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Heterogeneity and Global Climate Action

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Abstract

Countries respond differently to climate change, and while this resulting behavioral heterogeneity is empirically observed, its impact on the evolution of global climate action has not been analyzed. This leads to two related questions that we address: (i) what is the role of the variation of preferences in the global political economy of climate action; and (ii) what are the necessary conditions for sustained high levels of global action? We develop an evolutionary political economy integrated assessment model where heterogeneous countries, in each period, choose whether to take action to reduce emissions or not. Countries' choices are influenced by their current level of emissions, total participation in climate action, and other idiosyncratic factors capturing their heterogeneity, which depends on income inequality across countries, vulnerability to climate damages, and other political economy factors. Our model shows the possibility of various outcomes, where high levels of sustained global action is only one possibility. The key result is that sustained high levels of global action are achieved only if there is a low degree of heterogeneity in countries' preferences for action and a strong peer pressure effect.

Keywords: Climate action, Heterogeneous agents, Evolutionary dynamics, Integrated assessment
JEL codes: C62, E71, F5, Q54, Q58

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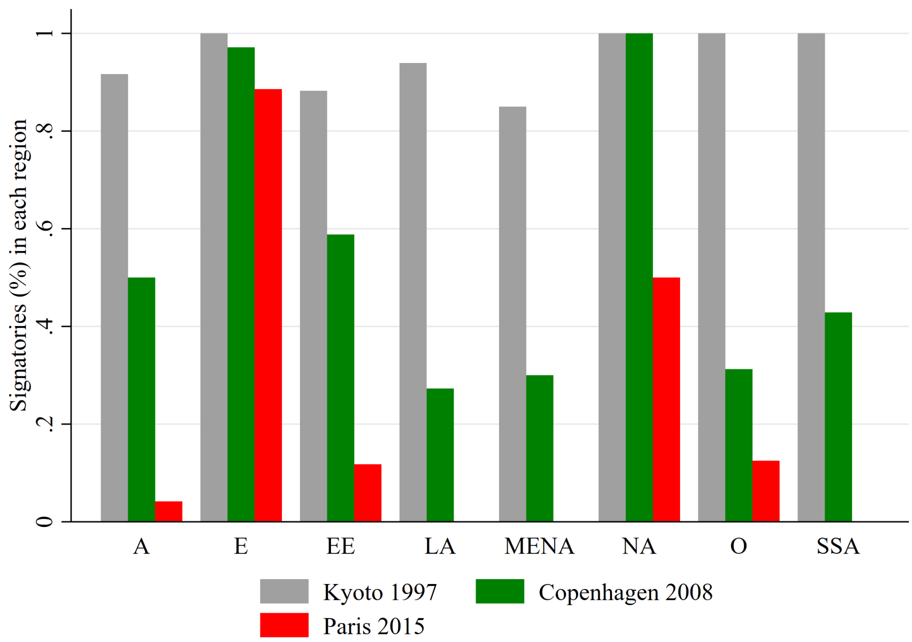
1 Introduction

Since the late 1980s, countries across the world have taken steady but insufficient action to stop climate change. Current mitigation pathways put the world on a turbulent path to exceed 1.5°C by the 2030s (IPCC, 2022), despite increasing numbers of countries signing up to international climate agreements and implementing national laws to reduce emissions (de Silva and Tenreyro, 2021). This is partly because countries disagree on the appropriate level of action. As Figure (1) illustrates, countries' preferences for climate action differ across both space and time (Lazkano et al., 2016; Li and Rus, 2019). These differences arise from several factors, including the unequal distribution of climate damages and the disparity in economic resources among countries (Peri and Robert-Nicoud, 2021; Yohe and Schlesinger, 2002). Taking into account this variation in preferences is relevant, especially in a dynamic context as countries' actions are known to have a positive impact on other countries' choices (Sauquet, 2014; Fankhauser et al., 2016; Carattini et al., 2023).

Figure 1: Signatures of key climate deals (% in each region)



(a) Notes: Data from de Silva and Tenreyro (2021). Regions: A= Asia; E= Europe; EE= Eastern Europe; MENA=North Africa and Middle East; SSA= Sub-Saharan Africa; LA= Latin America & the Caribbean; O= Oceania; NA= Northern America

While an extensive literature has studied various aspects of climate action including mitigation and adaptation policies (for example see Li and Rus, 2019), common property resource use (for example see Sethi and Somanathan, 1996; Noailly et al., 2007; Osés-Eraso and Viladrich-Grau, 2007) and environmental agreements (for example see Battaglini and Harstad, 2016; Harstad, 2016; 2023; Wagner, 2016; Günther and Hellmann, 2017; de Silva and Tenreyro, 2021; Bellelli et al., 2023), the dynamic impact of heterogeneity in countries' preferences for action has not been considered. The present paper aims to fill this gap by answering two related questions: (i) what is the role of the variation of preferences in the global political economy of climate action; and (ii) which are the necessary conditions for sustained high levels of global action?

We address these questions by developing an empirically driven evolutionary model in which countries decide whether to take action, building on Brock and Durlauf's (2001) discrete choice model with social interactions. This framework enables us to explicitly incorporate heterogeneity in agents' decision-making processes in a dynamic setting. Following Brock and Durlauf (2001), agents' preferences are shaped by three components: social, private, and idiosyncratic utility. In our setup, the social utility captures interdependence among countries, emphasizing the coordination game aspect of climate action, where collective efforts reduce emissions and carbon leakage while reinforcing global norms (Carraro and Siniscalco, 1995; Babiker, 2005; Nordhaus, 2015). This interdependence of actions can be understood as a form of peer pressure, where countries are influenced by the actions of others to align with global norms and expectations. This dynamic is supported by literature on policy diffusion (Perkins and Neumayer, 2012), reputational concerns (Barrett, 1994), and social norms (Nyborg et al., 2016), which highlight how peer behavior shapes individual decisions in climate cooperation.

The private utility concerns emission targets, which serve as a proxy for mitigating climate change. Given the short- to medium-run nature of the analysis and the high stock of existing emissions, emission targets effectively represent the trade-offs between reducing future climate damages and incurring immediate economic costs. Higher emissions lead to greater temperature increases, resulting in more severe economic damages, such as reduced agricultural productivity, increased frequency of extreme weather events, and higher adaptation costs. Conversely, reducing emissions involves significant economic costs, such as investments in clean technologies, transitioning away from carbon-intensive industries, or implementing regulatory measures. This creates a well-known tension: countries may avoid the immediate economic costs of mitigation while still benefiting from the global reduction in damages achieved through others' efforts—a classic free-riding dynamic (Hardin, 1968; Barrett, 1994; Stern, 2007).

Finally, the idiosyncratic utility accounts for heterogeneity in preferences due to factors such as economic resources (Bättig and Bernauer, 2009; Fankhauser et al., 2016), which influence countries' capacity to implement mitigation policies; vulnerability to climate damages (Fankhauser et al., 1999; Tubi et al., 2012; Tørstad et al., 2020), reflecting both the severity of expected climate impacts and the ability to adapt; fossil fuel rents (Brulle, 2018; Lamb and Minx, 2020; Victor et al., 2022), as resource-dependent countries may resist policies that threaten their economic interests; and political institutions (Keohane, 2001; Fredriksson and Neumayer, 2016; Finnegan, 2022), which shape policy responsiveness and governance structures. Additionally, the idiosyncratic utility captures the varying importance countries assign to social and private utilities, reflecting differences in priorities, values, and strategic considerations. Overall the heterogeneity of climate action preferences is shaped by global inequalities, as economic disparities, institutional differences, and climate vulnerability influence how countries prioritize mitigation efforts.

Using available data that capture the factors contributing to idiosyncratic utility, we develop an idiosyncratic utility index to empirically assess the variation in heterogeneity with respect to idiosyncratic preferences, which we refer to as the *degree of heterogeneity*. We find that the distribution of this index can be well approximated by a logistic distribution, a standard assumption in the discrete choice literature (McFadden, 2001; Brock and Durlauf, 2001; Train, 2009). This enables us to develop a large-population evolutionary perturbed best response (logit) model (Sandholm, 2010). Our model gives rise to different potential outcomes, including low levels of action, increasing levels of action followed by a decline and sustained high levels of action. The outcome which actually dominates depends on the relative importance of the social utility related to peer pressure effects and the degree of heterogeneity of the idiosyncratic part of the preferences. For sustained high levels of global climate action, strong peer pressure effects should be accompanied by a low degree of heterogeneity. If the degree of heterogeneity is not sufficiently low, then any increase of action will be only temporal and will be followed by a decrease.

To determine which type of dynamics best describes the current path, we first empirically estimate our model through a logit panel regression using data from the Climate Change Laws of the World Database (2020) on the frequency of mitigation laws as a proxy for climate action. Using estimated parameter values and initial conditions, we demonstrate that our model fits the observed dynamics of global GHG emissions and global climate action over the last three decades, from 1989 (the first full operational year of the IPCC) to the present. Building on this validation, we extend the simulation to 2050, a key date for countries' net-zero targets. Interestingly, the results show that global climate action does not continue to rise but instead converges to an equilibrium that implies a rising stock of emissions in the long run, suggesting that countries will fail to achieve net-zero emissions under current conditions. To explore potential pathways to net zero, we vary two key parameters: the peer pressure effect and the degree of heterogeneity. Our main finding is that achieving an equilibrium where all countries take action and global emissions continually decline to net zero is possible, but only if the peer pressure effect is strong and the degree of heterogeneity is low.

The intuition of the main result is as follows. While peer pressure among countries positively influences others to take action, free-riding may still emerge as more measures to reduce emissions are taken. When there is a high degree of heterogeneity, countries which are taking action due to peer pressure but have relative strong biases against action will likely abstain as net emissions start to reduce. Since the effects of global action on emissions take time, a reduction in participation has a delayed effect on increasing emissions, but an immediate impact on peer pressure. The unsynchronised timing of these effects means that the decreased peer pressure from an increase in abstention will lead more countries to abstain, further reducing peer pressure. Consequently, before net emissions rise enough to counteract this trend, peer pressure might shift to incentivise abstention instead. Without both high peer pressure and low degree of heterogeneity, climate action may increase in the short run but stop rising over the medium run.

The heterogeneity of climate action preferences is shaped by global inequalities, as economic disparities, institutional differences, and climate vulnerability influence how countries prioritize mitigation efforts. These inequalities affect both the ability and willingness of nations to engage in coordinated action, leading to fragmented policies. Moreover, as climate damages vary geographically across countries, they exacerbate existing inequalities and increase heterogeneity over time, making it more difficult to achieve high levels of global climate action. Addressing these disparities is essential, as climate change disproportionately harms vulnerable countries, deepening inequalities and further complicating collective efforts. Timing is also crucial for sustained global action, as the rising heterogeneity caused by increasing climate damages means that future levels of peer pressure will need to be stronger than those required today to maintain strong collective action.

Following Brock and Durlauf (2001), our framework assumes a large population of agents approximated by a continuum. While this assumption enables analytical results that provide intuition about the model's dynamics, in reality, countries are discrete in number, and their relative importance varies significantly in terms of both their impact on emissions and their influence through the social utility component. To test the robustness of our findings, we sequentially relax the assumptions regarding the number of countries and their relative importance while maintaining the model's general structure. First, we replace the continuum with a discrete set of 194 countries, corresponding to the number of countries for which data are available. Next, we introduce heterogeneity in country size through the social utility component, where larger countries exert greater influence. Finally, we allow countries to have different impacts on global emissions based on their emission levels. We find that while small variations arise due to these added complexities, the overall findings remain robust, highlighting the importance of accounting for heterogeneity in relevant models.

