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Emerging infectious diseases and the economy: climate change, natural world preservation, and containment policies

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Abstract

Scientific evidence suggests that anthropogenic impacts on the environment such as land use changes and climate change promote the emergence of infectious diseases in humans. We develop a two-region epidemic-economic (epi-econ) model which unifies short-run disease containment policies with long-run policies which could control the drivers and the severity of infectious diseases. We structure our paper by linking a susceptible-infected-susceptible (SIS) model with an economic model which includes land use choices for agriculture and climate change. In the SIS model the contact number depends on short-run containment policies (e.g., lockdown, social distancing, vaccination), and the long-run policies affecting land use and the preservation of the natural world, and climate change. Utility in each region is determined by a composite consumption good produced by labor, land devoted to agriculture, and energy. Climate change and land use changes which reduce the natural world have an additional cost in terms of infectious disease since they might increase the contact number in the long run. We provide a deterministic solution as a benchmark and we compare it with outcomes derived under ambiguity associated with important parameters of the epi-econ model and ambiguity aversion.

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1 Introduction

The COVID-19 crisis represents both a human health emergency and a severe economic and social threat. The economic aspect of the pandemic has been analyzed mainly in terms of ways of controlling the pandemic – lockdowns, social distancing, vaccine development – and the associated benefits and costs of these policies (see, for example, Eichenbaum et al. 2020, Thunström et al. 2020, Berger et al. 2021).

In a more general context, the problem of controlling an infectious disease can be analyzed both in a short-run and a long-run context. The short-run problem is associated with the control and the eventual containment-elimination or even eradication of an epidemic which has already emerged. The long-run problem is associated with the control of factors contributing to the emergence of an infectious disease (ID) and therefore represents a prevention policy aiming at reducing the probability of arrival of an ID.

In exploring the mechanisms underlying the emergence of IDs and consequently providing a basis for the design of efficient prevention policy, the anthropogenic impact has been identified as an important factor. Scientific evidence suggests that the total number and diversity of outbreaks and richness of IDs have increased significantly since 1980 (Smith et al. 2014). Jane Goodall (2020, p. 1):

> "...blamed the emergence of Covid-19 on the over-exploitation of the natural world, which has seen forests cut down, species made extinct and natural habitats destroyed. The coronavirus is thought to have made the jump from animals to humans late last year, possibly originating in a meat market in Wuhan, China. Intensive farming was also creating a reservoir of animal diseases that would spill over and hurt human society ... ."

ENSIA (2020), in a recent report, attributes the emergence of IDs such as COVID-19 to the destruction of habitats and loss of biodiversity, while Evans et al. (2020, p. 1) point out that:

- Degradation has significantly altered ecological systems worldwide and continues to expand into new areas.
- The majority of emerging ID threats are zoonotic, originate from wildlife, and often cause major social and economic impacts.
- Ecological degradation increases the overall risk of zoonotic disease outbreaks originating from wildlife. The key "ingredients" that accentuate the risk of an emerging ID spillover event are activities (e.g., land conversion, creation of new habitat edges, wildlife trade and consumption, agricultural intensification) in or linked to areas of high biodiversity that elevate contact rates between humans and certain wildlife species.

Almada et al. (2017) stress the need to recognize that the relationship between humanity and natural systems is becoming an urgent global health priority. Watts et al. (2021), in the 2020 report of the LANCET countdown on health and climate change, emphasize that the changing climatic conditions are increasingly suitable for the transmission of numerous IDs, while the recent statement of the LANCET COVID-19 Commission (Lancet 2021, p. 21) points out that:

> "...most known emerging diseases have originated in non-human animals, usually wildlife, and have emerged due to environmental and socioeconomic changes, such as land use change, agricultural expansion, and the wildlife trade."

A recent report on COVID-19 (The Independent Panel for Pandemic Preparedness and Response 2021, p. 19) stresses that:

> "Most of the new pathogens are zoonotic in origin. Driving their increasing emergence are land use and food production practices and population pressure. ... Accelerating tropical deforestation and incursion destroys wildlife health and habitat and speeds interchange between humans, wildlife and domestic animals. The threats to human, animal and environmental health are inextricably linked, and instruments to address them need to include climate change agreements and "30x30" global biodiversity targets."

