are indifferent between low- or high-carbon consumption but still one or more small groups of individuals with extreme low/high-carbon preferences emerge. Moreover, the ranges considered for the Beta parameters allows for the study of strong polarisation amongst the population.

To evaluate how the relative importance of model parameters and bolster the robustness of our previous results we conduct Sobol sensitivity analysis (Sobol 2001). This is implemented with the SALib python library (Herman and Usher 2017) for the cases of a SW, SBM and SF networks. Parameter ranges tested and fixed parameters are shown Table 1. For each of the 11 variables, we take 128 values with a mean of 20 stochastic variations for a total of 184,320 experiments. The total order sensitivity of final cumulative emissions is shown in Fig. 9, with the first order index depicted in Appendix Fig. 17. Cumulative emis-

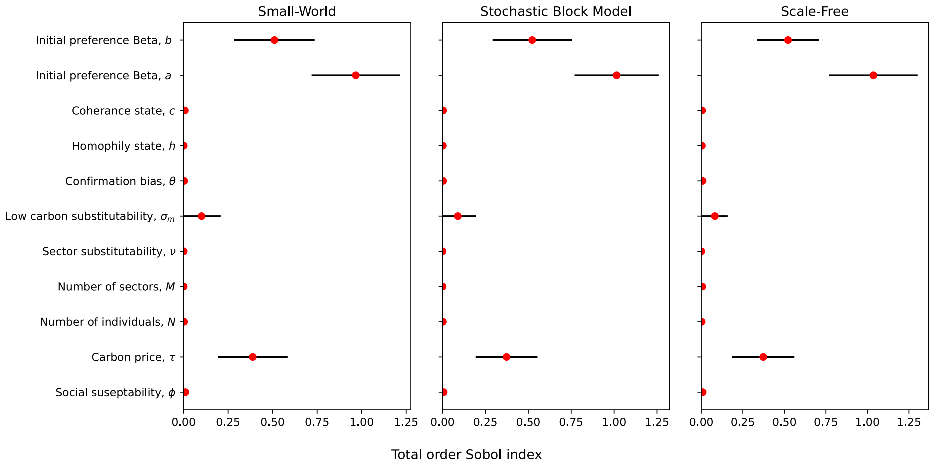


Fig. 9 Total Sobol sensitivity analysis for 128 parameter values for a total of 184,320 experiments

sions are primarily determined by the initial preferences Beta a parameter. A greater value relative to the Beta b parameter results in an initial preference distribution which results in more low-carbon consumption. The carbon price also strongly contributes to the cumulative emissions variance as these induce low-carbon consumption through price inequalities. Additionally, in the Total Sobol index, we see that the low-carbon substitutability is significant. This is due to greater non-linearity in consumption choices with greater substitutability as described in Appendix B. Lastly, in Fig. 9, we do not see variation across the different network structures in the importance of parameters.

4 Conclusions

This study has highlighted the joint effect of carbon pricing and cultural change in fostering low-carbon consumption. We extended the literature on carbon pricing with endogenous preference change through an analysis of the role of longer-term cultural change. To this end, we extended the concept of a social multiplier of environmental policy, increased emissions reduction from a carbon price due to social imitation (Konc et al. 2021) to the case of repeated social imitation in multiple consumption categories and define this as the cultural multiplier. In our novel agent-based model, individuals make consumption choices between low- and high-carbon goods across multiple categories. These individuals have heterogeneous and dynamic preferences for low-carbon goods, which evolve through repeated and weighted social interactions. The model assesses how cultural change may enhance or hinder the impact of carbon pricing. Additionally, we identify which socio-economic characteristics influence the magnitude of the cultural multiplier.

Our results show that incorporating change in endogenous preferences through the cultural multiplier significantly enhances the effectiveness of carbon pricing relative to a fixed preference counter case. Additionally, the cultural multiplier is found to be stronger than the social multiplier, particularly when the carbon price is low. This is due to the consensus-forming effect of the cultural multiplier, resulting in greater difficulty in individuals sustaining fringe consumption behaviours. However, this difference disappears for higher carbon prices where nuances between different social imitation schemes are dominated by the magnitude of the price signal.

Additionally, we show that with increasing substitutability of low- and high-carbon goods, the cultural multiplier strengthens, whilst the social multiplier weakens. In the absence of behavioural spillovers across different consumption categories, high substitutability amplifies polarization in consumption, reinforcing entrenched high-carbon preferences. Therefore, individuals with high-carbon preferences become less responsive to social influence due to their like-minded social bubble. Our findings suggest that greater similarity in environmental identity among peers connected via social networks increases the effective carbon price required to reach emission reduction targets. Additionally, a richer or more diverse representation of lifestyles, achieved by increasing the number of consumption categories, enhances the strength of the cultural multiplier at low carbon price levels. If a minimum quantity of high-carbon consumption is assumed, greater income inequality leads to higher emissions. This effect can be alleviated through the redistribution of revenue raised from carbon pricing. Our global sensitivity analysis confirms the robustness of our results over wide parameter ranges.

In future research, the model could be extended to include rebound between consumption categories due to context-dependent preferences. This might include the possibility of low-carbon consumption in one consumption category leading to increased emissions in other areas due to moral licensing effects (Gholamzadehmir et al. 2019). Whilst our results considered the role of homophily in environmental identity across different network structures, future research could examine other parallel sources of homophily, such as income, education, or geographic location in a multiplex network. Additionally, one could extend the model with a utility function possessing non-homothetic preferences to generate non-linear Engel curves in a more flexible fashion than the shifted NCES function considered, as this does not fully capture the heterogeneous behaviour of agents in different expenditure deciles. This would better capture the ease with which more wealthy individuals can switch to low-carbon alternatives (Oswald et al. 2020, 2023).

By fostering stronger pro-environmental identities, policymakers can leverage the cultural multiplier to reduce an effective carbon price, contributing to greater policy support. This may be achieved through the introduction of policies complementary to a carbon price. This may take the form of extending current visions of low-carbon lifestyles to be more systemic or rich in detail, including consumption in a high number of categories. For example information provision policies such as eco-labelling may correct misinformation on the true carbon impact of less socially salient consumption categories. Alternatively, increasing the substitutability of low- and high-carbon alternatives both through technological improvements (e.g. widespread charging infrastructure and higher battery capacity to alleviate EV range anxiety (Pevec et al. 2020)) and nudge techniques to increase the social acceptability of low-carbon alternatives (e.g. plant-based meat substitutes (Edenbrandt and Lagerkvist 2021; Coucke et al. 2022)). Additionally, policymakers should be mindful of network structures in which social imitation occurs when evaluating the expected effect of carbon pricing, as high similarity in pro-environmental identities amongst communities can act as roadblocks to decarbonisation.