The paper contributes to and brings together different literatures. Given the structure of our model, our work contributes to the broader environmental economics literature which integrates natural processes related to climate change and environmental damages with social and economic variables. While the key focus of this broad family of Integrated Assessment Models (IAMs) has been to assess the environmental economic feedback effects of various fiscal and financial policies (for example see Nordhaus, 1992, 2014; Stern, 2013; Dafermos et al., 2017, 2018; Lamperti et al. 2018 among others), to our knowledge there are no works which integrate (international) political economic processes related to climate action with processes related to the carbon cycle and climate damages. Our work contributes to this literature by explicitly accounting for the fact that countries' preferences for action may change over time. These changes arise from factors such as shifts in political power, as well as other political and economic conditions that vary geographically and are often beyond policymakers' control, leading to high levels of uncertainty. This uncertainty is linked to behavioral assumptions in our model rooted in bounded rationality (Simon, 1957, 1979) and the use of heuristics (Tversky and Kahneman, 1974; Kahneman, 2003), which, in our framework, are connected to the social utility component of preferences.

Given our focus on climate action, our model creates links between IAMs and the broader literature on climate action which has mainly focused on International Environmental Agreements (IEAs)[1]. More specifically, our model is empirically driven which is one of the exceptions compared to related works (Bellelli et al., 2023). In this way we aim to connect empirical findings related to the determinants of action (Bättig and Bernauer, 2009; Scheidel et al., 2020; Tubi et al., 2012; Victor et al., 2022) with dynamic models of environmental agreements (for example see van der Ploeg and de Zeeuw, 1992; Hoel, 1997; Long, 2012; among others and Calvo and Rubio, 2013 for a review) which are shown to be causally linked to climate action (de Silva and Tenreyro, 2021). Due to the evolutionary dynamics of our model, the closest paper within the dynamic IEAs literature is the one by Breton et al. (2010) who analyse stability of IEAs under the possibility of punishing non-signatories. Our model differs from Breton et al. (2010) in two fundamental ways. First, in our paper, action refers to the reduction of emissions rather than to signing an agreement. Second, our model focuses on the degree of heterogeneity which depends on damages (which in turn depend on the carbon cycle and a damage function).

From a methodological viewpoint our work has links with evolutionary game theoretic models which have studied common-pool resource problems (for example see Sethi and Somanathan, 1996; Noailly et al., 2007; Osés-Eraso and Viladrich-Grau, 2007). A key difference with these works is that instead of assuming the usual (in evolutionary game theory) replicator dynamics to govern the evolution of the agents' behaviour, here the evolution is modelled through a logit (perturbed best response) framework which is derived from empirical behavioural microfoundations rooted in the discrete choice tradition (Manski and McFadden, 1981; McFadden, 1974, 1978, 2001; Brock and Durlauf, 2001; Train, 2009). This modelling approach has its roots in the behavioural dynamic discrete choice literature starting from the works of Lux (1995) and Brock and Hommes (1997) who studied the effects of heterogeneous behaviours in financial markets. This heterogeneous interacting agents behavioural framework has been applied to different fields[2] including environmental economics focusing on the effects of heterogeneity in investment decisions (Cahen-Fourot et al., 2023), expectations (Campiglio et al., 2024) and attitudes towards green policies (Dávila-Fernández and Sordi, 2020; Dunz et al. 2021; Sordi and Dávila-Fernández, 2023). A key difference between our model and the previous ones, is that while all allow for heterogeneous

[1] For a recent review on IEAs see Bellelli et al. (2023)

[2] For example: behavioural finance (Lux, 1995; Brock and Hommes, 1997, 1998; Chiarella and He, 2002; Chiarella et al., 2006; Westerhoff and Dieci, 2006; Anufriev abd Tuinstra, 2013; Dieci and Westerhoff, 2016, among others), behavioural macroeconomics (De Grauwe, 2011, 2012; Flaschel et al., 2018; Hommes et al., 2018, 2019; Hommes and Lustenhouwer, 2019; Assenza et al., 2021, among others), voting (Di Guilmi and Galanis, 2021; Di Guilmi et al., 2022), physical distancing decisions (Galanis et al., 2021; Di Guilmi et al., 2022, Flaschel et al., 2022)

agents, we focus on the effect of the degree of heterogeneity on climate action.

The structure of the rest of the paper is as follows. Section 2, introduces the general setup of our model and the empirical observations upon which we base our analysis regarding the heterogeneity of preferences for climate action. Section 3 analyses the baseline version of the model which allows for analytical results. Section 4 relaxes the simplifying assumptions showing that the insights of the model hold under more realistic assumptions. The final section concludes.

2 Preferences for Climate Action

Our approach for analysing countries' decisions on whether to take climate action to mitigate expected climate damages is based on Brock and Durlauf's (2001) discrete choice model with social interactions. In this framework, agents' utility[3] consists of three components: a social, a private, and an idiosyncratic one; each of these capturing relevant theoretical and empirical insights related to our research questions. This model allows us to incorporate both social influences on decisions and allow for focusing on heterogeneity regarding agents' preferences.

Assume that the world economy consists of $2N$ countries, where each country faces a binary decision at every point in time: either take a costly climate action (C) to reduce greenhouse gas emissions, aiming for zero net emissions ($E_t = 0$), or choose to abstain (A) which corresponds to the business as usual scenario. Formally the action of country $i \in \{1, \dots, 2N\}$ at t is expressed as $a_t^i = \{C, A\}$ such that a country prefers to take action if the utility of choosing A at t, $U_t^i(C)$ is higher than $U_t^i(A)$, the utility of choosing A. Following Brock and Durlauf, the utility $U_t^i(a_t^i)$ is given by

$$U_t^i(a_t^i) = v_t(a_t^i) + S_t(a_t^i; \bar{m}_t^i) + \epsilon_t^i(a_t^i), \tag{1}$$

where here, $\bar{m}_t^i$ is given by

$$\bar{m}_t^i = \left(\sum_{j \neq i} \bar{m}_t^{i,j} \right) / (2N - 1) \tag{2}$$

and $\bar{m}_t^{i,j}$ represents country i's subjective expectation of country j's action. Then, $v(a_t^i)$, $S(a_t^i; \bar{m}_t^i)$ and

[3]While, in standard economic terms, the preferences in Brock and Durlauf (2001) align more closely with an indirect utility function, we adopt their terminology for simplicity and refer to it as "utility".

$\epsilon^i(a_t^i)$ are the private, social and idiosyncratic utility components respectively. For simplicity let

$$\pi_t^i = U_t^i(C) - U_t^i(A), \tag{3}$$

such that C is chosen when $\pi_t^i > 0$.

Private Utility

The private utility component reflects both the global public bad aspect of emissions linked to expected climate damages and incorporates free-riding effects, which are widely discussed in the relevant literature. Greenhouse gas emissions are considered a global public bad because they contribute to climate change, affecting all countries in different ways regardless of who emitted the gases. This creates a classic free-rider problem: countries may benefit from the emissions reductions of others without incurring the costs of taking action themselves. Since the benefits of reduced emissions are shared globally, individual countries have an incentive to free-ride, relying on others to bear the costs of action while still enjoying the benefits.

This type of behaviour is well-documented in the literature on international environmental agreements, where the non-excludability and non-rivalry of climate benefits lead to suboptimal levels of cooperation (Olson, 1965; Hardin, 1968; Barrett, 1994). Additionally, countries are more inclined to reduce net emissions when they are high and less inclined when net emissions are closer to zero, further capturing the free-riding behavior. This is particularly evident in the context of carbon-intensive economies, where the costs of transitioning to low-carbon technologies are perceived to be higher (Stern, 2007; Nordhaus, 2015). Following this we can assume that private utility for taking action depends positively on emissions such that

$$v_t(C) - v_t(A) = \beta_e E_t, \tag{4}$$

with $\beta_e > 0$. This implies that *ceteris paribus* higher net emissions create stronger incentives for action.

Social Utility

The social utility component formalizes the strategic interdependence of climate policy decisions across countries, capturing the coordination game dynamics that characterize global climate action. These dynamics are well established in environmental economics literature (Barrett, 1994; Carraro and Siniscalco, 1995; Heal and Kunreuther, 2010; Nordhaus, 2015), where each country's mitigation efforts become more effective as participation widens. Three key mechanisms drive this interdependence. First, collective action yields greater emission reductions while minimizing carbon leakage (Felder and Rutherford, 1993; Babiker, 2005; Eliot et al., 2010). Second, reputation preservation and norm conformity create peer pressures for policy alignment (Barrett, 2005; Keohane and Victor, 2011). Third, social contagion effects accelerate policy diffusion (Perkins and Neumayer, 2012; Dolšak and Prakash, 2022).

Climate policy decisions are made by governments operating under electoral constraints and shifting domestic preferences. This creates fundamental uncertainty about whether current policy actions will persist in the future. de Silva and Tenreyro (2021) show that while agreed quantifiable targets have a positive impact on climate action, the evidence regarding compliance to target is mixed. As a result, the social utility of climate action depends heavily on contemporaneous policy alignments rather than long-term commitments. Empirical evidence from Fankhauser et al. (2016) confirms these short-run strategic complementarities, demonstrating strong spatial correlations in policy adoption across countries.

Idiosyncratic Utility

Both in standard dynamic discrete choice models building on Brock and Hommes (1997, 1998) and in social interaction models following Brock and Durlauf (2001), the idiosyncratic utility $\epsilon_t^i(a_t^i)$ is typically (though often implicitly) assumed to follow an extreme value distribution. This implies that the difference:

$$\hat{\epsilon}_t^i \equiv \epsilon_t^i(C) - \epsilon_t^i(A) \tag{5}$$

follows a logistic distribution. While this specification is standard in the empirical discrete choice literature (Manski and McFadden, 1981; McFadden, 1974, 1978, 2001; Train, 2009), we provide an empirical justification for this distributional assumption. This empirical extercise furtther allows to get insights regarding the heterogeneity in preferences that cannot be explained by the common characteristics of the decision-makers or the alternatives they face.

The costs and benefits of climate action and/or discounting preferences vary significantly across countries for a variety of reasons beyond the private and public utility components (Aldy et al., 2010; IPCC, 2022, 2014). These variations arise not only from social, economic, and political factors not fully captured by the public and private utility components but also from differences in the relative importance that countries assign to these utilities— known as random taste variation in the discrete choice literature. Consistent with discrete choice theory, this random taste variation can be captured by the idiosyncratic utility component under certain conditions regarding the variation of preferences for each of the non-idiosyncratic factors.[4]

Relevant empirical literature has identified a range of factors related to global inequalities and political economy aspects that can be viewed as components of the idiosyncratic utility in climate decision-making. These factors include economic resources, which influence a country's capacity to invest in mitigation and adaptation measures (Bättig and Bernauer, 2009; Fankhauser et al., 2016); vulnerability to climate damages, which shapes countries' perceptions of risks and incentives for action (Fankhauser et al., 1999; Tubi et al., 2012 Dell et al., 2014; Ricke et al., 2018; Tørstad et al., 2020); fossil fuel rents, which create economic and political barriers to decarbonization in resource-dependent economies (Brulle, 2018; Colgan et al., 2021; Dolphin et al., 2020; Lamb and Minx, 2020; Victor et al., 2022); and democratic and long-term political institutions, which shape the ability of governments to implement and sustain effective climate policies (Keohane, 2001; Fredriksson and Neumayer, 2016; Davidson et al., 2021; Finnegan, 2022).[5]

In order to see if the logistic distribution assumption is reasonable in our framework we develop an idiosyncratic utility index which is a simple average of the four political economy factors mentioned above. We take the z transformation of each factor to make them comparable. With the z transformation, we convert our variables/distributions to a set of z values with mean equal to 0 and a standard deviation equal to 1.

Figure (2) presents two maps of this index. The upper panel shows the index for 2019 - the latest pre-COVID-19 year with available data. Countries in darker red prefer to take climate action to those with lighter colors. The bottom panel shows the change in the index between 2005 (the first year with available data) and 2019. Preferences for action increased in dark green countries, declined in green

[4]For a discussion, see Train (2009) and Galanis et al. (2025).