In the context of associating anthropogenic activities with the emergence of IDs, the contribution of climate change is also significant. Scientific evidence (e.g., Wyns 2020) suggests that infections which are transmitted through water or food, or by vectors such as mosquitoes and ticks, are highly sensitive to weather and climate conditions. The warmer, wetter and more variable conditions resulting from climate change are therefore making it easier to transmit diseases such as malaria, dengue fever, chikungunya, yellow fever, Zika virus, West Nile virus and Lyme disease in many parts of the world. Furthermore, permafrost thaw, caused by climate change, also carries consequences in terms of increased risks of ID outbreaks at the hands of live pathogens liberated from thawed permafrost (Walsh et al. 2018, Meredith et al. 2019).

Nova et al. (2022, section 5) state that:

> "The activities that lead to anthropogenic disturbances of the environment – primarily, climate change, land-use change, urbanization, and global movement of humans, other organisms, and goods – affect societies and ecosystems in ways that favor the emergence of novel infectious diseases in human populations, expansions or shifts of diseases to new geographic regions, or re-emergence of diseases in various places."

They also explicitly provide links between disease transmission and changes in temperature and rainfall as well as between changes in land use and disease incidence. For example, intensification of agriculture and industrial agriculture promotes Aedes-born viruses (e.g., dengue, Zika and yellow fever), Lyme disease and the Hendra virus.

The above discussion makes clear that in order to have efficient management of an emerging ID in both the short and the long run, there is a need for the development of coupled models of the economy and the natural world which will include links associated with the ID reservoirs. This approach parallels the development of coupled models of the economy and climate through the appropriate integrated assessment models (IAMs). Augeraud-Véron et al. (2020) develop such a model in which the reduction of biodiversity increases the probability of emergence of zoonotic IDs. Boppart et al. (2020) propose "epi-econ IAMs" and discuss economic instruments for controlling the epidemic after its emergence.

The discussion regarding emergence of IDs indicates that the disease reservoirs are located mainly in the tropical-subtropical climate zones in the Koepen-Geiger classification system (with the notable exception of permafrost). These climate zones contain hot spots for the natural world in terms of natural habitats, tropical forests, biodiversity. A disease outbreak which might emerge from the anthropogenic pressure on the disease reservoirs and the impact of climate change in these zones, if it occurs, diffuses to the rest of the world through transportation channels. In this paper we will identify the tropical-subtropical zones as region 1 and the temperate-snow zones as region 2. Sachs (2001) points out that agricultural technologies and health conditions are weak in the tropical relative to temperate zone, inducing a development gap. Thus a distinction between the two regions when land use and disease impacts are concerned is relevant.

We consider two stages of analysis. In the first stage, which we call the short run, the outbreak of the ID has occurred. After the outbreak, both regions introduce policies to contain/eliminate the epidemic. Throughout the paper we assume that containment policies in the short run are decided in each region in a non-cooperative way. This assumption draws on the fact that national health policies during the COVID period are decided by an independent national health system based on the specific characteristics of each country and not by a supranational authority. In designing containment policies in the short run, the regions do not consider any anthropogenic impacts (encroachment in the natural world or climate change) on the specific characteristics of the ongoing ID.

In the second stage, which we will call the long run, the regions take into account the evolution of climate change and the encroachment on the natural world by agricultural activities on the specific characteristics related to the transmission of the ID. Changes in land use and encroachment in the natural world are induced mainly by industrial agriculture and by the need, for example, to satisfy the demand in wet markets, or the clearing of tropical forests to satisfy demands for products such as palm oil, meat or soybeans, or the establishment of industrial concentrated animal feeding operations. The long-run policy relates, therefore, to the regulation of land use which directly affects disease reservoirs as well as to the adequate control of temperature increase relative to the preindustrial period through climate policy. In the long run we also assume that the regions commit to decisions about land-use and climate policy that maximize own welfare.[1] This implies that long-run analysis will be conducted in a noncooperative context.