Appendix A Analytical Results for the NCES Utility Function

In the M-dimensional case we have low and high-carbon goods for each consumption category, L_m and H_m, with an associated preference between the two A_m, and substitutability between goods σ. Between categories there is a further preference for consumption a_m where $\sum_{m=1}^{M} a_m = 1$ and substitutability across categories ν.

$$\max_{L_1,...,L_M,H_1,...,H_M} U(L_1,...,L_M,H_1,...,H_M,a_1,...,a_M,A_1,...,A_M,\sigma_1,...,\sigma,\nu) \tag{20}$$

the utility function to maximise is given by,

$$U = \left(\sum_{m=1}^{M} a_m U_m^{\omega}\right)^{\frac{1}{\omega}}, \tag{21}$$

where the pseudo-utility U_m is given by

$$U_m(L_m, H_m, A_m, \sigma) = \left(A_m L_m^{\psi} + (1 - A_m) H_m^{\psi}\right)^{\frac{1}{\psi}} \tag{22}$$

to simplify notation of the substitutabilities between low- and high-carbon goods for each category σ, and the between categories ν, we use $\psi = \frac{\sigma-1}{\sigma}$ and $\omega = \frac{\nu-1}{\nu}$. This is subject to the budget constraint,

$$B = \sum_{m=1}^{M} L_m P_{L,m} + H_m P_{H,m} \tag{23}$$

To derive the demand functions for the utility function we require the Lagrangian for the system, given by

$$\mathcal{L} = \left(\sum_{m=1}^{M} a_m U_m^{\omega}\right)^{\frac{1}{\omega}} - \lambda \left(\sum_{m=1}^{M} L_m P_{L,m} + H_m P_{H,m} - B\right), \tag{24}$$

This produces general first-order conditions of low and high-carbon goods

$$\frac{\partial \mathcal{L}}{\partial L_m} = a_m \left(\sum_{m=1}^{M} a_m U_m^{\omega}\right)^{\frac{1}{\omega}-1} U_m^{\omega-1} \frac{\partial U_m}{\partial L_m} - \lambda P_{L,m} = 0 \tag{25}$$

$$\frac{\partial \mathcal{L}}{\partial H_m} = a_m \left(\sum_{m=1}^{M} a_m U_m^{\omega}\right)^{\frac{1}{\omega}-1} U_m^{\omega-1} \frac{\partial U_m}{\partial H_m} - \lambda P_{H,m} = 0 \tag{26}$$

In order to find L_m in terms of H_m we use the first order conditions with respect to the low and high-carbon good of the same category (same top level CES nest), re-arranging for λ and equating the two

$$\frac{1}{P_{L,m}}\frac{\partial U_m}{\partial L_m} = \frac{1}{P_{H,m}}\frac{\partial U_m}{\partial H_m} \tag{27}$$

$$\frac{\left(\frac{\partial U_m}{\partial H_m}\right)}{\left(\frac{\partial U_m}{\partial L_m}\right)} = \frac{P_{H,m}}{P_{L,m}} \tag{28}$$

We now produce the derivative of the pseudo-utilities U_m with respect to H_m and L_m

$$\frac{\partial U_m}{\partial L_m} = \left(A_m L_m^{\psi} + (1-A_m)H_m^{\psi}\right)^{\frac{1}{\psi}-1} A_m L_m^{\psi-1} \tag{29}$$

$$\frac{\partial U_m}{\partial H_m} = \left(A_m L_m^{\psi} + (1-A_m)(H_m - h_m)^{\psi}\right)^{\frac{1}{\psi}-1} (1-A_m)H_m^{\psi-1} \tag{30}$$

Note that Eqs. 29 and 30 do not contain any between category terms. Substituting in the partial differentials or U_m with respect to H_m and L_m into our equated first order conditions in Eq. 28 we produce a relationship between the quantity of low-carbon L_m and high-carbon good H_m

$$\frac{(1-A_m)H_m^{\psi-1}\left(A_m L_m^{\psi} + (1-A_m)H_m^{\psi}\right)^{\frac{1}{\psi}-1}}{A_m L_m^{\psi-1}\left(A_m L_m^{\psi} + (1-A_m)H_m^{\psi}\right)^{\frac{1}{\psi}-1}} = \frac{P_{H,m}}{P_{L,m}} \tag{31}$$

$$\frac{H_m^{\psi-1}}{L_m^{\psi-1}} = \frac{P_{H,m}A_m}{P_{L,m}(1-A_m)} \tag{32}$$

$$\frac{L_m}{H_m} = \left(\frac{P_{H,m}A_m}{P_{L,m}(1-A_m)}\right)^{\frac{-1}{\psi-1}}, \tag{33}$$

in terms of substituabilities between low- and high-carbon goods, using the property $\sigma = \frac{-1}{\psi-1}$, the general ratio between the low and high-carbon good for the m^{th} category is defined as

$$\Omega_m = \frac{L_m}{H_m} = \left(\frac{P_{H,m}A_m}{P_{L,m}(1-A_m)}\right)^{\sigma}. \tag{34}$$

Next, we compare low-carbon goods from different categories to derive the ratio between high-carbon goods for two different categories (H_p and H_q). Re-arranging the first-order conditions of two low-carbon goods and equating them, where p, q are dummy variables for the m'th category,

$$\frac{1}{P_{L,p}}\frac{\partial U}{\partial L_p}=\frac{1}{P_{L,q}}\frac{\partial U}{\partial L_q} \tag{35}$$

$$\frac{1}{P_{L,p}}a_p\left(\sum_{m=1}^{M}a_mU_m^{\omega}\right)^{\frac{1}{\omega}-1}U_p^{\omega-1}\frac{\partial U_p}{\partial L_p}=\frac{1}{P_{L,q}}a_q\left(\sum_{m=1}^{M}a_mU_m^{\omega}\right)^{\frac{1}{\omega}-1}U_q^{\omega-1}\frac{\partial U_q}{\partial L_q} \tag{36}$$

$$\frac{1}{P_{L,p}}a_pU_p^{\omega-1}\frac{\partial U_p}{\partial L_p}=\frac{1}{P_{L,q}}a_qU_q^{\omega-1}\frac{\partial U_q}{\partial L_q} \tag{37}$$

Substituting our expression of the partial differential from Eq. 29 and the pseudo-utility U_m from Eq. 22,

$$\frac{1}{P_{L,p}}a_p\left(A_pL_p^{\psi_p}+(1-A_p)H_p^{\psi_p}\right)^{\frac{\omega-1}{\psi_p}}\frac{\partial U_p}{\partial L_p}=\frac{1}{P_{L,q}}a_q\left(A_qL_q^{\psi_q}+(1-A_q)H_q^{\psi_q}\right)^{\frac{\omega-1}{\psi_q}}\frac{\partial U_q}{\partial L_q} \tag{38}$$

$$\begin{aligned}&\frac{1}{P_{L,p}}a_p\left(A_pL_p^{\psi_p}+(1-A_p)H_p^{\psi_p}\right)^{\frac{\omega-1}{\psi_p}}\left(A_pL_p^{\psi_p}+(1-A_p)H_p^{\psi_p}\right)^{\frac{1}{\psi_p}-1}A_pL_p^{\psi_p-1}\\&\quad=\frac{1}{P_{L,q}}a_q\left(A_qL_q^{\psi_q}+(1-A_q)H_q^{\psi_q}\right)^{\frac{\omega-1}{\psi_q}}\left(A_qL_q^{\psi_q}+(1-A_q)H_q^{\psi_q}\right)^{\frac{1}{\psi_q}-1}A_qL_q^{\psi_q-1}\end{aligned} \tag{39}$$