[5]One aspect of this relates to corruption. Fredriksson and Neumayer (2016) argue that controlling corruption promotes climate action, as effective climate mitigation policies require overcoming opposition from cost-bearing organized groups (Finnegan, 2022).

countries and stayed the same in white ones.

Figure (3) plots the distribution of the idiosyncratic utility index for a single year (2019) and shows that preferences seem to follow a relatively symmetric unimodal distribution, which may be reasonably proxied by a logistic distribution. Moreover, as the lower panel of Figure (2) shows, for most countries, the index changes over time, implying that for the same global factors the idiosyncratic factors change over time. In addition to this, there are likely to be a set of other non observable idiosyncratic shocks that influence a country's willingness to take action. For example, countries which had previously signed up to climate commitments may suddenly change direction due to political shocks, such as the USA dropping out of the Paris agreement in 2016 and again recently, or the UK shifting its approach to net zero commitments in 2023. This provides empirical justification for assuming that preferences have an idiosyncratic time variant component. Both of these findings allow us to reasonably assume that ϵ_t^i follows a logistic distribution.

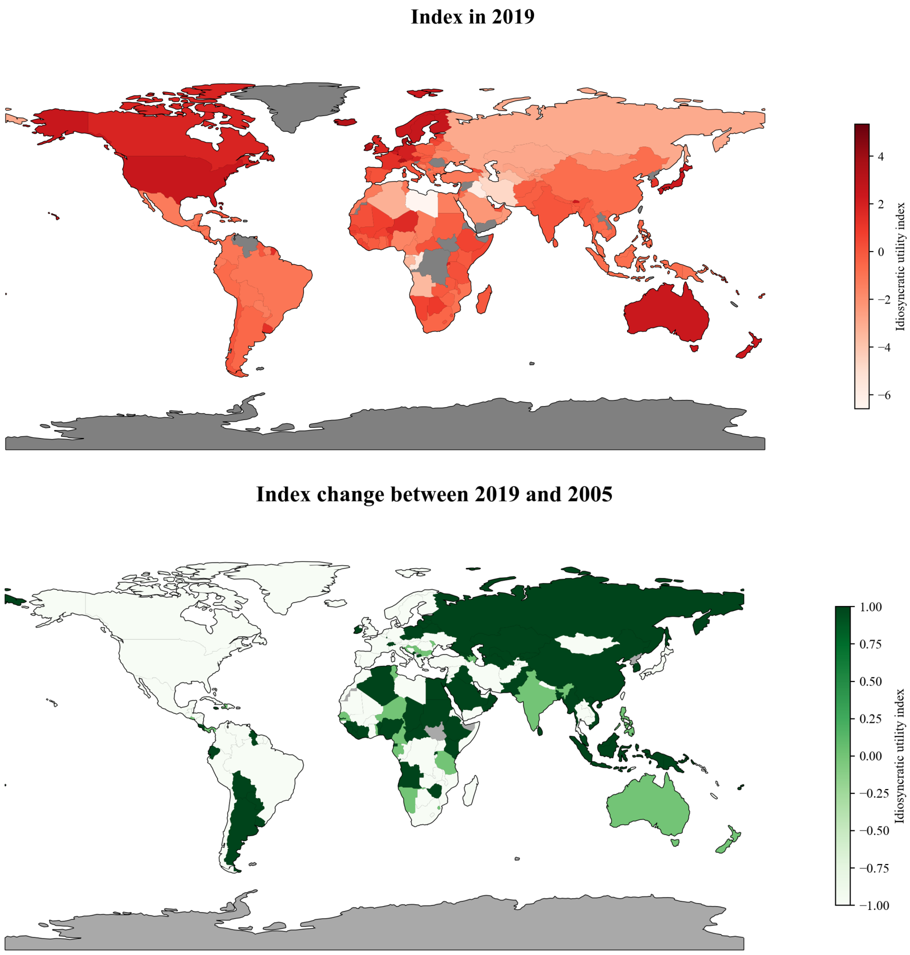
Let $-\mu$ be mean of the distribution of $\hat{\epsilon}_t^i$ and $\frac{s_t^2\pi^2}{3}$ its variance, where s_t is the value of the scale parameter of the logistic distribution at time t. We define $\gamma_t = \frac{1}{s_t}$ as the *degree of heterogeneity* of the idiosyncratic component of the utility. High (low) values of γ_t correspond to a low (high) dispersion.[6]

3 Baseline model

To develop a complete model, we need to make specific assumptions about the importance of countries in reducing emissions and their relative significance in the social utility component. Our analysis begins with a simplified version of the model, where all countries are assumed to be of the same size and importance, and the number of countries is sufficiently large to be approximated by a continuum (as in Brock and Durlauf, 2001). Next, we relax this assumption in three steps. First, we present a computational version of the model with a discrete number of countries, where each country is considered separately. This step demonstrates that the results of the simplified model remain valid even when the continuum assumption is dropped. Second, we introduce heterogeneity by allowing countries to differ in their relative influence on other countries through the social utility component. Third, we incorporate heterogeneity in countries' emissions, reflecting differences in their contribution to global emissions. In

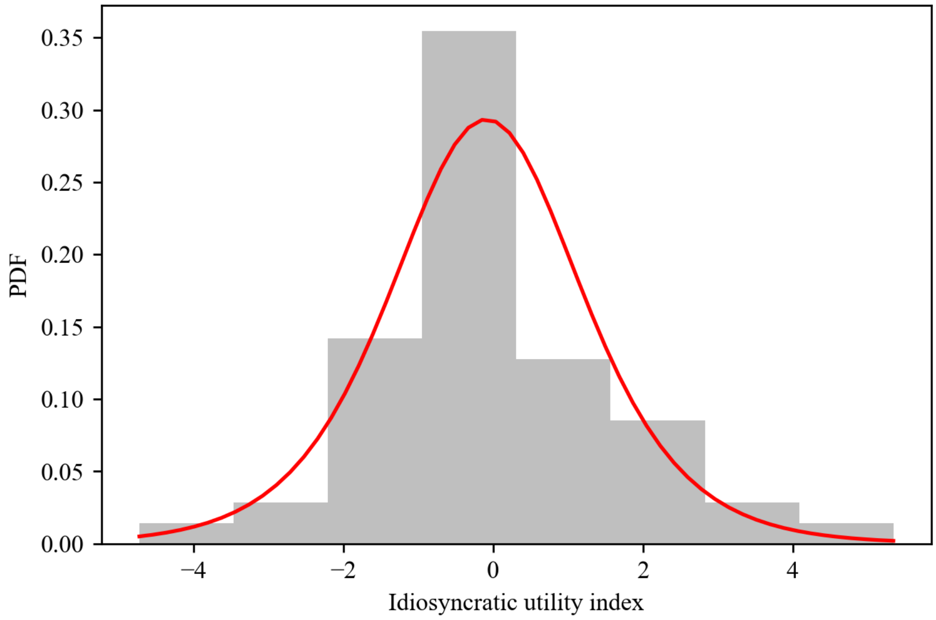
[6] The parameter γ_t is also known as *intensity of choice* in the relevant literature. For example, see Brock and Hommes (1997).

Figure 2: Idiosyncratic utility index



(a) Notes: The idiosyncratic utility index is constructed from the unweighted sums of four variables: (i) GDP/capita in current USD from the World Bank; (ii) vulnerability Index from Notre Dame-Global; (iii) fossil fuel rents/GDP from World Bank; (iv) a corruption control index from Worldwide Governance Indicators World Bank. The variables are z-transformed to make them comparable. High preferences for climate action are represented by greater index values. The upper panel takes the index value in 2019. The bottom panel demonstrates the change in the index between 2005 and 2019 where dark green indicates increased preferences, light green indicates no change, and white indicates a decline in preferences.

Figure 3: Logistic PDF and Histogram of Idiosyncratic Utility Index



(a) Notes: The line plots the fitted logistic probability density function (PDF) to the data. The bar chart represents the histogram with 8 bins.

all cases, we find that climate action has a positive effect in reducing emissions, while in the absence of action, emissions continue to grow.

In the simple version of our model, we express the strategic complementarity in countries' action the following way which will allow for closed form solutions and stability analysis. Assume a large number of countries where each has the same size as the others. Let n_t^C be the share of countries who take an action at time t and n_t^A the share who don't, with $n_t^C + n_t^A = 2N$. Also let x_t be the relative share of countries which take climate action at t, such that

$$x_t = \frac{n_t^C - n_t^A}{2N}. \tag{6}$$

This implies that $x_t \in [-1, 1]$, for all t with $x_t > 0$ when $n_t^C > n_t^A$. Then we can express the difference in social utilities as

$$S_t(C; \bar{m}_t^i) - S_t(A; \bar{m}_t^i) = \beta_x x_t, \tag{7}$$

with $\beta_x > 0$. Substituting (4), (7) and (5), into (11), we get:

$$\pi_t^i = S(a_t^j) + u(E_t) + \hat{\epsilon}_t^i, \tag{8}$$

where $\hat{\epsilon}_t^i$ is assumed to follow a logistic distribution.

As shown in de Silva and Tenreyro (2022), actions have an impact on the growth rate of countries' emissions. However it is not clear whether assuming equal country size, as we do here, implies that the relative share of participation has a statistically significant impact on the growth rate of global net emissions $\hat{E}_t$. Following this we assume and estimate[7] that the evolution of global emissions is given by:

$$\hat{E}_{t+1} = -\alpha x_t, \tag{9}$$

with $1 >> \alpha > 0$.

Given that $\hat{\epsilon}_t^i$ incorporates different influences, its dispersion captured by $1/\gamma_t$ depends on the combined variation of these factors across countries. As climate damages vary across countries and are expected to increase over time (Hsiang et al., 2022; Calel et al., 2020; Callahan and Mankin, 2022), countries' preferences for taking action will also become more heterogeneous, i.e. increasing the degree of heterogeneity, hence reducing γ_t. Formally this can be expressed through the following linear form:

$$\gamma_{t+1} = \gamma - \delta\Omega_t, \tag{10}$$

where $\Omega_t \in [0, 1]$ captures the global level of damages and $\gamma > \delta > 0$, such that γ corresponds to the degree of heterogeneity excluding the impact of damages and δ is the marginal effect of damages on the degree of heterogeneity. Note that a high degree of heterogeneity also implies high importance of the idiosyncratic factors relative to the global ones. This is due to the fact that a high dispersion of idiosyncratic factors, means that there will always be a considerable number of countries that will almost always want to take action and also a considerable number of countries that almost never want to take action, regardless of the global factors.

[7] The estimation results can be found in column 2 of table (1) in the appendix. We also test the relation with a constant, $\hat{E}_{t+1} = \alpha_0 - \alpha x_t$. We find that α_0 is not significant and α is significant at significance level 5% level. These estimation results can be found in column 1 of table (1). Given that the constant is insignificant, we build the model using equation (9) without a constant.

Given the assumption of a large number of countries and logistic distribution of $\hat{\epsilon}_t^i$, we can express the probability that a country chooses C at time t for given x_t and E_t as[8]

$$P(C|\pi_t) = \frac{e^{\gamma_t \pi_t}}{1 + e^{\gamma_t \pi_t}}, \tag{11}$$

where

$$\pi_t = \beta_x x_t + \beta_e E_t - \mu, \tag{12}$$

Then, the probability of no action is

$$P(A|\pi_t) = 1 - P(C|\pi_t) = \frac{1}{1 + e^{\gamma_t \pi_t}}, \tag{13}$$

High values of γ_t (low degree of heterogeneity) means π_t is relatively more important in determining the choices of the countries, while low values of γ_t (high degree of heterogeneity) means that π_t plays less of a role and the idiosyncratic factors become relatively more important. For example for $\gamma_t \to 0$ ($s_t \to \infty$), $P(C|\pi_t) = P(A|\pi_t) = \frac{1}{2}$, meaning that the population of countries as a whole makes their choices mainly due to the influence of the idiosyncratic factors.