The contribution of our paper consists of developing an epi-econ IAM which unifies disease containment policies which are appropriated when a disease has already occurred with long-run policies which could control the drivers and the severity of IDs. We structure our paper by linking a susceptible-infected-susceptible (SIS) model (e.g., Hethcote 1989, 2000) with an economic model which includes land-use choices for agriculture and climate change.

In the SIS model, the contact number – which is the average number of adequate contacts (with both susceptibles and others) of an infective during the infectious period – is not a fixed number as is standard in epidemiological models, but rather depends on policy parameters which in the short run could be containment policies (e.g., lockdown, social distancing, vaccination), and the long-run policies affecting land use and the preservation of the natural world, and climate change. For the economy part, utility in each region is determined by a composite consumption good produced by labor, land devoted to agriculture, and energy. Climate change induced by energy use not only harms the composite consumption good but has an additional cost in terms of ID since it might increase the contact number in the long run. Reduction of the natural world through changes in land use to expand agriculture also has a disease-cost in terms of the long-run contact number.

Given the high uncertainty associated with structure and the parametrization of such a model, we provide a deterministic solution as a benchmark and we compare it with outcomes derived under ambiguity associated with important parameters of the epi-econ model and ambiguity aversion.

2 An SIS model with containment

We follow Hethcote (1989) in considering a simple two-region SIS model, with regions indexed by $i = 1, 2$ for Tropics and Temperate zones respectively. In the SIS model, infection does not confer immunity and individuals return to the susceptible class when they recover from infection. Since

[1] Note that in the implementation of the Paris accord, countries commit to carbon emissions paths. It is reasonable to assume that these paths are decided with reference to own welfare.

naturally-occurring births or deaths do not affect the behavior of the solution, we exclude them from the model for the sake of simplicity. Let susceptibles be denoted by S and the infective by I. Then the simple SIS model in terms of fractions of the total population can be written, in discrete time, as:

$$\dot{S}_i(t) = -\lambda_i(t) I_i(t) S_i(t) + \gamma_i I(t) \ , \ S(0) > 0 \tag{1}$$

$$\dot{I}_i(t) = \lambda_i(t) I_i(t) S_i(t) - \gamma_i I_i(t) \ , \ I_i(0) > 0 \tag{2}$$

$$I_i(t) + S_i(t) = 1 \ , \ i = 1, 2, \tag{3}$$

where $\lambda_i(t)$ is the regional contact rate, γ_i is the recovery or removal rate, and $\sigma_i(t) = \lambda_i(t)/\gamma$ is the regional contact number. From (3), the dynamic system can be written as

$$\begin{aligned} \dot{I}_i(t) &= \lambda_i(t) I_i(t)[1 - I_i(t)] - \gamma I_i(t) = \gamma I_i(t)\left[\frac{\lambda_i(t)(1 - I_i(t))}{\gamma} - 1\right] \\ \dot{I}_i(t) &= \gamma I(t)[\sigma_i(t)(1 - I_i(t)) - 1]. \end{aligned} \tag{4}$$

From Hethcote (1989, theorem 4.1) we know that the solution for $S_i(t)$ approaches $1/\sigma_i(t)$ as $t \to \infty$ if $\sigma_i > 1$ and approaches 1 as $t \to \infty$ if $\sigma_{it} \leq 1$. In the context of an infinite-time planning horizon, the containment policy for an emerging ID takes place within a relatively small period of time. This implies that the SIS dynamics can be regarded as operating in fast time and the SIS system relaxes to the steady state $I_i(t) = 1 - 1/\sigma_i(t)$ or $S_i(t) \equiv 1/\sigma_i(t)$ for any point in time. The contact number $\sigma_i(t)$ is the threshold quantity with the critical threshold value 1. We consider a time dependent contact number $\sigma_i(t)$ since it could refer to different emerging IDs at different points in time, or change over time in response to policies.