$$\begin{aligned}&\frac{1}{P_{L,p}}a_pA_pL_p^{\psi_p-1}\left(A_pL_p^{\psi_p}+(1-A_p)H_p^{\psi_p}\right)^{\frac{\omega-1}{\psi_p}+\frac{1}{\psi_p}-1}\\&\qquad=\frac{1}{P_{L,q}}a_qA_qL_q^{\psi_q-1}\left(A_qL_q^{\psi_q}+(1-A_q)H_q^{\psi_q}\right)^{\frac{\omega-1}{\psi_q}+\frac{1}{\psi_q}-1}\end{aligned} \tag{40}$$

$$\frac{1}{P_{L,p}}a_pA_pL_p^{\psi_p-1}\left(A_pL_p^{\psi_p}+(1-A_p)H_p^{\psi_p}\right)^{\frac{\omega}{\psi_p}-1}=\frac{1}{P_{L,q}}a_qA_qL_q^{\psi_q-1}\left(A_qL_q^{\psi_q}+(1-A_q)H_q^{\psi_q}\right)^{\frac{\omega}{\psi_q}-1} \tag{41}$$

Substituting in the general ratio of low to high-carbon goods within a branch, $L_m=H_m\Omega_m$,

$$\begin{aligned}&\frac{1}{P_{L,p}}a_pA_p\Omega_p^{\psi_p-1}H_p^{\psi_p-1}\left(A_p\Omega_p^{\psi_p}H_p^{\psi_p}+(1-A_p)H_p^{\psi_p}\right)^{\frac{\omega}{\psi_p}-1}\\&=\frac{1}{P_{L,q}}a_qA_q\Omega_q^{\psi_q-1}H_q^{\psi_q-1}\left(A_q\Omega_q^{\psi_q}H_q^{\psi_q}+(1-A_q)H_q^{\psi_q}\right)^{\frac{\omega}{\psi_q}-1}\end{aligned} \tag{42}$$

$$\frac{1}{P_{L,p}}a_pA_p\Omega_p^{\psi_p-1}H_p^{\omega-1}\left(A_p\Omega_p^{\psi_p}+1-A_p\right)^{\frac{\omega}{\psi_p}-1}=\frac{1}{P_{L,q}}a_qA_q\Omega_q^{\psi_q-1}H_q^{\omega-1}\left(A_q\Omega_q^{\psi_q}+1-A_q\right)^{\frac{\omega}{\psi_q}-1} \tag{43}$$

Now gathering high-carbon consumption terms,

$$\frac{H_p^{\omega-1}}{H_q^{\omega-1}}=\frac{a_qA_q\Omega_q^{\psi_q-1}\left(A_q\Omega_q^{\psi_q}+1-A_q\right)^{\frac{\omega}{\psi_q}-1}}{P_{L,q}}\frac{P_{L,p}}{a_pA_p\Omega_p^{\psi_p-1}\left(A_p\Omega_p^{\psi_p}+1-A_p\right)^{\frac{\omega}{\psi_p}-1}} \tag{44}$$

$$\frac{H_p}{H_q}=\left(\frac{a_qA_q\Omega_q^{\psi_q-1}\left(A_q\Omega_q^{\psi_q}+1-A_q\right)^{\frac{\omega}{\psi_q}-1}}{P_{L,q}}\frac{P_{L,p}}{a_pA_p\Omega_p^{\psi_p-1}\left(A_p\Omega_p^{\psi_p}+1-A_p\right)^{\frac{\omega}{\psi_p}-1}}\right)^{\frac{1}{\omega-1}} \tag{45}$$

In terms of category substitutabilities the ratio between the high-carbon quantities from different categories is given by, where we substitute in $\psi=\frac{\sigma-1}{\sigma}$ and $\omega=\frac{\nu-1}{\nu}$,

$$\frac{H_p}{H_q}=\left(\frac{P_{L,q}\Omega_q^{\frac{1}{\sigma_q}}}{a_qA_q\left(A_q\Omega_q^{\frac{\sigma_q-1}{\sigma_q}}+1-A_q\right)^{\frac{\nu-\sigma_q}{\nu(\sigma_q-1)}}}\frac{a_pA_p\left(A_p\Omega_p^{\psi_p}+1-A_p\right)^{\frac{\nu-\sigma_p}{\nu(\sigma_p-1)}}}{P_{L,p}\Omega_p^{\frac{\sigma_p-1}{\sigma_p}}}\right)^{\nu} \tag{46}$$

To simplify notation of the quantities we introduce an interaction term χ_m

$$\chi_m=\left(\frac{a_mA_m}{P_{L,m}\Omega_m^{\frac{1}{\sigma}}}\right)^{\nu}\left(A_m\Omega_m^{\frac{\sigma-1}{\sigma}}+1-A_m\right)^{\frac{\nu-\sigma}{(\sigma-1)}} \tag{47}$$

such that the quantity of dummy category p may be expressed in terms of the quantity of dummy category q

$$H_p=\left(\frac{\chi_p}{\chi_q}\right)H_q \tag{48}$$

Lastly to derive demand functions for the low- and high-carbon goods in terms of preferences, prices and substitutabilities we consider the budget constraint and use previous definition of low to high-carbon goods from Eq. 34

$$B=\sum_{p=1}^{M}L_pP_{L,p}+H_pP_{H,p} \tag{49}$$

$$=\sum_{p=1}^{M}(H_p\Omega_pP_{L,p}+H_pP_{H,p}) \tag{50}$$

$$=\sum_{p=1}^{M}H_p(\Omega_pP_{L,p}+P_{H,p}) \tag{51}$$

Note that again p is a dummy variable representing any category. Now substituting in the interaction term χ_m between different categories defined in Eq. 47 we express the high-carbon quantity of a given dummy category q in terms of the preferences, prices and substitutabilities,

$$B = \sum_{p=1}^{M} \left(\frac{\chi_p}{\chi_q} H_q \right) (\Omega_p P_{L,p} + P_{H,p}) \tag{52}$$

$$= \sum_{p=1}^{M} \frac{\chi_p}{\chi_q} (H_q (\Omega_p P_{L,p} + P_{H,p}) \tag{53}$$

$$= \frac{H_q}{\chi_q} \sum_{p=1}^{M} \chi_p (\Omega_p P_{L,p} + P_{H,p}) \tag{54}$$

$$H_q = \frac{\chi_q B}{\sum_{p=1}^{M} \chi_p (\Omega_p P_{L,p} + P_{H,p})} \tag{55}$$

Thus the quantity of the m^{th} good is given by,

$$H_m = \frac{B \chi_m}{Z} \tag{56}$$

$$L_m = \frac{B \Omega_m \chi_m}{Z} \tag{57}$$

where to simplify notation Z is defined as,

$$Z = \sum_{m=1}^{M} \chi_m (\Omega_m P_{L,m} + P_{H,m}) \tag{58}$$

this serves as a normalization term across categories.

Appendix B Social Imitation of Consumption Behaviour

The existence of a social multiplier relies on two key features regarding the model of social imitation; firstly, that the preferences of individuals for low-carbon goods are not observable and secondly that the utility function is not common knowledge. It is important to note that in the case that either of these assumptions does not hold the social multiplier effect vanishes, as the carbon price no longer has a channel through which to affect preferences. However, if we assume that some portion of social information is, in fact, a direct observation of preferences then we still find a non-linearity in decarbonisation if that signal is not entirely preference-based information.