Based on this, the evolution of x_t is given by

$$\Delta x_{t+1} = (1 - x_t)\frac{e^{\gamma_t \pi_t}}{1 + e^{\gamma \pi_t}} - (1 + x_t)\frac{1}{1 + e^{\gamma_t \pi_t}} = \frac{e^{\gamma_t \pi_t} - 1}{1 + e^{\gamma_t \pi_t}} - x_t, \tag{14}$$

which is the logit/perturbed best response dynamics used in evolutionary game theory (Sandholm, 2010). While this revision protocol is less commonly used in evolutionary models compared to the replicator one, given its derivation from behavioural microfoundations, it allows for explicitly studying the effects of the degree of heterogeneity.

3.1 No damages

Before we analyse the setup which allows for the feedback effects between countries' climate action, GHG emissions and climate damages, we focus on the no damage scenario such that $\gamma_t = \gamma$. This allows

[8] For details of the derivation, see chapter 1 in Train (2009).

us to get some analytical insights regarding the equilibria, where $\Delta x_t = \Delta E_t = 0$. We provide results regarding both the existence and the local asymptotic stability of the equlibria for different parameter values. Given the non-linearities, we complement the analytical results with simulations. The equilibria of our model are also known as *evolutionary equilibria* (Friedman, 1991, 1998) as they describe an equilibrium of an evolutionary process. However, in order not to confuse the notion of asymptotic stability, which implies that the outcome is Nash Equilibrium with the static notion of evolutionary stability which is not always implied by asymptotic stability (see Sandholm, 2010), we will refer to the evolutionary equilibria simply as equilibria.

Assuming that $\Omega_t = 0$, means that the evolution of countries' participation in climate action is given by

$$x_{t+1} = \frac{e^{\gamma \pi_t} - 1}{1 + e^{\gamma \pi_t}} \tag{15}$$

Hence the economy in the baseline version of the model can be described by a system of two difference equations: (9) and (15).

Proposition 1. *Consider the economy described by* (9) *and* (15) *.*

(i) $(E, x) = (\frac{\mu}{\beta_e}, 0)$ *is an equilibrium for all parameter values.*

(ii) There exists an equilibrium $(E, x) = (0, x')$ *for all parameter values, with* $x' \in (0, 1]$ *for* $\mu < 0$ *and* $x' \in [-1, 0]$ *for* $\mu > 0$*.*

The first equilibrium corresponds to an outcome where net emissions are stable at a positive or negative level and the total number of countries are equally split between the ones taking action and the ones abstaining. Whether emissions are positive or negative at this equilibrium depends on the sign of μ. A positive (negative) μ implies that the mean of idiosyncratic factors is such that there is a bias against (in favour of) action, which in turn leads to positive (negative) net emissions. The second part of the Proposition shows two different possible outcomes with zero net emissions which depend on the average influence of idiosyncratic factors. As we see below, the degree of heterogeneity will determine the (local) stability of these equilibria and also the existence of others.

Proposition 2. *Let* $\bar{\gamma} = \frac{2\left(\beta_x + 2\alpha\mu - \sqrt{(\beta_x + 2\alpha\mu)^2 - \beta_x^2}\right)}{\beta_x^2}$*, then* $(E, x) = (\frac{\mu}{\beta_e}, 0)$ *is*

(i) locally asymptotically stable for $\mu > 0$ *and* $\gamma < \frac{2}{\beta_x + \alpha\mu}$ *and a spiral node for* $\gamma > \bar{\gamma}$*.*

(ii) unstable otherwise.

Proposition 2, shows that when the average idiosyncratic preferences are in favour of action ($\mu < 0$) then $(E, x) = (\frac{\mu}{\beta_e}, 0)$ cannot be stable. Intuitively, this occurs because the steady-state emission level is negative (since $\mu < 0$), triggering a free-rider effect even with the smallest shock. Countries with strong biases against taking action will be the first to exhibit this behavior. This, in turn, will influence other countries' reluctance to act, with this effect becoming increasingly pronounced over time—at least until emissions begin to rise again.

A positive μ leads to stability of $(E, x) = (\frac{\mu}{\beta_e}, 0)$ when the degree of heterogeneity is relatively high (low γ). For given levels of peer pressure (β_x) and impact of action on emissions (α), γ has to be low (less than $\bar{\gamma}$) otherwise positive net emissions would lead to higher incentives for action. If the degree of heterogeneity is not sufficiently high ($\gamma > \bar{\gamma}$), then cyclical dynamics will emerge around $(E, x) = (\frac{\mu}{\beta_e}, 0)$. The latter dynamics suggest that what we currently observe in global climate mitigation (i.e. increasing levels of climate action) might not necessarily lead towards high sustained levels but may be simply the upward trend of a cyclical variation.

The intuition of the cyclical dynamics is as follows. When there is significant heterogeneity among countries, those strongly opposed to taking action are likely to abstain once net emissions move towards approaching net zero levels. Since the impact of global efforts to reduce emissions takes time, a drop in participation will quickly weaken peer pressure, rather than immediately limiting emissions reductions. This weakened peer pressure will lead to more countries abstaining, hence further reducing peer pressure. As a result, before net emissions increase enough to reverse this trend, the majority of countries can shift towards abstention. As the effect of lowering participation on emissions becomes more apparent, these dynamics will slowly change with more and more countries shifting towards action.

This potential oscillatory convergence offers some interesting insights worth emphasizing. When the degree of heterogeneity satisfies $\frac{2}{\beta_x + \alpha\mu} > \gamma > \bar{\gamma}$, the level of action may rise significantly above the equilibrium value of $x_t = 0$ before eventually decreasing. The extent to which participation exceeds the equilibrium level before declining will depend on the specific parameter values, which reflect the relative strength of the various factors influencing action. This suggests that the observed increase in climate action participation since the late 1980's could represent a short term transitory dynamic, with potential declines in action levels still to come.

Proposition 3. *There exists a* $\gamma^* = \gamma^*(\beta_x, \mu)$ *such that for* $\mu < \beta_x$ *and* $\gamma > \gamma^*$*, two more equilibria exist:* $(E, x) = (0, x^1)$ *and* $(E, x) = (0, x^2)$ *, with* $x^1, x^2 \in (0, 1)$ *for* $\mu > 0$ *and* $x^1, x^2 \in (-1, 0)$ *for* $\mu < 0$*, while for* $\gamma = \gamma^*$*,* $x^1 = x^2$*.*

Proposition 3 shows the possibility of more equilibria where the level of participation is positive (negative) when the average bias μ is also positive (negative). These equilibria exist when the peer pressure effect is stronger than average negative biases for climate action and the degree of heterogeneity is sufficiently low. Note that when the average bias towards action is positive ($\mu < 0$), then the peer pressure condition $\mu < \beta_x$ always holds. For $\mu < 0$ ($\mu > 0$), the equilibrium level of participation to climate action is such that the minority (majority) participates, however due to the non linear nature of the model we are not able to have information about the local stability.

We next estimate the parameters of the model to get insights regarding it's medium-run dynamics under different specifications.

Simulations

We first estimate the no-damages version assuming a fixed degree of heterogeneity. More specifically, without loss of generality we assume $\gamma = 1$. For α, we estimate equation (9) using a simple ARDL time series regression at the global level. $\hat{E}_{t+1}$ is the yearly growth rate in global annual net Greenhouse gas emissions in CO2 equivalents, measured using data from Our World In Data. As this dataset includes land-use emissions (which can be negative), technically $\hat{E}_{t+1}$ (our dependent variable) captures the change in the *net* GHG emissions at the global level. x_t is given by the number of countries that pass at least one climate mitigation law in a given year minus the number of countries that do not pass any laws in that year, divided by the total number of countries. Data on climate mitigation laws is from the Climate Laws of the World database.

We estimate equation (9) for the period from 1950 to 2019 using robust standard errors. The time period stops in 2019 in order to not include the sharp drop in emissions due to the COVID-19 shutdown and starts in 1950 to allow for enough observations (70) to estimate the ARDL equation. The results are presented in column 2 of table (1) in the appendix. The estimated parameter α is 0.022 and this is significant at the 1% significant level.

To estimate β_x, β_e, μ, we estimate equation (12) using panel data at the country level. We use a dummy variable that equals 1 if a country adopts a mitigation law in a given year and 0 if it does not adopt a law, again from the Climate Laws of the World database. This panel regression is estimated using a logit random effects panel estimator, in order to estimate a value for the constant (μ, the average bias). The regressions are estimated on data from 1980 to 2019. The results are presented in table (2). The estimated $\beta_x = 1.098$, $\beta_e = .181, \mu = 9.77$ and they are significant at the 10%, 1% and 1% level respectively.

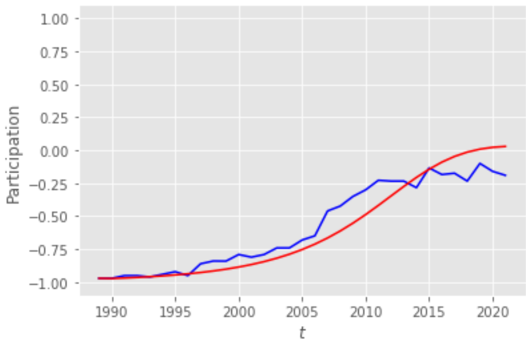
We first present a validation exercise, which compares the model simulation of the two endogenous variables (E_t and x_t) with their actual observed values. We set the initial conditions to be their observed values in 1989. This is the year the IPCC became operationalised and therefore could be considered as a good starting point for global climate negotiations. Net emissions in 1989 were $E_0 = 36.8$ in billion metric tons of CO2 equivalent emissions and the relative share of countries taking action was $x_0 = -0.97$. Figure (4) shows the trajectory of the simulation (given initial conditions and estimated baseline parameters) and the observed values from 1989 to 2019. The simulated model aligns closely with the observed data, effectively capturing the dynamics of emissions and global climate action over the past three decades.

Next, figure (5) simulates the baseline model over the coming decades (until 2050). The model expects participation to convergence to a low level of participation ($x^* = 0$), corresponding to positive net emissions ($E^* \approx 54.4$). This outcome is interesting and relevant from a policy perspective as it shows that the increase in climate participation observed over the last three decades is not expected to continue over the next three decades. Participation will plateau and net zero emissions will not be reached. This result can be seen in Proposition 2: local asymptotic stability of $(E, x) = (\frac{\mu}{\beta_e}, 0)$ requires $\mu > 0$ and $\gamma < \frac{1}{\beta_x + \alpha\mu}$ which for the estimated parameter values becomes $1 < \frac{2}{1.098+0.02*9.77} = \frac{2}{1.2934}$ showing that the equilibrium is locally stable. Also note that $\bar{\gamma} = \frac{2\left[1.4908-\sqrt{(1.4908)^2-(1.098)^2}\right]}{(1.098)^2} = \frac{2(1.4908-\sqrt{2.2224-1.205604})}{1.205604} \approx 0.8 < \gamma = 1$, which implies that the equilibrium is also a spiral node.[9]

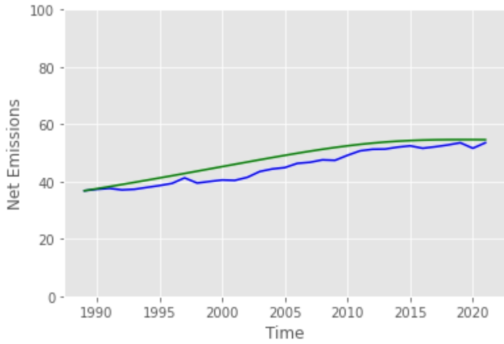
We now explore what happens to the dynamics of our endogenous variables when we adjust two key parameters: β_x and γ. As Propositions 2 and 3 show β_x and γ define to a great extent the dynamics of the model. Moreover, policy makers have some control over these parameters as they can either exerting more peer pressure on countries (β_x) and/or reducing global inequalities (γ).