It is natural to assume that short-run containment and long-run prevention policies will target the contact number σ. The containment policies adopted for the COVID-19 pandemic included policies such as lockdowns, social distancing, quarantine and vaccination. In further specifying the contact number, we assume costly containment such as vaccination will reduce the contact number, and that the output-producing labor force includes workers who are asymptomatic in the sense that, although infected, they do not have symptoms that require treatment, so they are neither in the infected class nor in quarantine but they can spread the disease and increase the contact number. The fraction of susceptible individuals should be increasing both in short-run containment policies once the disease emerges, but also in long-term prevention policies.

2.1 Coupling the epidemic model with the economy

Let $R(t))$ represent the natural world. In the sense of Goodall (2020), the natural world includes the viral-host reservoir. Human encroachment and destruction of the natural world emerges through changes in land use due to land-intensive agriculture, L_{LI}, and hydroponic/greenhouse high energy intensity agriculture, L_H. The two agricultural technologies introduce a trade-off between output production and ID emergence. Land-intensive agriculture will reduce the natural world, while high energy agriculture might increase emissions of greenhouse gasses (GHGs). These effects might increases the transmission of IDs.[2] Let R in each region $i = 1, 2$ be defined as:

$$R_i(t) = \bar{L}_i(t) - L_{i,LI}(t) - L_{i,H}(t) \ , R_i(t) \geq 0, \tag{5}$$

where $\bar{L}_i(t)$ represents aggregate land availability in each region. Reduction of R, as agricultural activities expand, indicates a reduction in the "distance" between human activities and disease reservoirs.

In considering the impact of climate change, we assume that energy production by fossil fuels generates emissions of GHGs. Let $X(t)$ denote the stock of GHGs at time t relative to the preindustrial period with temporal evolution according to:

$$\dot{X}(t) = E_1(t) + E_2(t) - dX(t) \ , X(0) = X_{preindustrial}, \tag{6}$$

where $E_i(t)$ denotes emissions of GHGs from each region and d is a small GHG depreciation parameter. The accumulation of GHGs increases global average temperature relative to the preindustrial level (the temperature anomaly). Using Matthews et al.'s (2009) approximation with Λ_i representing the regional transient climate response to cumulative carbon emissions (RTCRE)(Leduc et al. 2016), the temperature anomaly in each region can

[2]Restoration activities, such as reforestation, REDD+ policies and payments for ecosystem services, could increase R and reduce the probability of emergence. We do not include such activities in order to simplify the model.

be defined as

$$T_i\left(t\right)=\Lambda_i X\left(t\right). \tag{7}$$

To incorporate the impacts of disease reservoirs and climate change in the evolution of the ID, we assume that once the disease emerges, the speed of the evolution of the infection could be variable, so we write (4) as:

$$\epsilon \dot{S}_i\left(t\right)=\left(1-S_i\left(t\right)\right)\left[\lambda_i(t)S_i(t)-\gamma\right],$$

where ϵ is a small positive parameter. To provide a clear picture of a short-run containment policy, when both the land allocation and the regional temperature are for all practical purposes fixed, we assume that $\epsilon \to 0$ so that when the infection emerges it relaxes fast to a steady state in which the fraction of susceptibles is determined as:

$$\begin{aligned} S_i\left(t\right)) &\equiv \frac{1}{\sigma_i\left(t\right))}= \\ & \phi_{0i}\left(R_i(t),T_i(t)\right)+\phi_{1i}\left[b_i v\left(t\right))-m_i S_i\left(t\right))-q_j\left(1-S_{jt}\right)\right] \end{aligned} \tag{8}$$

$$I_j(t) = 1-\frac{1}{\sigma_j(t)}\ ,\ i,j=1,2,\ i\neq j. \tag{9}$$

In (8), ϕ_{0i} is the part of the contact rate $\lambda_i(t)$ (and contact number $\sigma_i(t)$) which is exogenous relative to short-run containment policies. Its value is determined by the current state of the natural world in the regions $R(t)=(R_1(t),R_2(t))$, which includes the disease reservoirs, along with the current temperature anomaly. In the long run, encroachment in the natural environment due to changes in land use and agricultural expansion – which "reduces" the natural world – along with global warming increase the contact number. We assume, therefore,