To understand how the quantities of low- and high-carbon goods consumed affect the social imitation process, we require an understanding of how changes in preferences result in changes to low-carbon consumption ratio $C_{t,i,m}$ as a function of prices and substitutability.

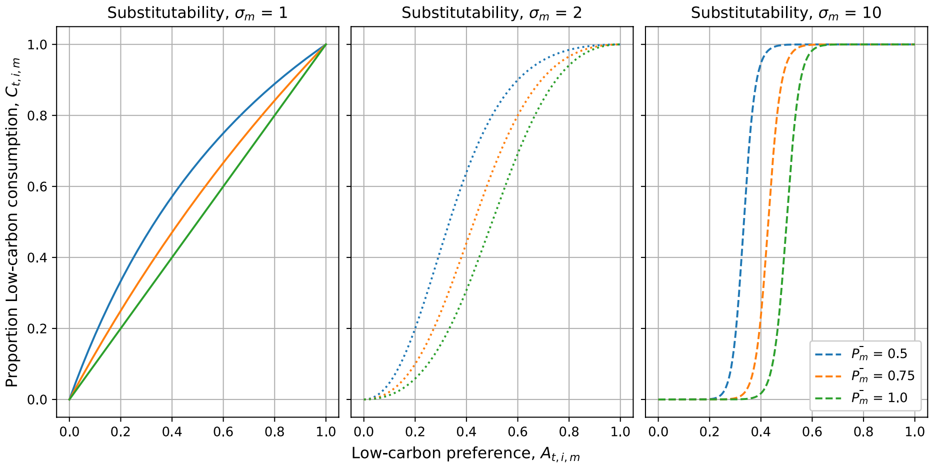


Fig. 10 The proportion of total consumption assigned to low-carbon good within a category $C_{t,i,m}$ as a function of the preference for that low-carbon good $A_{t,i,m}$ and price ratio between low- and high-carbon goods $\bar{P}_m$

$$C_{t,i,m} = \frac{L_{t,i,m}}{L_{t,j,m} + H_{t,i,m}} \tag{59}$$

$$= \frac{H_{t,i,m}\Omega_{t,i,m}}{H_{t,i,m}\Omega_{t,i,m} + H_{t,i,m}} \tag{60}$$

$$= \frac{\Omega_{t,i,m}}{\Omega_{t,i,m} + 1} \tag{61}$$

Now substituting in the ratio of low to high-carbon consumption $\Omega_{t,i,m}$

$$C_{t,i,m} = \frac{\left(\frac{P_{H,m}A_{t,i,m}}{P_{L,m}(1-A_{t,i,m})}\right)^{\sigma}}{\left(\frac{P_{H,m}A_{t,i,m}}{P_{L,m}(1-A_{t,i,m})}\right)^{\sigma} + 1} \tag{62}$$

To simplify notation the ratio of prices between low- and high-carbon goods $\bar{P}_m$ is defined as

$$\bar{P}_m = \frac{P_{L,m}}{P_{H,m}} \tag{63}$$

We substitute in the price ratio to obtain a simplified low-carbon consumption proportion

$$C_{t,i,m} = \frac{\left(\frac{A_{t,i,m}}{\bar{P}_m(1-A_{t,i,m})}\right)^{\sigma}}{\left(\frac{A_{t,i,m}}{\bar{P}_m(1-A_{t,i,m})}\right)^{\sigma} + 1} \tag{64}$$

$$= \frac{A^{\sigma}_{t,i,m}}{A^{\sigma}_{t,i,m} + \left(\bar{P}_m(1 - A_{t,i,m})\right)^{\sigma}} \tag{65}$$

The smaller the value of the price ratio $\bar{P}_m$ the smaller the value of the low-carbon preference $A_{t,i,m}$ required to induce a complete switch to low-carbon good consumption in that category. Figure 10 shows the dependence of $C_{t,i,m}$ on $A_{t,i,m}$. Small differences in preferences for goods can lead to large changes in consumption proportions due to the non-linear impact of substitutability between the goods and price differences.

Additionally, under the conditions $\sigma \to 1$ and prices between low- and high-carbon goods equal $\bar{P}_m = 1$ then

$$C_{t,i,m} = A_{t,i,m} \tag{66}$$

Therefore, under these conditions the preferences dynamics collapses to those studied in Torren-Peraire et al. (2024). On the other hand, when goods are perfect substitutes $\sigma \to \infty$ then $C_{t,i,m}$ tends to a step function in terms of $A_{t,i,m}$, where the location of the step in preference space is given by

$$A_{step,m} = \frac{\bar{P}_m - 1}{\bar{P}_m}. \tag{67}$$

Appendix C Additional Simulation Results

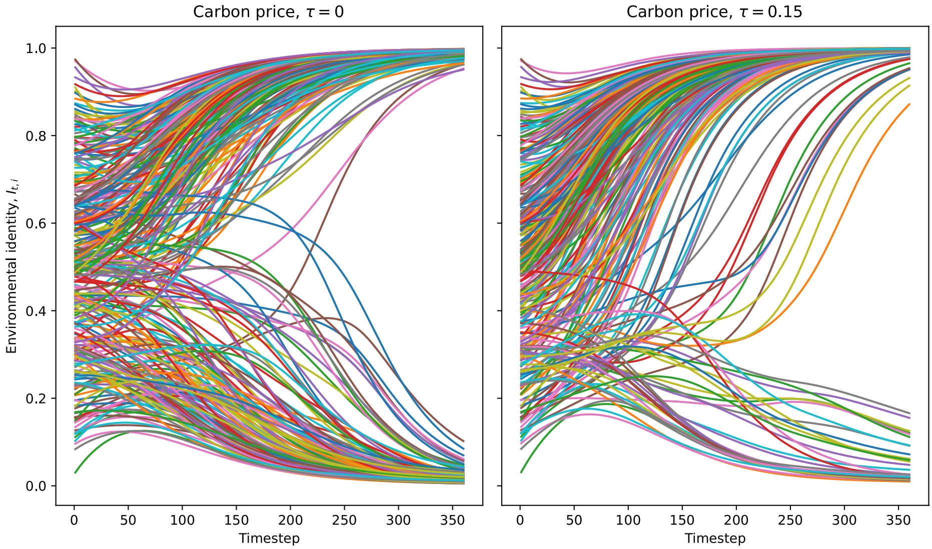


Fig. 11 Environmental identity over time for two carbon prices for the small-world network