[9] While the equilibrium is a spiral node for the estimated parameter values, this is not directly obvious from figure (5). To add clarity we present phase plots for different values of γ and β_x in the appendix.

Figure 4: Actual and Simulated x_t and E_t



(a) red line: Baseline Simulated Model, blue line: Actual Values



(b) green line: Baseline Simulated Model, blue line: Actual Values

Parameters for simulation: $E_0 = 36.8$, $x_0 = -0.97$, $\gamma = 1$, $\beta_x = 1.1$, $\beta_e = 0.18$, $\alpha = 0.02$, $\mu = 9.77$

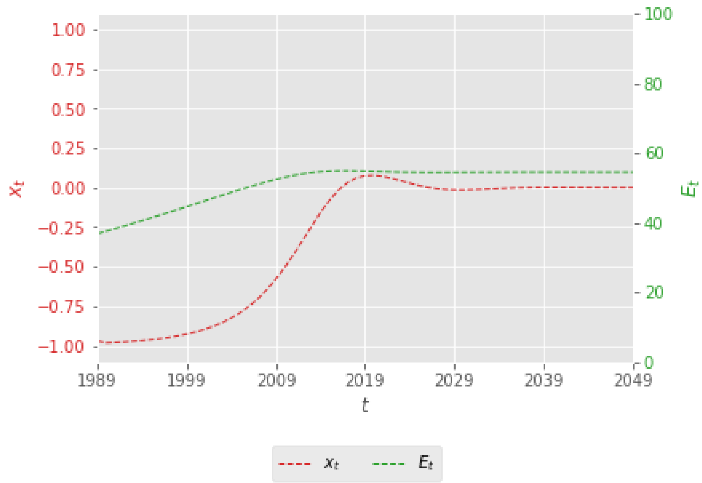
Figure (6) illustrates the impact of increasing the peer pressure effect (β_x). We consider three scenarios: the baseline ($\beta_x = 1.1$), blue line ($\beta_x = 3$) and ($\beta_x = 15$).[10] Increasing the peer pressure from the baseline to $\beta_x = 3$ (but not enough so that β_x is greater than μ), we observe clear oscillations. There is a shift from high levels of participation to high levels of abstention among countries. Concurrently, there is a pronounced decline in net emissions followed by a surge, without the attainment of a long-term equilibrium.

Increasing the peer pressure effect further to $\beta_x = 15$ (such that it is greater than μ) leads to all countries taking action and therefore a sustained decline in emissions (the black line). This is the only case where there is a sustained high level of action and the potential to reach net zero.

What this shows is that a very strong peer pressure effect is needed in order to get sustained participation. This is because there is a "fight" between peer pressure on the one hand and free riding on the other. In the high sustained participation case, the high peer pressure effect offsets the free-riding effect. Looking at equation (15) can help gain more insights regarding this balance. An increase in peer pressure β_x (with $\beta_x > \mu$) effectively offsets the (negative) impact of average idiosyncratic biases against action ($\mu > 0$) influencing countries' decisions. In the case with oscillations, the peer pressure is not enough to offset free riding. When emissions start to decline, due to an increase in climate action, countries will start to free ride, as there is not a strong enough peer pressure effect, leading to a turning

[10] We use these scenarios of $\beta_x = 3$ and $\beta_x = 15$ to simulate two cases where β_x is smaller and larger than μ as discussed in proposition 3. See the Phase plots for different values of β_x in the Appendix.

Figure 5: Participation and Emissions with estimated parameters and exogenous γ



Parameters: $E_0 = 36.8$, $x_0 = -0.97$, $\gamma = 1$, $\beta_x = 1.1$, $\beta_e = 0.18$, $\alpha = 0.02$, $\mu = 9.77$

point in participation.

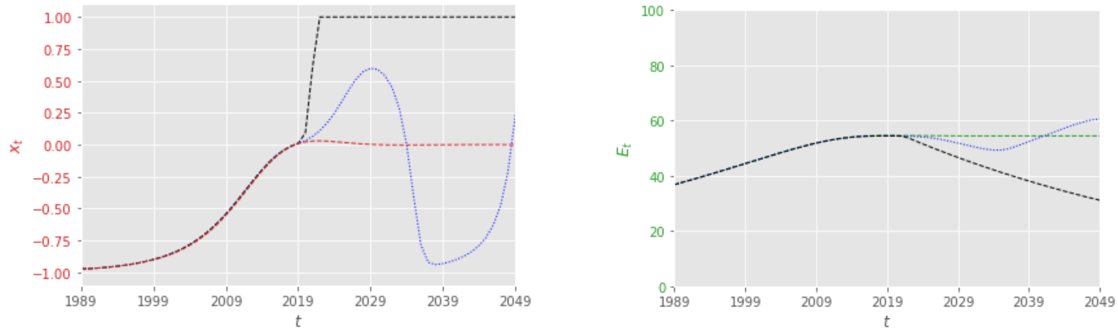
Lastly, Figure (7) shows how the simulation changes when we decrease the degree of heterogeneity (i.e. increasing γ), keeping the other baseline parameters and initial conditions constant. We consider three scenarios: the baseline ($\gamma = 1$), blue line ($\gamma = 3$) and the black line ($\gamma = 15$). If we increase gamma (reduce inequality) from the baseline to $\gamma = 3$, we also observe oscillations in participation - and by extension emissions. Reducing inequality further to $\gamma = 15$ increases the amplitude of these oscillations but does not lead to a situation where participation is sustained at high levels. If countries are more equal, their behaviour is similar. They move together in the same direction. Either they all participate together or, due to declining emissions and the free riding effect, they all decide not participate.[11]

Does the degree of heterogeneity not therefore matter in achieving sustained global climate action, and therefore net zero? To answer this question, figure (8) presents a bifurcation diagram which shows the stability (and instability) of x_t for different values for the degree of heterogeneity (bifurcation parameter). We set $\beta_x = 15$ as this was the only case where sustained participation is possible, as discussed above in figure (6).

Consistent with the analytical results and our simulations, the bifurcation shows that relatively high heterogeneity (low γ) for a given level of peer pressure leads to stability of the equilibrium with $x_t = 0$,

[11] Technically there is less dispersion in the logistic distribution, so all countries are close to the mean.

Figure 6: Evolution of x_t and E_t for different values of β_x



(a) red line: Baseline Model   **(b)** green line: Baseline Model

Note: after 2019 $\beta_x = 3$ (Blue line) and $\beta_x = 15$ (Black line)
Parameters: $E_0 = 36.8$, $x_0 = -0.97$, $\beta_e = 0.18$, $\gamma = 1$, $\alpha = 0.02$, $\delta = 0$, $\mu = 9.77$

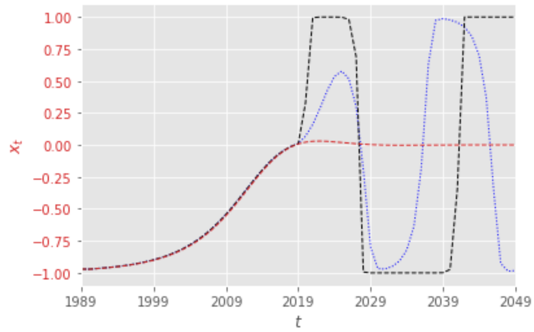
as indicated by the straight line observed in the beginning of the diagram. Increasing γ leads initially to cyclical dynamics corresponding to the light red area in the diagram. The more pronounced red areas on the top and bottom of the diagram for values of γ around 2 to a bit higher than 8, show that the cyclical dynamics can be such that for example a short period of high participation which might appear as stable can be followed by a sharp decrease. Finally we observe stability of the high participation equilibrium for high values of γ.

This shows that heterogeneity among countries must be low (i.e. γ greater than around 0.75) in order to achieve the aim of net zero emissions. In other words, we need both a strong peer pressure effect and a low degree of heterogeneity in order to achieve sustained global climate action.

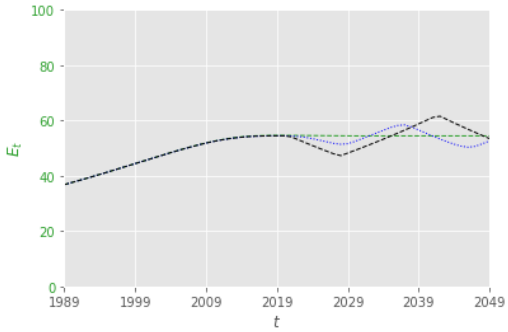
3.2 IAM version

Up to now we treated the degree of heterogeneity, captured by γ, as exogenous. This has allowed us to gain intuition regarding the effects of heterogeneity on participation to climate action and net zero. However, as both damages and the capacity to deal with these varies greatly across countries, it is likely that more global emissions will increase the degree of heterogeneity (i.e. a reduction in γ). These effects could imply that an endogenous degree of heterogeneity may make it harder to reach high levels of climate action. However, given the nonlinear dynamics observed above and a further introduction of nonlinearities related to the carbon cycle and climate damages, it is far from obvious whether new

Figure 7: Evolution of x_t and E_t for different values of γ



(a) red line: Baseline Model



(b) green line: Baseline Model

Note: after 2019 $\gamma = 3$ (Blue line) and $\gamma = 15$ (Black line)
Parameters: $E_0 = 36.8$, $x_0 = -0.97$, $\beta_x = 1.1$, $\beta_e = 0.18$, $\alpha = 0.02$, $\delta = 0$, $\mu = 9.77$

possibilities might emerge.

In our IAM version, the degree of heterogeneity evolves according to equation (10) which depends on climate damages (Ω_t). Regarding the specific functional form of damages we consider two cases which are widely used in related literature. The first is according to DICE2013 (Nordhaus, 2014)

$$\Omega_t = 1 - \frac{1}{1 + 0.0022(T_t^{AT})^2}, \tag{16}$$

and the second follows Weitzman (2012):

$$\Omega_t = 1 - \frac{1}{1 + (T_t^{AT}/20.46)^2 + (T_t^{AT}/6.081)^{6.754}}. \tag{17}$$

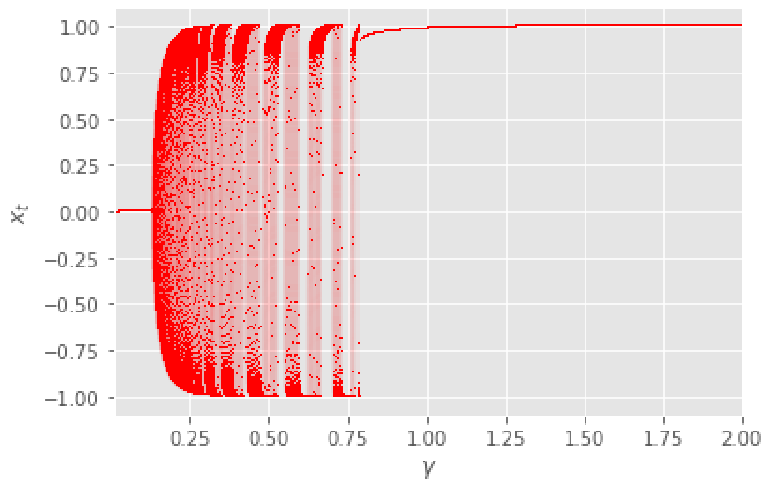
In both cases T_t^{AT} is the atmospheric temperature at t and is given by the *carbon cycle*[12].

In figure (9), we present the dynamics of climate action of the IAM version of the baseline model for the two different damage functions above and we compare these dynamics with the baseline version for the estimated values showed above.

We note in figure (9)a that the dynamics for the estimated parameter values for the two variations of the IAM version are almost indistinguishable from the dynamics of model without explicit damages.

[12]For the equations and the values of the parameters used, please see Appendix.