$$\phi_{0i}\left(R_i(t),T_i(t)\right)=\phi_{0iR}(R_i(t))+\phi_{0iT}(T_i(t))\geq 0, \tag{10}$$

where $\phi_{0iR}(R_1(t)),\phi_{0iT}(T(t))$ are convex decreasing, concave increasing respectively. The function is decreasing in R since it is assumed that augmenting the natural world (i.e., reducing the relative size of the disease reservoirs and increasing their distance from human activities) reduces the contact number of any specific epidemic, while global warming increases the contact number.

On the other hand, ϕ_{1i} characterizes the effectiveness of the containment policy in each region. In the short run, containment effort $v_i(t))$ reduces the contact number $\lambda_i(t))$, with effectiveness b_i and convex costs $c_i(v_i(t))$. The contact number increases by the potential spread of the disease by asymptomatic susceptible workers at the rate $m_i \geq 0$. We assume no migration between regions,[3] but individuals from one region can make short visits to the other by regular means of transportation (e.g., airplanes, ships). Infected individuals from region j traveling to region i infect individuals in region i proportional to those infected in region j and vice versa, with proportionalities (q_j, q_i) respectively.

To link the economy with the epidemic model we introduce a composite good $C_i(t)$. This good is produced by labor, energy and land devoted to land-intensive or hydroponic/greenhouse agriculture.[4]

Labor is offered by susceptible individuals – who are not contained because of lockdowns – and is allocated among the non-agricultural part of the composite, and the land-intensive and hydroponic agricultural parts. Costs related to energy, $c_{j,E,i}$, containment of the epidemic, c_{vi}, and climate damages, ω_i, fractionally lower the composite good. After dropping t to ease notation, the composite good can be defined as:

$$C_i = \left[\left(l_{c,i}^{\beta_{l,c,i}} E_{ci}^{\beta_{c,E,i}}\right)^{\alpha_{c,i}}\right] \times \left[\left(l_{LI,i}^{\beta_{l,LI,i}} \left(\gamma_{LI,i} L_{LI,i}\right)^{\beta_{L,LI,i}} E_{LI,i}^{\beta_{E,LI,i}}\right)^{\alpha_{LI,i}}\right] \times$$
$$\left[\left(l_{H,i}^{\beta_{l,H,i}} \left(\gamma_{H,i} L_{LI,i}\right)^{\beta_{L,H,i}} E_{H,i}^{\beta_{E,H,i}}\right)^{\alpha_{H,i}}\right] \times$$
$$\exp\left[-\left(\sum_h c_{h,E,i} E_{hi}\right)\right] \times \exp\left[-c_{vi}(v_i^2/2\right] \times \exp\left(-\omega_i T_i^2/2\right) \tag{11}$$

$$S_i = l_{c,i} + l_{LI,i} + l_{H,i} \ , \ i = 1, 2 \tag{12}$$

$$R_i = \bar{L}_i - L_{LI,i} - L_{H,i}. \tag{13}$$

Let the utility function in each region be

$$U_i(t) = \log C_i(t) + \psi_i \log R_i \ , \ \psi_i \geq 0, \tag{14}$$

where the term $\psi_i \log R_i$ captures potential concave existence values in each region for the part of the natural world not used for human activities.[5]

[3] Considering the possibility of infections from large scale migration flows between the two regions is beyond the scope of this paper, but it is an interesting area for further research.

[4] To simplify the model, we do not include capital formation.

[5] REDD+ activities can be introduced by adding a term RD for REDD+ to the right

We study the optimal management of the epi-econ model in the context of two different time frames. In the first – the short-term management – the epidemic has emerged and the objective is to choose containment control, labor allocation and energy use to maximize discounted utility. In this time horizon the regional natural world and temperature anomaly (R_i, T_i) are considered as fixed, since their evolution is slow relative to the the evolution of the pandemic and the primary objective is the containment of the pandemic. In this time frame, the short-term optimal controls depend parametrically on (R_i, T_i).