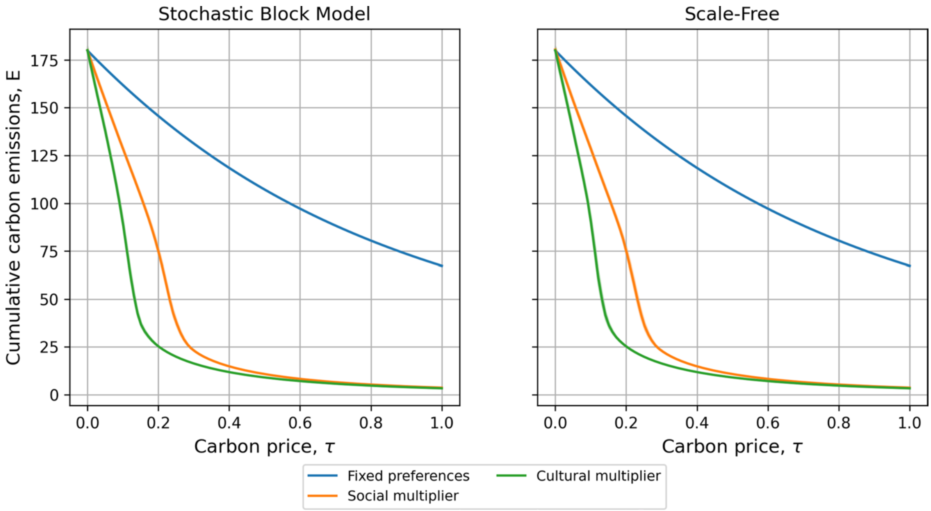


Fig. 12 Cumulative emissions for the case of fixed preferences (blue), cultural multiplier (green) and social multiplier (orange) using a stochastic block model and scale free network. Shading around curves indicates 95% confidence interval (small due to high number of simulation runs)

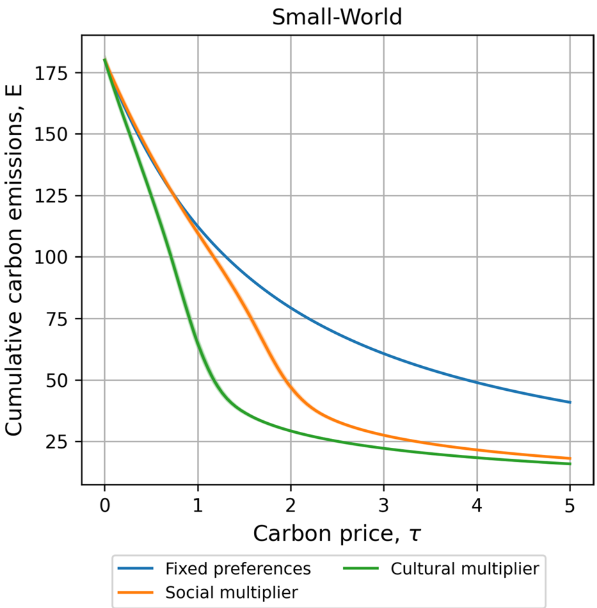


Fig. 13 Cumulative emissions for the case of linearly increasing carbon price, horizontal axis indicates the carbon price at end of 360 periods, in a small-world network

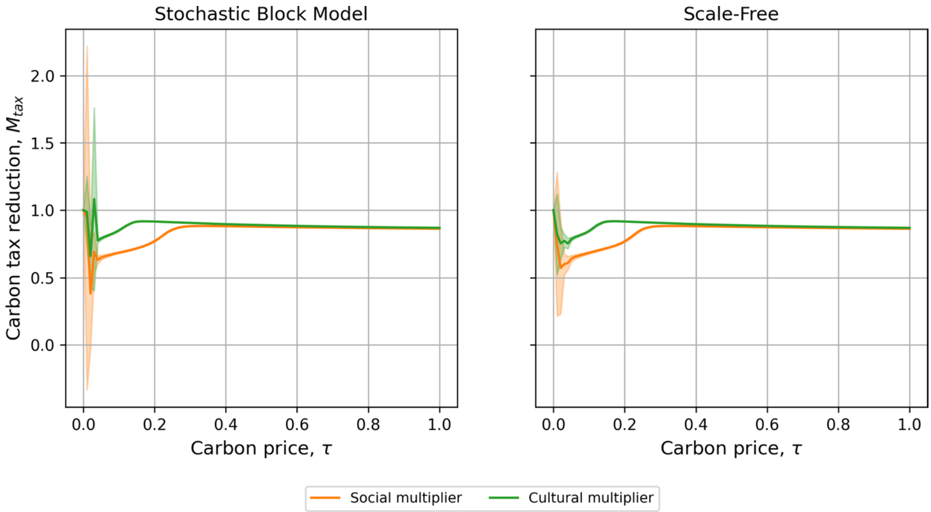


Fig. 14 Carbon price reduction relative to fixed preferences for cultural multiplier (green) and social multiplier (orange) using a stochastic-block model and scale-free network. Shaded region indicates 95% confidence interval for 100 stochastic runs

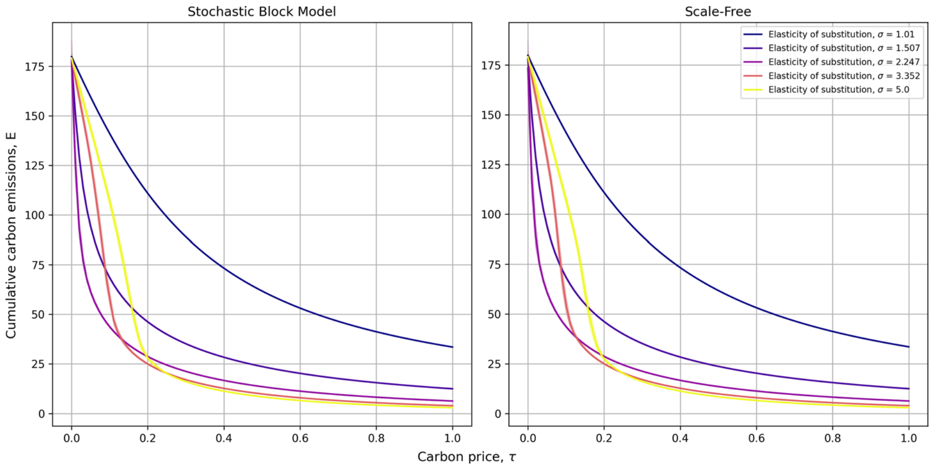


Fig. 15 Varying substitutability between the low- and high-carbon good alternatives

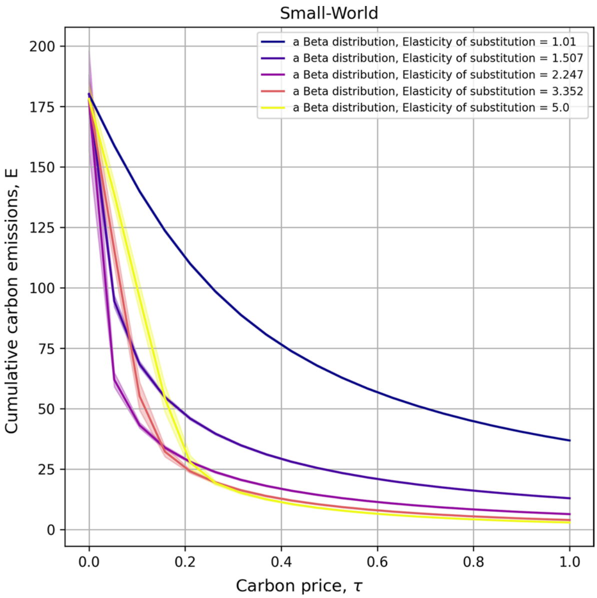


Fig. 16 Cumulative emissions for diversity amongst individuals of elasticity-of-substitution values between low- and high-carbon goods. Based on a Beta distribution with shape parameters (2,2) and bounded with range 1 between min and max values