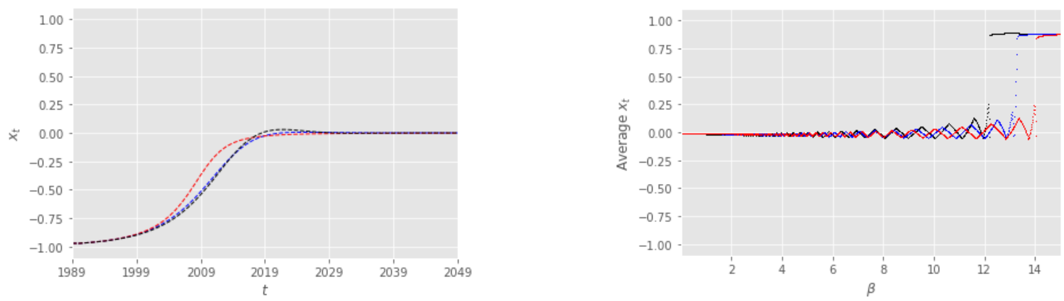
Figure 8: Bifurcation Diagram of x_t for γ, with $\beta_x > \mu$



Parameters: $E_0 = 36.8$, $x_0 = -0.97$, $\beta_x = 15$, $\beta_e = 0.18$, $\alpha = 0.02$, $\delta = 0$, $\mu = 9.77$

There are only small differences in reaching the long-run equilibrium. This shows that the intuition of the baseline model without damages also holds here, as such it is a good approximation of the IAM version.

Figure 9: Climate action and damages



(a) $\beta_x = 1.1$ and $\gamma = 1$

(b) for different values of β_x and $\gamma = 2$

Black Line: Baseline Model ($\delta = 0$); Blue line: DICE ($\delta = 0.99$); Red line: Weitzman ($\delta = 0.99$).
Parameters: $E_0 = 36.8$, $x_0 = -0.97$, $\beta_e = 0.18$, $\alpha = 0.02$, $\mu = 9.77$.

We next compare the IAM version with the version without damages regarding the feasibility reaching the high level global action equilibrium. Figure (9)b depicts the average participation for varying values of β_x with damages using the DICE function (blue line) and the Weitzman specification (red line) and without damages influencing the degree of heterogeneity (black line).[13] Just like above, convergence to the high levels of action equilibrium requires higher peer pressure when the effects of damages are taken into account. However, what is interesting is that introducing damages requires a higher peer pressure effect to reach this high level of action equilibrium. Without damages, $\beta_x = 12$ is sufficient, while with the DICE and Weitzman damage function $\beta_x = 13$ and $\beta_x = 14$ is required respectively. In other words, introducing more damages makes it harder to reach the equilibrium (i.e. there must be more peer pressure).

On the one hand this result is surprising as one might expect damages to incentivize countries to take more action in order to avoid future costs. In fact the opposite seems to be occurring. This is because damages influence the degree of heterogeneity. By increasing the degree of heterogeneity (i.e. reducing γ), damages increase the number of countries who are likely to not take action in any case. To compensate against this, a higher peer pressure effect is required to achieve high sustained levels of global action.

4 Heterogeneity in Country Characteristics

To derive analytical results, we made a key simplifying assumption: a large number of countries approximated by a continuum. It meant that we only accounted for one type of heterogeneity, heterogeneity of preferences captured in the idiosyncratic utility. However, countries' actions have a heterogeneous impact on both total emissions and peer pressure, as captured through the social utility component of preferences. Incorporating these effects could lead to different dynamics. In this section, we relax this assumption while maintaining the general structure of the model. To ensure that our previous findings remain consistent with the framework when the assumption is relaxed, we proceed step by step.

First, we simulate the model from the previous section but replace the continuum assumption with a discrete number of countries. Next, we introduce heterogeneity regarding country size into the model in two steps: initially through the social utility component of preferences, where larger countries are assumed to exert greater influence, and then through their actual impact on global emissions.

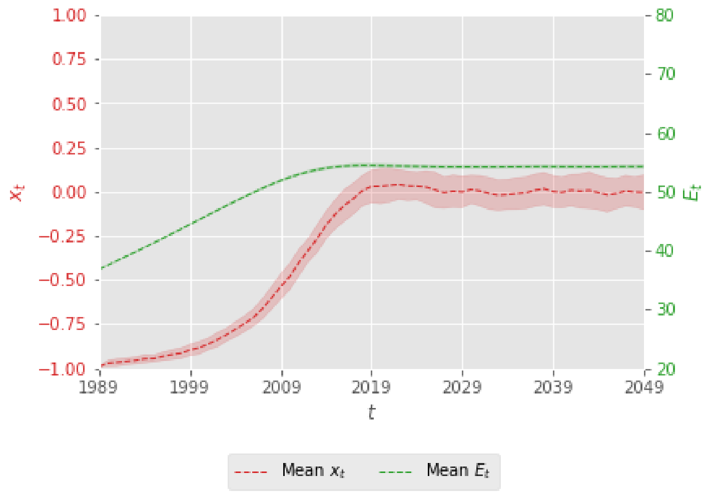
[13] Note this is similar to the bifurcation diagram above, but showing the average value of x_t rather than all values of x_t to make it comprehensible.

4.1 Baseline IAM with 194 countries

Consider a setup where the world economy is composed by $2N = 194$ countries instead of a continuum[14]. In this case, for each country i, the idiosyncratic impact on action, captured by ϵ_t^i is drawn by a logistic distribution with the same assumptions about its scale parameter as outlined above. Figure (10) shows the average global action and emission dynamics simulated through a Monte Carlo process (100 runs) for 194 countries, using the estimated parameter values, without taking into account the effects of damages on heterogeneity (the shaded area indicates the range of one standard deviation from the mean).

Note that assuming a discrete number of countries does not qualitatively alter the results shown in Figure (5). The only noticeable difference is that the dynamics become less smooth. This is because, with discrete countries, the idiosyncratic characteristics can no longer be approximated as before and instead manifest themselves as countries' shocks at each time step.

Figure 10: Evolution of Participation and Net Emissions with 194 countries and exogenous γ



Note: The graph presents the results of nested Monte Carlo simulations. The dashed line represents the mean value across all simulations, while the shaded area indicates the range of one standard deviation from the mean. The first Monte Carlo process (100 runs) accounts for the stochasticity in the error term, while the second captures variability in the initial conditions, with each simulation starting from a different configuration among 194 countries.

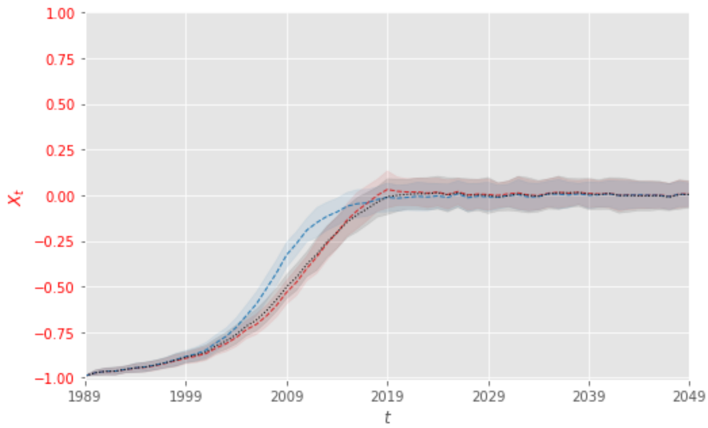
Parameters: $2N = 194$, $\beta_x = 1.1$, $\beta_e = 0.18$, $\alpha = 0.02$, $\mu = 9.77$, $E_0 = 36.8$, $\gamma = 1$

Finally, Figure (11) presents the time series of average relative participation X_t for 194 countries

[14]We chose 194 countries because they are the ones for which we have data.

with Monte Carlo process. The chart compares three different model versions: the baseline model, represented by the red line; the IAM baseline version using the DICE damage function, shown by the black line; and the IAM baseline version employing the Weitzman damage function, depicted by the blue line.

Figure 11: Evolution of Participation with 194 countries and endogenous γ_t



Note: The graph presents the results of nested Monte Carlo simulations. The dashed line represents the mean value across all simulations, while the shaded area indicates the range of one standard deviation from the mean. The first Monte Carlo process (100 runs) accounts for the stochasticity in the error term, while the second captures variability in the initial conditions, with each simulation starting from a different configuration among 194 countries.

Red Line: Baseline Model ($\gamma_t = 1$); Black line: DICE ($\delta = 0.99$); Blue line: Weitzman ($\delta = 0.99$).

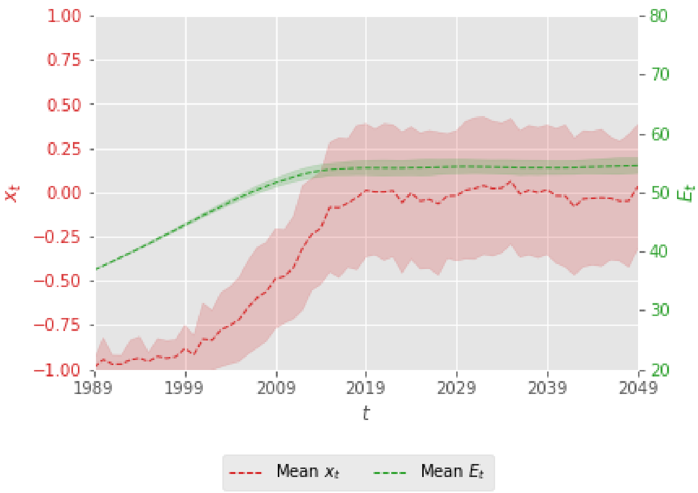
Parameters: $2N = 194$, $\beta_x = 1.1$, $\beta_e = 0.18$, $\alpha = 0.02$, $\mu = 9.77$, $E_0 = 36.8$

When comparing this to Figure (9)a, it becomes evident that the results remain robust when instead of a continuum, 194 countries are assumed. As expected, when we have a discrete number of countries, the differences between the baseline version without damages and the versions with endogenous degree of heterogeneity are less obvious. The graphs collectively demonstrate that the core insights derived from the model hold even when the large number of countries assumption is dropped.

4.2 Heterogeneity in influence

Up to this point, we have assumed that countries differ only in their preferences, treating their economic size as uniform. However, countries vary in size, and this matters not only for their emissions - which affect the private utility component of preferences - but also because larger countries' actions should have a greater impact on the social utility part of their preferences. To determine the weight of each country, we use World Data Bank data, calculating the average share of its GDP in global GDP over the 30-year period from 1989 to 2019.[15] This approach accounts for the fact that peer pressure varies between countries, depending on their economic size and influence on the international stage.

Figure 12: Evolution of Participation and Net Emissions with heterogeneity in country size



Note: The graph presents the results of nested Monte Carlo simulations. The dashed line represents the mean value across all simulations, while the shaded area indicates the range of one standard deviation from the mean. The first Monte Carlo process (100 runs) accounts for the stochasticity in the error term, while the second captures variability in the initial conditions, with each simulation starting from a different configuration among 194 countries' size. Parameters: $N = 194$, $\beta_x = 1.1$, $\beta_e = 0.18$, $\alpha = 0.02$, $\mu = 9.77$, $E_0 = 36.8$, $\gamma = 1$

The baseline results are shown in Figure (12). Notably, our findings are consistent with those presented in (10) and (5). Over the long term, countries are expected to become polarized into two distinct groups, with net zero emissions slightly below 60 gigatons of equivalent GHG net emissions. Additionally, country size increases the variability, but it does not alter our main conclusion. Under a business-as-usual scenario, countries will fail to achieve net zero emissions within the required time frame.

[15]Given that this weight evolves slowly over time, we treat it as exogenously determined, leaving the analysis of endogenous changes to future research.