In the second – the long-term management – it is assumed that the epidemic, which is the fast system, has been optimized and relaxed to a steady state which depends parametrically on the natural world R_i and the evolution of regional temperature T_i which is slow relative to the evolution of the epidemic. As (R_i, T_i) evolve, the optimal controls for the management of the epidemic system also evolve. The relation between the epidemic system and the natural world is reflected in (10), which is the policy-independent – in the short-run – component of the contact number.

For reasons explained in the introduction, we focus on non-cooperative solutions in which each region maximizes own welfare. For a social optimization management problem, a social planner would maximize global welfare defined as

$$W = \log\left(C_1^w C_2^{1-w}\right). \tag{15}$$

3 Short-run disease containment

We study the optimal containment problem in regions $i = 1, 2$ once the epidemic has emerged. In this case the planners take the natural world $R_i(t)$ and the temperature anomaly $T_i(t)$ as exogenous, and decide about the containment policy $v_i(t)$, along with labor allocation and energy use. Thus the controls for the short-run problem are $u_i = (l_{c,i}, E_{c,i}, l_{LI,i}E_{Li,i}, l_{H,i}, E_{H,i}, v_i)$. The solution concept for containment policy will be a non-cooperative Nash equilibrium solution in which the region's planner maximizes own regional welfare taking the actions of the other region as given. Given that during the COVID pandemic, countries have been designing containment policies

hand side of (13) and including a cost for these activities which fractionally reduces the composite good.

mainly unilaterally though their own health systems, the Nash equilibrium concept might be a more realistic representation.

3.1 Non-cooperative solutions

Assuming that the objective is to contain and/or eliminate the epidemic, then the short-run time problem with fixed R_i, dropping t to ease notation, is:

$$\max_{u_i} \log C_i(t) \tag{16}$$

subject to

$$S_i(t) = l_{c,i} + l_{LI,i} + l_{H,i} \tag{17}$$

$$\hat{S}_i(t) = \bar{\varphi}_{0i} + \varphi_{1i}\left[b_i v_i - q_j\left(1 - S_j\right)\right] \tag{18}$$

$$S_i(t) = \min\left\{\hat{S}_i, 1\right\} \tag{19}$$

$$\bar{\varphi}_{0i} = \frac{\bar{\phi}_{0i}}{1 + \varphi_{1i} m_i}, \varphi_{1i} = \frac{\phi_{1i}}{1 + \varphi_{1i} m_i}, \tag{20}$$

with $\bar{\varphi}_{0i}$ being the part of the contact number which is independent of short-term policies.

The optimality conditions for problem (16), in which infections I_{jt} in region j are taken as given, imply that:

$$v_i^* = \frac{\zeta_i \varphi_{1i} b_i}{c_{vi}} \tag{21}$$

$$\frac{a_{c,i}\beta_{l,c,i}}{l_{c,i}^*} = \frac{a_{Li,i}\beta_{l,LI,i}}{l_{LI,i}^*} = \frac{a_{H,i}\beta_{l,H,i}}{l_{H,i}^*} = \zeta_i \tag{22}$$

$$\frac{a_{c,i}\beta_{c,E,i}}{E_{c,i}^*} = \frac{a_{LI,i}\beta_{LI,E,i}}{E_{LI,i}^*} = \frac{a_{H,i}\beta_{H,E,i}}{E_{H,i}^*} = c_{E_i}, \tag{23}$$

where ζ_i is the Lagrangian multiplier associated with constraint (18) and c_{E_i} is the common marginal cost of energy for all uses. Containment policy v_i (e.g., vaccinations) is positive as long as its effectiveness is positive. Condition (22) indicates that the optimal labor allocation across the three possible land uses implies equalization of marginal products, while (23) indicates that, at the regional optimum, the marginal cost of energy equals regional marginal costs. Substituting (22) into (17) and solving for ζ_i we obtain:

$$v_i^* = \left(\frac{\varphi_{1i} b_i}{c_{v_i}}\right)\left(\frac{B_i}{S_i}\right), \; B_i = a_{c,i}\beta_{l,c,i} + a_{Li,i}\beta_{l,LI,i} + a_{H,i}\beta_{l,H,i}\,, \; \zeta_i = \frac{B_i}{S_i}, \quad (24)$$

where B_i can be interpreted as an indicator of average labor productivity in each region.