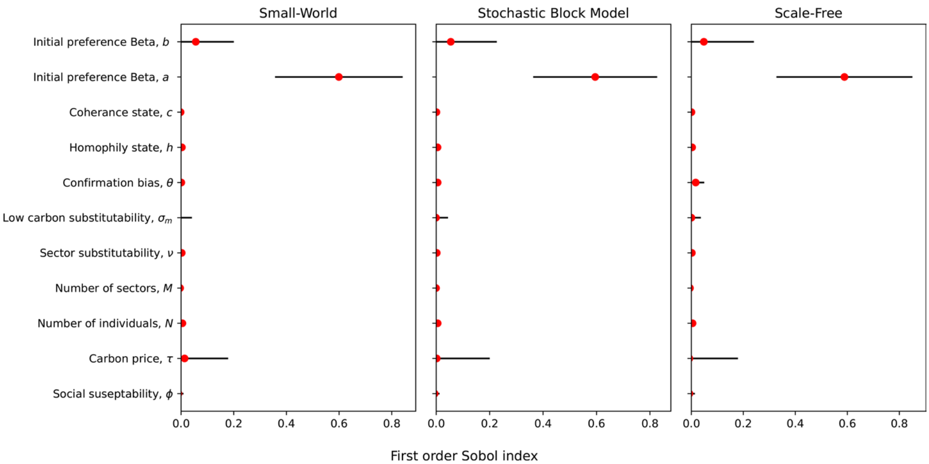


Fig. 17 First order sobol sensitivity analysis for 128 parameter values for a total of 184,320 experiments

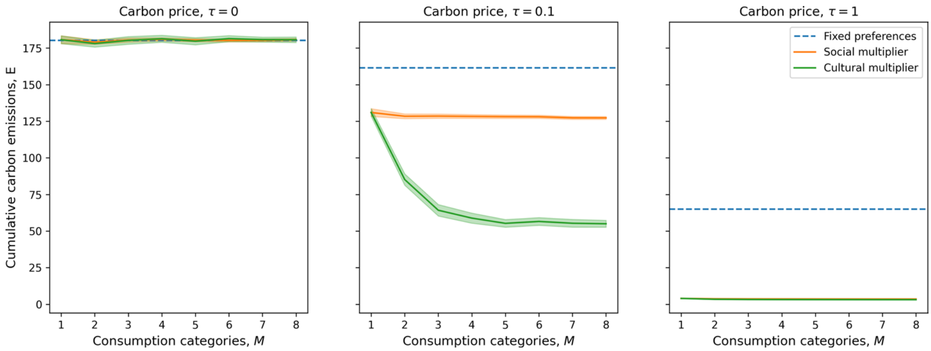


Fig. 18 Cumulative emissions for increasing number of consumption categories at different carbon prices

Network Structure and Homophily in Initial Environmental Identity

To investigate the role of initial homophily (similarity in environmental identity) in shaping decarbonisation dynamics, we use the SW network and SBM. Specifically, we examine whether initial homophily creates barriers or promotes social tipping points towards the adoption of low-carbon alternatives. On the other hand, for the SF network, the large asymmetries in a number of social connections mean that similarities in the initial environmental identity of central agents are of key interest. We label this concentration of similar environmental identities in high-degree nodes as a low- or high-carbon hegemony. Note that this section builds on the social learning module whereby individuals socially imitate in a weighted fashion based on similarity in identity (cultural multiplier). Therefore, we consider how homophily in environmental identity change the effectiveness of a carbon price.

The results in Fig. 19 show that the introduction of homophily reduces the strength of the cultural multiplier both in the SW and SBM networks. Greater initial homophily in environmental identity sustains high-carbon consumption practices (relative to the no or low homophily counter-case) of individuals as they closely imitate each other. For the SBM, greater homophily means that low carbon prices are unable to induce a major change in consumption behaviours of all individuals. However, when a critical carbon price is reached, the system tips towards low-carbon consumption.

This tipping behaviour is a result of the block structure of the network, which allows for a mixed distribution of preferences both between and within block communities. One community can exhibit high-carbon consumption while the other adopts low-carbon behaviours, or each community can have a mix of both high- and low-carbon consumption. Due to this effect, the cultural multiplier is negative for low tax values as greater decarbonisation would be achieved with fixed preferences (dashed black line). In contrast, for the SW network, we see a more gradual decline in emissions due to a more homogenous distribution of the node degree in the network, meaning no single individual or small community can tip the system towards low-carbon consumption. This is also seen in the lower magnitude of price elasticities for the SW network in Appendix Fig. 21, relative to the SBM.

In some social contexts, such as online social networks, peer influence can be highly asymmetric. To capture this, we introduce the concept of hegemony, where a high-carbon hegemony reflects a concentration of high-carbon environmental identities amongst the most connected individuals. Figure 20 shows how, in the case of low-carbon hegemony, even without a carbon price, emissions are significantly reduced relative to the no-homophily case. This occurs because centrally placed individuals exert strong influence over many neighbours with preferences for high-carbon consumption while selectively imitating those with similar environmental identities, thereby minimising exposure to opposing behaviours. Under high-carbon hegemony, the cultural multiplier is negative for low carbon prices, impeding decarbonisation efforts, but may become positive for a sufficiently high carbon price. In the case of high-carbon hegemony, the social network shifts towards low-carbon consumption from the periphery to the highly connected centre. Due to this the SF network has a greater price elasticity than the SW network but lower than the SBM, see Appendix Fig. 21.

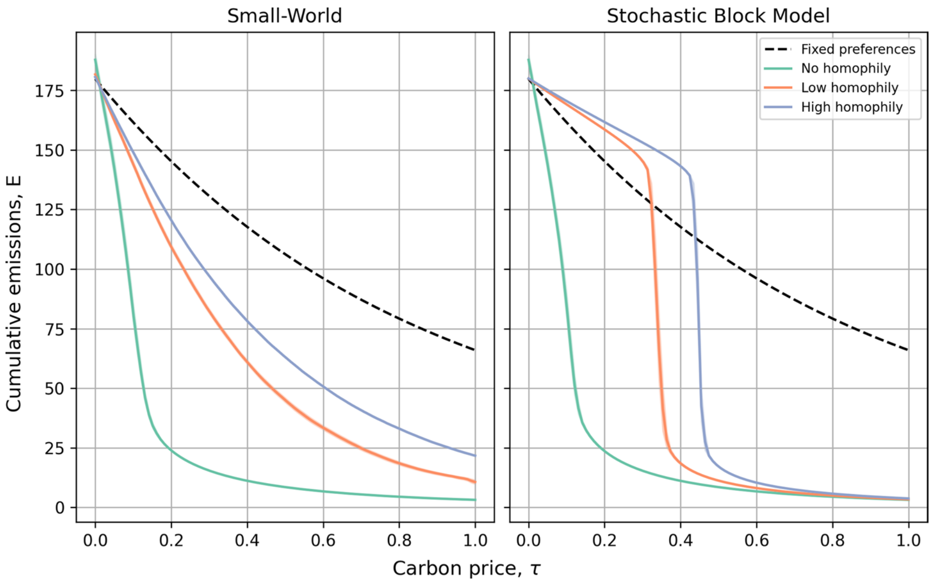


Fig. 19 Emissions reduction due to carbon pricing for different degrees of initial homophily in environmental identity, for a total of 18,000 experiments. The dashed line is the mean emissions of 100 stochastic runs for the case of fixed preferences