4.3 Heterogeneity in emissions

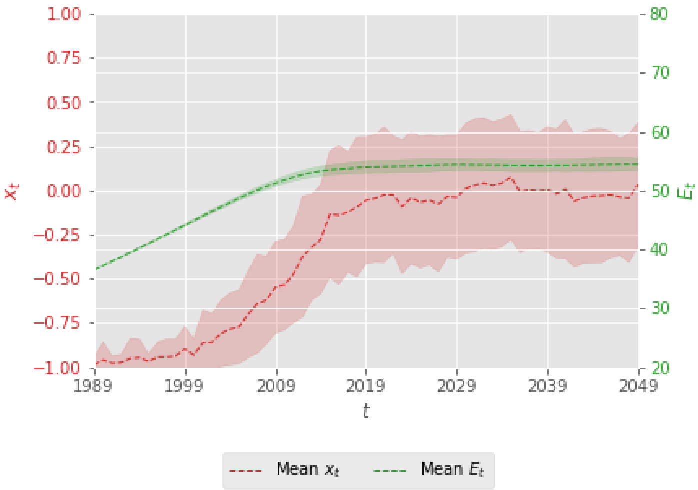
A second factor that contributes to the heterogeneity among countries is emissions. While countries size influences peer pressure, examining emissions at the country level enables us to highlight the impact of individual actions on global emissions. The payoff function for each country (eq. 12) remains unchanged; however, the actions of countries now affect their own emissions and, in turn, have a retroactive and cumulative impact on subsequent actions. Indeed, we now assume that at each point in time country's $i \in \{1, \ldots, 2N\}$ apply two strategies[16]. They take required action in order to reduce the CO2 emissions by 2% or they do not take action and emissions will increase at a rate comparable to what has been observed in a Business as Usual Scenario (2%). Based on this, the emissions of country i at t are given by $E_t^i = E_{t-1}^i(1 + g_t^i)$, where

$$g_t^i(\pi_t) = \begin{cases} -0.02, & \text{if } \pi_t > 0 \\ 0.02, & \text{if } \pi_t < 0 \end{cases}$$

We emphasize that, in calculating their respective payoffs, countries take into account the total value of net emissions, which, at each time step, is determined by the sum of emissions from all countries. We report the related results of Monte Carlo simulations in Figure 13. Again, the expected results are maintained.

[16] We opted to apply a straightforward rule to the evolution of emissions at the country level in order to maintain the model's alignment with its original formulation. Nevertheless, we acknowledge that introducing additional complexity, such as linking emissions with GDP, would be a valuable direction for future research.

Figure 13: Evolution of Participation and Net Emissions with heterogeneous country's size and emissions



Note: The graph presents the results of nested Monte Carlo simulations. The dashed line represents the mean value across all simulations, while the shaded area indicates the range of one standard deviation from the mean. The first Monte Carlo process (100 runs) accounts for the stochasticity in the error term, while the second captures variability in the initial conditions, with each simulation starting from a different configuration among 194 countries' size. Parameters: $N = 194$, $\beta_x = 1.1$, $\beta_e = 0.18$, $\alpha = 0.02$, $\mu = 9.77$, $E_0 = 36.8$, $\gamma = 1$

5 Conclusion

Over the past decades an increasing number of countries have taken climate action, from implementing domestic mitigation laws to signing quantifiable binding targets at international climate agreements. Despite these collective efforts, they are not sufficient to prevent global temperatures from rising. As we face an increasingly warmer world, there is no assurance that countries will continue to pursue more ambitious climate actions, especially given the growing complexity of geopolitical and economic crises, and how these dynamically interact with the unequal impacts of climate change. These crises can divert attention and resources away from climate commitments, as governments are likely to prioritise immediate political stability and economic recovery over long-term environmental goals. To effectively mitigate against climate change, we need a better understanding of the conditions under which most countries will adopt sustained levels of global action.

In this paper, we develop an evolutionary international political economy model of climate action with heterogeneous agents to analyze the relative importance of different factors empirically known to influence countries' decisions regarding climate action. The key motivating issue we address is the fact that countries globally have heterogeneous climate action preferences due to varying idiosyncratic factors. While this heterogeneity is discussed in empirical studies on climate action, its role in shaping overall global climate action has not been systematically analyzed until now. Our model demonstrates that incorporating this missing aspect is crucial for understanding the range of possible outcomes in global climate action and emissions dynamics.

The outcomes of the model depend on the relative importance of the various factors influencing decisions and, to a great extent, on the degree of heterogeneity in countries' preferences. A key finding is that when the degree of heterogeneity is high, more countries with strong preferences against taking action are likely to abstain as net emissions approach zero, compared to when heterogeneity is low. Since the effects of global efforts to reduce emissions take time to manifest, this decline in participation weakens peer pressure gradually, rather than immediately reducing emissions. This weakened peer pressure, driven by countries with idiosyncratic preferences against action, leads to even more countries abstaining, further diminishing collective peer pressure. As a result, before net emissions increase enough to reverse this trend, peer pressure shifts toward further abstention from action, creating a self-reinforcing cycle.

Using available data to estimate the parameters in the model's behavioral equations and set initial conditions, we find that the expected outcome is one where participation in climate action stops increasing, and global net emissions remain positive. In other words, the world fails to achieve net-zero emissions. While the model effectively reproduces the observed increase in participation in climate action over the last few decades, it predicts a decline in action in the coming years.

An interesting result is that while the degree of heterogeneity in preferences is crucial, the outcomes do not depend significantly on heterogeneity in countries' size on average. To achieve high levels of global participation in emissions reduction efforts, two key conditions must be met: relatively low heterogeneity among countries and strong peer pressure. Our analysis demonstrates that these conditions are both necessary and sufficient to counteract the average negative idiosyncratic factors that act as barriers to climate action across countries. Low heterogeneity implies that countries have more aligned interests and face similar costs and constraints, making collective action through peer pressure more feasible.

The insights of our model have direct policy implications. Since the degree of heterogeneity in climate action preferences is shaped, in part, by global inequalities, our findings highlight the importance of addressing these disparities—not only from a normative perspective but to be able to achieve environmental goals. Inequalities can directly impact countries' ability to participate in coordinated climate efforts and, indirectly, their willingness to do so. Additionally, while increasing peer pressure is crucial to encouraging stronger climate commitments, the timing of these efforts is equally important. Climate damages disproportionately affect countries, exacerbating existing inequalities and increasing heterogeneity over time. This makes it more challenging to achieve a high level of global climate action in the future.

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Appendix

Carbon Cycle

$$M_t^{AT} = Stock_t^E + \phi_{11} M_{t-1}^{AT} + \phi_{21} M_{t-1}^{UP}, \tag{18}$$

$$M_t^{UP} = \phi_{12} M_{t-1}^{AT} + \phi_{22} M_{t-1}^{UP} + \phi_{32} M_{t-1}^{LO}, \tag{19}$$

$$M_t^{LO} = \phi_{23} M_{t-1}^{AT} + \phi_{33} M_{t-1}^{LO}, \tag{20}$$

where M_t^{AT}, M_t^{UP} and M_t^{LO} correspond to the mass of carbon in reservoir for atmosphere, upper oceans and lower oceans respectively. And $Stock_t^E$ is the stock of emissions.

$$F_t = \eta\{log_2[M_t^{AT}/M_p^{AT}]\} + F_t^{EX}, \tag{21}$$

where F_t is the total radiative forcing and F_t^{EX} is the exogenous radiative forcing increasing at a rate f per unit of time, given by

$$F_t^{EX} = F_{t-1}^{EX} + f \tag{22}$$

$$T_t^{AT} = T_{t-1}^{AT} + \xi_1\{F_t - \xi_2 T_{t-1}^{AT} - \xi_3[T_{t-1}^{AT} - T_{t-1}^{LO}]\}, \tag{23}$$

where T_t^{LO} is the temperature of the lower oceans.

$$T_t^{LO} = T_{t-1}^{LO} + \xi_4[T_{t-1}^{AT} - T_{t-1}^{LO}] \tag{24}$$

To run the carbon cycle model, we use the following initial conditions and parameters:

$M_0^{AT} = 3120$, $M_0^{UP} = 5628.8$, $M_0^{LO} = 36706.7$, $F_0^{EX} = 0.28$, $T_0^{AT} = 1$, $T_0^{LO} = 0.0068$, $Stock_0^E = 1730$, $f = 0.005$, $\eta = 3.8$, $\xi_1 = 0.027$, $\xi_2 = \eta/3$, $\xi_3 = 0.018$, $\xi_4 = 0.005$, $\phi_1 1 = 0.9817$, $\phi_2 1 = 0.0080$, $\phi_1 2 = 0.0183$, $\phi_2 2 = 0.9915$, $\phi_2 3 = 0.0005$, $\phi_3 2 = 0.0001$, $\phi_3 3 = 0.9999$, $M_p^{AT} = 2156.2$.

Estimation results for parameter values

The dependent variable is the yearly growth rate of GHG emissions. The first column estimates the equation without a constant to demonstrate its insignificance, as discussed above.The second column estimates equation (9).

Table 1: Estimating α

	(1)	(2)
Relative Participation (t-1)	-0.014**	-0.022***
	(0.006)	(0.003)
Constant	0.008	
	(0.005)	
R^2	0.042	0.511
N	70	70

Notes: Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To estimate β_x, β_e , μ, we estimate equation (12) using country level panel data. π_t^i is a dummy variable that equals 1 if a country adopts a mitigation law in a given year and 0 if it doesn't adopt a law using the Climate Change Laws Database . x_t is constructed using the method above and E_t is the global level of net GHG in billion metric tons of C02 equivalent using the Our World In Data dataset. This panel regression is estimated using a logit random effects panel estimator, given that the dependent variable is binary and the constant needs to be estimated (which a fixed effects estimator does not allow for). The regressions are estimated on data from 1980 to 2019. (**??**).

Data and summary statistics

Table (3) sets out an overview of all the data used in these estimations and the introductory empirical motivation for the paper. Table (4) presents the summary statistics for the regressions to estimate α. Table (5) presents the summary statistics for the other regression estimation.

The parameter values are:

- $\alpha = 0.02$
- $\beta_x = 1.1$

Table 2: Estimating β_x, β_e , ϵ_t^i

	(1)
Relative Participation (t)	1.104**
	(0.542)
Net Emissions (t)	0.177***
	(0.029)
Idiosyncratic Factors (t)	-9.777***
	(1.591)
N	7772

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Data sources

Name	Source
Vulnerability to climate damages	ND-GAIN Country Index
GDP per capita	World Bank in current USD
Fossil fuels rents/GDP	World Bank
Control of corruption index	Worldwide Governance Indicators
Relative number of mitigation laws x_t	Climate Change Laws Database
Signatures of key climate deals (% in each region)	Tenreyro and de Silva (2021)
Annual GHG emissions in CO2 equivalents GHG	Our World In Data

- $\beta_e = 0.18$
- $\mu = 9.77$

Table 4: Summary statistics for equation 2

	mean	p50	min	max	sd
Growth rate of Emissions (t)	.018688	.0179086	-.0436626	.0787522	.0188763
Relative Participation (t)	-.8220485	-.9899498	-1	-.1	.2868757
Observations	70				

Table 5: Summary statistics for equation 3

	mean	p50	min	max	sd
Payoffs	.1556557	0	0	1	.3625513
Relative Participation	-.6886887	-.81	-1	-.1	.3183948
Net Emissions	42.24234	40.54943	32.15487	53.5514	6.795554
Observations	7992				

Proofs

Proposition 1

Note that $\hat{E}_{t+1} = 0$ for $x_t = 0$ or $E_t = 0$.

(i) If $x_t = x_{t+1} = 0$, then $\frac{e^{\gamma(\beta_e - \mu)} - 1}{1 + e^{\gamma(\beta_e - \mu)}} = 0$ for $E = \frac{\mu}{\beta_e}$.