Substituting conditions (21) and (22) into (18), we obtain the best response (or reaction) function of each region to the susceptibles of the other. The best response functions are nonlinear of the form

$$S_i(t) = \Omega_i(t) + \varphi_{1i} q_j S_j(t), i, j = 1, 2, i \neq j \quad (25)$$

$$\Omega_i(t) = \bar{\varphi}_{0i} + \varphi_{1i} \left[b_i v_i^* - q_j\right]. \quad (26)$$

A Nash equilibrium solution for the two regions will exist if the system (25) has a solution in $(0, 1]$. In this case, the susceptibles (i.e., non-infected in each region) act as strategic complements, so the containment effect in one region will help the other region. This is shown in figure 1.

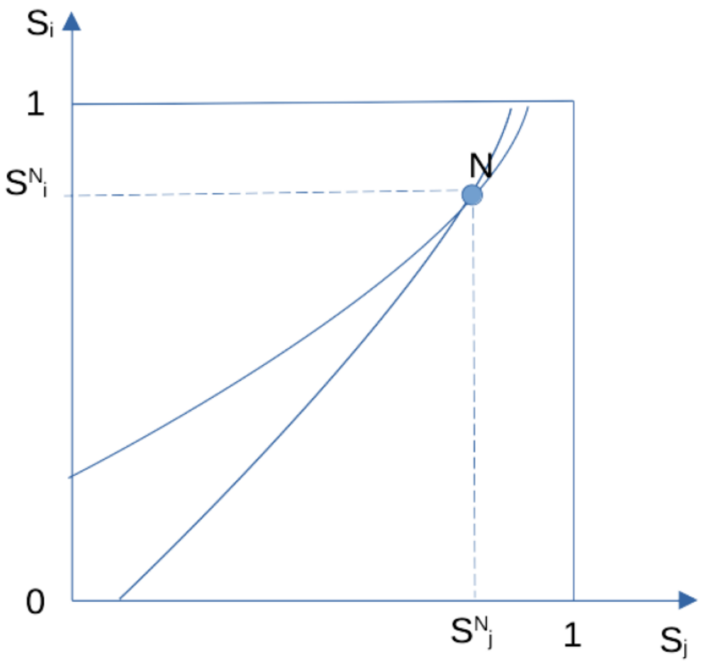

Figure 1: Nash equilibrium

If a Nash equilibrium solution exists, then from the definition of ζ_i in (24) and (21), labor allocation is a function of the equilibrium level of susceptibles

$\left(S_1^N, S_2^N\right)$.

Another way of looking at the short-run solution is to assume that both regions' objective is to eliminate the disease and seek control instruments $\hat{u}_i$ such that $S_i(t) = S_j(t) = 1$. The disease-eliminating instruments are obtained using (24) for $S_i(t) = S_j(t) = 1$.

Finally, we can explore the question of what is the minimum size, $\hat{R}_i$, for the natural world so that a disease, if it emerges, will not spread because the contact number is below 1 (i.e., $\sigma_i(t) < 1$, $i = 1, 2$). In such a case, no containment is required and $v_{it}^* = 0$. Using (18) and setting $S_i(t) = S_j(t) = 1$, $\hat{R} = \widehat{\left(R_1, \hat{R}_2\right)}$ can be defined, for any given temperature anomaly, as

$$\hat{R} = \left\{ \min_{(R_i, R_2)} : \left(\bar{\varphi}_{01}\left(R_1(t), ; T_i(t)\right), \bar{\varphi}_{01}\left(R_2(t); T_2(t)\right)\right) > (1, 1) \text{ for all } t \right\}.$$

We will call these values the Goodall thresholds. If $R_i(t) < \hat{R}_i$ for some time t, an emerging ID will spread in at least one of the two regions and may invade the second region through transport. The containment of the disease in this case requires costly interventions.