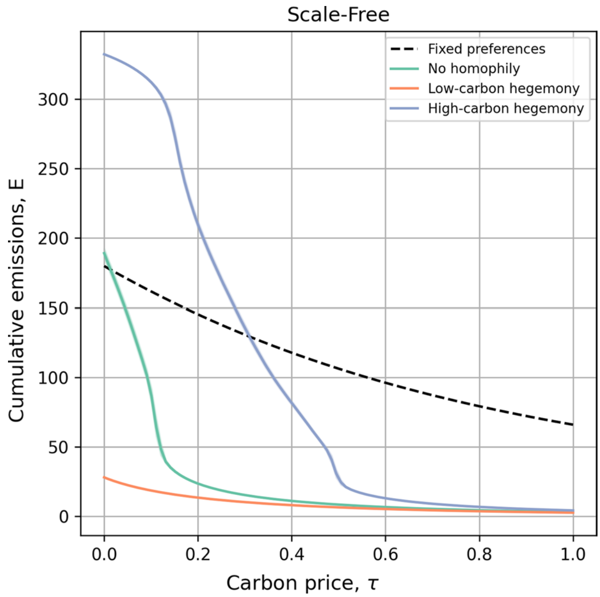


Fig. 20 Cumulative emissions for a scale-free network where central nodes are grouped by environmental identity at the start of the experiment, for a total of 9,000 experiments.The dashed line is the mean emissions of 100 stochastic runs for the case of fixed preferences

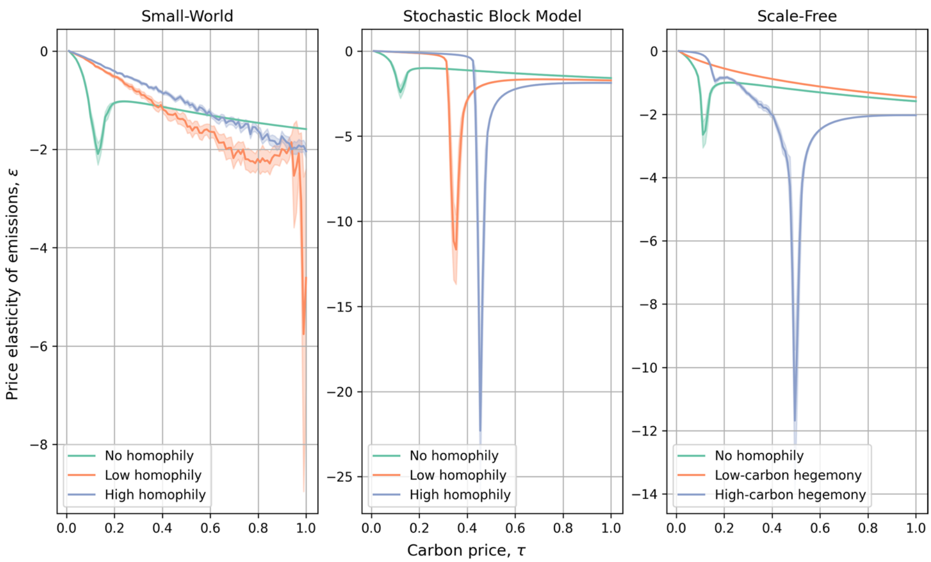


Fig. 21 Price elasticities for three network structures with different distributions of initial environmental identity (homophily and hegemony)

Funding Open Access Funding provided by Universitat Autonoma de Barcelona. This work has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No 956107, "Economic Policy in Complex Environments (EPOC)".

Code Availability The model code and documentation is available at: https://www.comses.net/codebases/b00ad1a3-dc5a-4610-83df-e869650f2714/releases/1.0.0/

Declarations

Conflict of Interest The authors have no conflicts of interest to declare.

References

Albert R, Barabási A-L (2002) Statistical mechanics of complex networks. Rev of Mod Phys 74(1):47
Andersson D, Nässén J (2022) Measuring the direct and indirect effects of low-carbon lifestyles using consumption data. J Clean Prod 135739
Axelrod R (1997) The dissemination of culture: a model with local convergence and global polarization. J Confl Resolut 41(2):203–226
Banerjee A, Chandrasekhar AG, Duflo E, Jackson MO (2013) The diffusion of microfinance. Science 341(6144):1236498
Baranzini A, Van den Bergh J, Carattini S, Howarth R, Padilla E, Roca J (2015) Seven reasons to use carbon pricing in climate policy
Bezin E (2019) The economics of green consumption, cultural transmission and sustainable technological change. J Econ Theory 181:497–546
Bhat FA, Verma M, Verma A (2022) Measuring and modelling electric vehicle adoption of Indian consumers. Transp Dev Econ 8(1):6
Bollinger B, Gillingham K (2012) Peer effects in the diffusion of solar photovoltaic panels. J Acad Mark Sci 31(6):900–912
Bollinger B, Gillingham KT, Ovaere M (2020) Field experimental evidence shows that self-interest attracts more sunlight. Proc Natl Acad Sci 117(34):20503–20510
Clark AF, Scott DM (2013) Does the social environment influence active travel? an investigation of walking in hamilton, Canada. J Transp Geogr 31:278–285
Coucke N, Vermeir I, Slabbinck H, Geuens M, Choueiki Z (2022) How to reduce agri-environmental impacts on ecosystem services: the role of nudging techniques to increase purchase of plant-based meat substitutes. Ecosystem Serv 56:101444
Cui L, Wang Y, Chen W, Wen W, Han MS (2021) Predicting determinants of consumers' purchase motivation for electric vehicles: an application of maslow's hierarchy of needs model. Energy Pol 151:112167
Dandekar P, Goel A, Lee DT (2013) Biased assimilation, homophily, and the dynamics of polarization. Proc Natl Acad Sci 110(15):5791–5796
Davis T, Hennes EP, Raymond L (2018) Cultural evolution of normative motivations for sustainable behaviour. Nat Sustain 1(5):218–224
DeGroot MH (1974) Reaching a consensus. J Am Stat Assoc 69(345):118–121
Döbbeling-Hildebrandt N, Miersch K, Khanna TM, Bachelet M, Bruns SB, Callaghan M, Edenhofer O, Flachsland C, Forster PM, Kalkuhl M et al (2024) Systematic review and meta-analysis of ex-post evaluations on the effectiveness of carbon pricing. Nat Commun 15(1):4147
Edenbrandt AK, Lagerkvist C-J (2021) Is food labelling effective in reducing climate impact by encouraging the substitution of protein sources? Food Policy 101:102097
Epstein JM, Axtell R (1996) Growing artificial societies: social science from the bottom up. Brookings Institution Press
Falkenberg M, Galeazzi A, Torricelli M, Di Marco N, Larosa F, Sas M, Mekacher A, Pearce W, Zollo F, Quattrociocchi W et al (2022) Growing polarization around climate change on social media. Nat Clim Chang 12(12):1114–1121