(ii) Note that $-1 < \frac{e^{\gamma(\beta_x x - \mu)} - 1}{1 + e^{\gamma(\beta_x x - \mu)}} < 1$ is increasing in $x \in [-1, 1]$. From continuity and Bolzano's theorem there exists a $x' \in (-1, 1)$: $\frac{e^{\gamma(\beta_x x' - \mu)} - 1}{1 + e^{\gamma(\beta_x x' - \mu)}} = x'$. Note that $\frac{e^{-\gamma\mu} - 1}{1 + e^{-\gamma mu}} > 0$ for $\mu < 0$ and $\frac{e^{-\gamma\mu} - 1}{1 + e^{-\gamma mu}} < 0$ for $\mu > 0$. This implies that $x' > 0$ for $\mu < 0$ and $x' < 0$ for $\mu > 0$.

Proposition 2

Writing the evolution of E_t as

$$E_{t+1} = E_t - E_t \alpha x_t$$

the general form of the Jacobian of (9) and (15) is given by

$$J(E_t, x_t) = \begin{bmatrix} 1 - \alpha x_t & -\alpha E_t \\ 2\gamma\beta_e e^{\gamma(\beta_x x_t + \beta_e E_t - \mu)} / (1 + e^{\gamma(\beta_x x_t + \beta_e E_t - \mu)})^2 & 2\gamma\beta_x e^{\gamma(\beta_x x_t + \beta_e E_t - \mu)} / (1 + e^{\gamma\beta(\beta_x x_t + \beta_e E_t - \mu)})^2 \end{bmatrix}$$

At $(E,x) = (\frac{\mu}{\beta_e}, 0)$, $e^{\gamma(\beta_x x_t + \beta_e E_t - \mu)} = e^0 = 1$ the Jacobian becomes

$$J(\frac{\mu}{\beta_e}, 0) = \begin{bmatrix} 1 & -\frac{\alpha\mu}{\beta_e} \\ \gamma\beta_e/2 & \gamma\beta_x/2 \end{bmatrix}$$

with

$$Tr(J) = 1 + \gamma\beta_x/2 > 0$$

and

$$Det(J) = \gamma\beta_x/2 + \alpha\mu\gamma/2$$

For stability $|Tr(J)| < |Det(J)| + 1 < 2$, or

1. $1 + Tr(J) + Det(J) > 0$
2. $1 - Tr(J) + Det(J) > 0$
3. $Det(J) < 1$,

As $Tr(J) > 0$, the first condition is redundant as if the second holds, so will the first. The second condition implies that $1 + Det(J) > Tr(J)$, or

$$1 + \gamma\beta_x/2 + \alpha\mu\gamma/2 > \gamma\beta_x/2 + 1$$

or

$$\alpha\mu\gamma/2 > 0$$

which is true only if $\mu > 0$. The third condition requires

$$\gamma\beta_x/2 + \alpha\mu\gamma/2 < 1$$

or

$$\gamma\beta_x + \alpha\mu\gamma < 2$$

or

$$\gamma(\beta_x + \alpha\mu) < 2$$

For $\mu > 0$, the stability condition is

$$\gamma < \frac{2}{\beta_x + \alpha\mu}$$

The equilibrium is spiral node if for $\gamma < \frac{2}{\beta_x+\alpha\mu}$, also $Tr^2 < 4Det$. The last is true when

$$(1 + \gamma\beta_x/2)^2 < 2\gamma\beta_x + 2\alpha\mu\gamma,$$

or

$$(1 - \gamma\beta_x/2)^2 < 2\alpha\mu\gamma,$$

or

$$1 - \gamma(\beta_x + 2\alpha\mu) + (\gamma\beta_x)^2/4 < 0$$

which implies that γ should be between the solutions of the above, which are given by

$$\gamma = \frac{2\left(\beta_x + 2\alpha\mu \pm \sqrt{(\beta_x + 2\alpha\mu)^2 - \beta_x^2}\right)}{\beta_x^2} \tag{25}$$

or

$$\gamma = \frac{2\left(\beta_x + 2\alpha\mu \pm \sqrt{4\alpha\mu(\beta_x + \alpha\mu)}\right)}{\beta_x^2}$$

We need to prove that given that $\gamma < \frac{2}{\beta_x+\alpha\mu}$ the following should also hold:

1.
$$\frac{2}{\beta_x + \alpha\mu} < \frac{2\left(\beta_x + 2\alpha\mu + 2\sqrt{\alpha\mu(\beta_x + \alpha\mu)}\right)}{\beta_x^2}$$

   or

$$\frac{1}{\beta_x + \alpha\mu} < \frac{\beta_x + 2\alpha\mu + 2\sqrt{\alpha\mu(\beta_x + \alpha\mu)}}{\beta_x^2}$$

   or

$$\beta_x^2 < (\beta_x + \alpha\mu)^2 + 2(\beta_x + \alpha\mu)\sqrt{\alpha\mu(\beta_x + \alpha\mu)} + \alpha\mu(\beta_x + \alpha\mu)$$

which is always true.

2.

$$\beta_x^2 > (\beta_x + \alpha\mu)^2 - 2(\beta_x + \alpha\mu)\sqrt{\alpha\mu(\beta_x + \alpha\mu)} + \alpha\mu(\beta_x + \alpha\mu)$$

or

$$3\beta_x\alpha\mu + 2(\alpha\mu)^2 - 2(\beta_x + \alpha\mu)\sqrt{\alpha\mu(\beta_x + \alpha\mu)} < 0$$

or

$$4(\beta_x + \alpha\mu)^2[\alpha\mu\beta_x + (\alpha\mu)^2] > [3\beta_x\alpha\mu + 2(\alpha\mu)^2]^2$$

or

$$4(\beta_x + \alpha\mu)^2 > 3\beta_x\alpha\mu + 2(\alpha\mu)^2$$

or

$$4\beta_x^2 + 8\beta_x\alpha\mu + 4(\alpha\mu)^2 > 3\beta_x\alpha\mu + 2(\alpha\mu)^2$$

or

$$4\beta_x^2 + 5\beta_x\alpha\mu + 2(\alpha\mu)^2 > 0$$

which is true.

□

Proposition 3

For $E = 0$, we consider two cases regarding μ:

First case: $\mu > 0$

In this case the midpoint ($x' = \frac{\mu}{\beta_x}$) of the sigmoid $F(x) = \frac{e^{\gamma(\beta_x x - \mu)} - 1}{1 + e^{\gamma(\beta_x x' - \mu)}}$ is positive which implies that if there exist three equilibria, two of these will be for $x' > 0$. Consider two further cases:

- $\mu > \beta_x$. In this case $x = F(x)$ only for some $x' < 0$, hence only one equilibrium can exist.
- $\mu < \beta_x$. To prove that there exist two values of $x > 0$ for which $x = F(x)$, it is sufficient to prove

that for some $x > 0$, $F(x) > x$, or

$$\frac{e^{\gamma(\beta_x x' - \mu)} - 1}{1 + e^{\gamma(\beta_x x' - \mu)}} > x. \tag{26}$$

For $x > 0$, after taking the natural logarithms in both sides and some rearrangement, (26) can be equivalently expressed as

$$\gamma\beta_x x > ln(x+1) - \ln(1-x) + \gamma\mu. \tag{27}$$

Note that the RHS of (27) is a strictly increasing and convex function of x, equal to $\gamma\mu$ for $x = 0$. This implies that there exists a value for $\gamma\beta_x$, call this c for which the LHS of (27) is tangent to the RHS of (27). Then for values higher than c, (27) holds. At $\gamma\beta_x = c$ the derivatives of the two sides of the inequality should be equal:

$$c = \frac{1}{1+x} + \frac{1}{1-x}, \tag{28}$$

which after some rearrangement and given that $x > 0$ gives the point at which the two lines are tangent:

$$x = \sqrt{1 - \frac{2}{c}}, \tag{29}$$

which is also the value of x for which

$$\gamma\beta_x x = ln(x+1) - \ln(1-x) + \gamma\mu. \tag{30}$$

Note that as $x > 0$ for (29) to be able to hold,

$$1 > \frac{2}{c}$$

which implies that γ should be such that

$$\gamma > \frac{2}{\beta_x}, \tag{31}$$

which in turn implies that for $\gamma < \frac{2}{\beta_x}$, $F(x)$ crosses x only for $x < 0$.

Substituting $x = \sqrt{1 - \frac{2}{\gamma\beta_x}}$ gives the value of γ given β_x and μ for which $F(x)$ is tangent to x for $x > 0$. Call this value of $\gamma(\beta_x, \mu)$, γ^*. Then γ^* is the solution of

$$\gamma\beta_x\sqrt{1 - \frac{2}{\gamma\beta_x}} = ln\left(1 + \sqrt{1 - \frac{2}{\gamma\beta_x}}\right) - \ln\left(1 - \sqrt{1 - \frac{2}{\gamma\beta_x}}\right) + \gamma\mu. \tag{32}$$

Then for $\gamma > \gamma^* > \frac{2}{\beta_x}$, there exist three values of x, (two positive and one negative) for which (**??**) holds.

Second case: $\mu < 0$

Here, the midpoint ($x' = \frac{\mu}{\beta_x}$) of the sigmoid $F(x) = \frac{e^{\gamma(\beta_x x - \mu)} - 1}{1 + e^{\gamma(\beta_x x' - \mu)}}$ is negative which implies that if there exist three equilibria, two of these will be for $x' < 0$. Note that in this case μ is always smaller than $\beta_x < 0$. As was the case above, in order for three equilibria to exist, there must be values of $x < 0$ for which

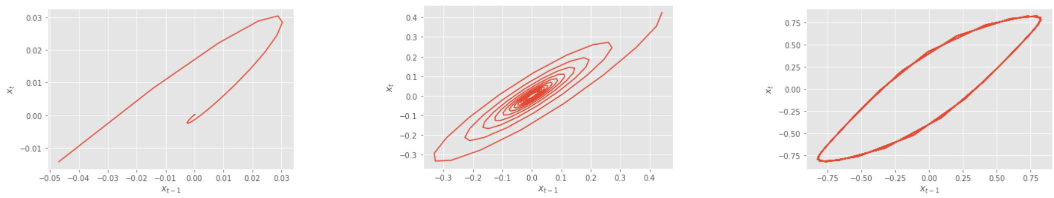
$$\frac{e^{\gamma(\beta_x x - \mu)} - 1}{1 + e^{\gamma(\beta_x x - \mu)}} < x. \tag{33}$$

which is equivalent to (26). Hence for three equilibria to exist we need $\mu < \beta_x$ and $\gamma > \gamma^*$.

□

Phase Plots

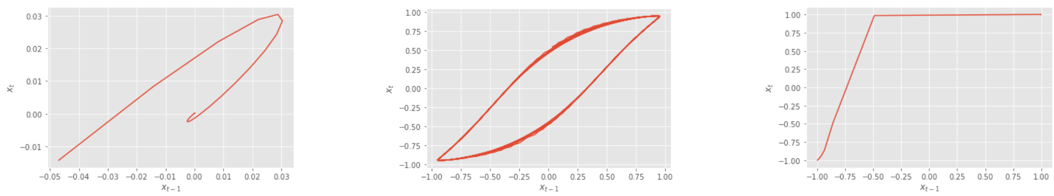
Figure 14: Phase Plot of x_t for different values of γ



(a) $\gamma = 1$ **(b)** $\gamma = 1.5$ **(c)** $\gamma = 2$

Parameters: $E_0 = 36.8$, $x_0 = -0.97$, $\beta_x = 1.1$, $\beta_e = 0.18$, $\alpha = 0.02$, $\mu = 9.77$

Figure 15: Phase Plot of x_t for different values of β_x



(a) $\beta_x = 1.1$ **(b)** $\beta_x = 3$ **(c)** $\beta_x = 15$

Parameters: $E_0 = 36.8$, $x_0 = -0.97$, $\gamma = 1$, $\beta_e = 0.18$, $\alpha = 0.02$, $\mu = 9.77$