Foramitti J, Savin I, van den Bergh JC (2024) How carbon pricing affects multiple human needs: an agent-based model analysis. Ecol Econ 217:108070
Gholamzadehmir M, Sparks P, Farsides T (2019) Moral licensing, moral cleansing and pro-environmental behaviour: the moderating role of pro-environmental attitudes. J Environ Psychol 65:101334
Girod B, van Vuuren DP, Hertwich EG (2014) Climate policy through changing consumption choices: options and obstacles for reducing greenhouse gas emissions. Glob Environ Change 25:5–15
Glaeser EL, Sacerdote BI, Scheinkman JA (2003) The social multiplier. J Eur Econ Assoc 1(2–3):345–353
Granovetter M (1978) Threshold models of collective behavior. Am J Sociol 83(6):1420–1443
Hartmann P, Marcos A, Barrutia JM (2023) Carbon tax salience counteracts price effects through moral licensing. Glob Environ Change 78:102635
Herman J, Usher W (2017) SALib: an open-source python library for sensitivity analysis. J Open Source Software 2(9)
Holland PW, Laskey KB, Leinhardt S (1983) Stochastic blockmodels: first steps. Soc Networks 5(2):109–137
Jacobs B, van der Ploeg F (2019) Redistribution and pollution taxes with non-linear engel curves. J Environ Econ Manag 95:198–226
Kaaronen RO, Strelkovskii N (2020) Cultural evolution of sustainable behaviors: pro-environmental tipping points in an agent-based model. One Earth 2(1):85–97
Kim J, Rasouli S, Timmermans HJ (2018) Social networks, social influence and activity-travel behaviour: a review of models and empirical evidence. Transp Rev 38(4):499–523
Koessler A-K, Engel S et al (2021) Policies as information carriers: how environmental policies may change beliefs and consequent behavior. Int Rev Environ Resour Econ 15(1–2):1–31
Konc T, Savin I (2019) Social reinforcement with weighted interactions. Physical Review E 100(2):022305
Konc T, Savin I, van den Bergh J (2021) The social multiplier of environmental policy: application to carbon taxation. J Environ Econ Manag 105:102396
Köppl A, Schratzenstaller M (2023) Carbon taxation: a review of the empirical literature. J Econ Surv 37(4):1353–1388
Kuperman MN (2006) Cultural propagation on social networks. Physical Review E 73(4):046139
Lanzini P, Thøgersen J (2014) Behavioural spillover in the environmental domain: an intervention study. J Environ Psychol 40:381–390
Liu D, Qi S, Xu T (2023) Visual observation or oral communication? The effect of social learning on solar photovoltaic adoption intention in rural China. Energy Res Soc Sci 97:102950
Mattauch L, Hepburn C, Spuler F, Stern N (2022) The economics of climate change with endogenous preferences. Res Energy Econ 69:101312
Mattioli G, Büchs M, Scheiner J (2023) Who flies but never drives? Highlighting diversity among high emitters for passenger transport in England. Energy Res Soc Sci 99:103057
Nezlek JB, Forestell CA (2020) Vegetarianism as a social identity. Curr Opin in Food Sci 33:45–51
Nielsen KS, Nicholas KA, Creutzig F, Dietz T, Stern PC (2021) The role of high-socioeconomic-status people in locking in or rapidly reducing energy-driven greenhouse gas emissions. Nat Energy 6(11):1011–1016
Orléan A (1995) Bayesian interactions and collective dynamics of opinion: herd behavior and mimetic contagion. JEBO 28(2):257–274
Oswald Y, Millward-Hopkins J, Steinberger JK, Owen A, Ivanova D (2023) Luxury-focused carbon taxation improves fairness of climate policy. One Earth
Oswald Y, Owen A, Steinberger JK (2020) Large inequality in international and intranational energy footprints between income groups and across consumption categories. Nat Energy 5(3):231–239
Papageorgiou C, Saam M, Schulte P (2017) Substitution between clean and dirty energy inputs: a macroeconomic perspective. Rev Econ Stat 99(2):281–290
Pevec D, Babic J, Carvalho A, Ghiassi-Farrokhfal Y, Ketter W, Podobnik V (2020) A survey-based assessment of how existing and potential electric vehicle owners perceive range anxiety. J Clean Prod 276:122779
Sancho F (2024) Stone–geary meets ces: the properties of an extended linear expenditure system. J Econ Struct 13(1):10
Sato K (1967) A two-level constant-elasticity-of-substitution production function. Rev Econ Stud 34(2):201–218
Schumacher I (2015) The endogenous formation of an environmental culture. Eur Econ Rev 76:200–221
Sobol IM (2001) Global sensitivity indices for nonlinear mathematical models and their monte carlo estimates. Math Comput Simulat 55(1–3):271–280
Sovacool BK, Griffiths S (2020) Culture and low-carbon energy transitions. Nat Sustain 3(9):685–693
Torren-Peraire D, Savin I, van den Bergh J (2024) An agent-based model of cultural change for a low-carbon transition. J Artif Soc Soc Simul 27(1):13
Truelove HB, Carrico AR, Weber EU, Raimi KT, Vandenbergh MP (2014) Positive and negative spillover of pro-environmental behavior: an integrative review and theoretical framework. Glob Environ Change 29:127–138

Van der Werff E, Steg L, Keizer K (2014) I am what i am, by looking past the present: the influence of biospheric values and past behavior on environmental self-identity. Environ Behav 46(5):626–657
von Flüe L, Vogt S (2024) Integrating social learning and network formation for social tipping towards a sustainable future. Curr Opin Phychol 101915
Wang T, Shen B, Springer CH, Hou J (2021) What prevents us from taking low-carbon actions? A comprehensive review of influencing factors affecting low-carbon behaviors. Energy Res Soc Sci 71:101844
Watts DJ (2002) A simple model of global cascades on random networks. Proc Natl Acad Sci 99(9):5766–5771
Watts DJ, Strogatz SH (1998) Collective dynamics of 'small-world'networks. Nature 393(6684):440–442
Yang J, Chen F (2021) How are social-psychological factors related to consumer preferences for plug-in electric vehicles? Case studies from two cities in China. Renew Sustain Energy Rev 149:111325

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Authors and Affiliations

Daniel Torren-Peraire[1,2] · **Jeroen C. J. M. van den Bergh**[1,3,4] · **Ivan Savin**[5,1,6]

✉ Daniel Torren-Peraire
daniel.torren@uab.cat

1 Institute of Environmental Science and Technology, Universitat Autònoma de Barcelona, Barcelona, Spain

2 Department of Economics, Ca' Foscari University of Venice, Venice, Italy

3 ICREA, Barcelona, Spain

4 School of Business and Economics & Institute for Environmental Studies, Vrije Universiteit Amsterdam, Amsterdam, The Netherlands

5 ESCP Business School, Madrid Campus, Madrid, Spain

6 Graduate School of Economics and Management, Ural Federal University, Yekaterinburg, Russian Federation