3.2 A cooperative solution

The cooperative solution corresponds to the case in which a social planner decides containment policy for both regions by maximizing an unweighted sum of regional utilities. The problem is therefore

$$\max_u \left\{ W = w \log C_1 + (1 - w) \log C_2 \right\}, \tag{27}$$
$$\text{subject to the relevant constraints for } i, j = 1, 2, i \neq j.$$

The optimality conditions, dropping t when appropriate to ease notation, imply:

$$v_i^C(t) \quad : \quad w\left(\frac{\partial C_i}{\partial v_i}\right) + (1 - w)\left(\frac{\partial C_j}{\partial v_i}\right) = 0, \; \frac{\partial C_j}{\partial v_i} = \frac{\partial C_j}{\partial S_i}\frac{\partial S_i}{\partial v_i} \tag{28}$$

$$v_i^C(t) \quad = \quad w v_i^* + (1 - w)\left(\varphi_{1i}\varphi_{1j} b_i q_i\right)\frac{B_j}{S_j}. \tag{29}$$

4 Containment policy in the short run under aversion to ambiguity and model misspecification

A major issue in the design of containment policies is uncertainty regarding certain crucial parameters of the epi-econ model and concerns about misspecification of the model. Following Hansen and Miao (2018), we explore the implications of aversion to ambiguity and concerns regarding possible misspecifications of the epi-econ model from the regulators' point of view.

4.1 Robustness and entropy penalization

Assume that a parameter ν of the epi-econ model, such as b_i, u_i, φ_{0i}, or φ_{1i}, $i = 1, 2$, has a prior density π, with $\nu \in \mathcal{V}$. In the context of Hansen and Miao's (2018) approach to ambiguity and model misspecification aversion, the regulator solves the problem:

$$\max_{u_i(t)} \min_{\pi} \int_{\mathcal{V}} U_i\left(C_i; \nu\right) \pi\left(\nu\right) d\nu + \kappa_i \int_{\mathcal{V}} \left[\log \pi\left(\nu\right) - \log \hat{\pi}\left(\nu\right)\right] \pi\left(\nu\right) d\nu, \quad (30)$$

where $u_i = (l_{c,i}, E_{c,i}, l_{LI,i}E_{Li,i}, l_{H,i}, E_{H,i}, v_i)$. In (30), aversion to ambiguity and model misspecification is modeled by introducing a fictitious adversarial or minimizing agent (MA) who distorts the baseline prior density of an uncertain parameter, in order to impose a cost on the regulator who is the maximizing agent. This cost reflects the impact of aversion to uncertainty and model misspecification. By designing regulation based on (30), the regulator derives a decision rule which incorporates this aversion.

In (30), $\hat{\pi}\left(\nu\right)$ is the baseline density for the parameter ν,and $\kappa > 0$ is a parameter which penalizes deviations from the baseline density $\hat{\pi}\left(\nu\right)$ with $\int_{\mathcal{V}} \left[\log \pi\left(\nu\right) - \log \hat{\pi}\left(\nu\right)\right] \pi\left(\nu\right) d\nu$ being the relative entropy discrepancy from the baseline density. For $\kappa \to \infty$, the regulator is committed to the baseline density, which can be interpreted as the case in which, when the cost of distorting the prior to the MA is infinite, then decision making is based on the baseline. As $\kappa \to 0$, the distortion tends to the worst case prior. In problem (30), the regulator maximizes utility using the controls of the epi-econ model, while "Nature", acting the MA, distorts the baseline prior density of parameters associated with the controls. The regulator is concerned about the distortion of the prior of the epi-econ model parameters and follows robust control regulation. The solution of the minimization part of problem (30) is given by (see Hansen and Miao 2018):

$$\pi^*(\nu) = \frac{\exp\left[-\frac{1}{\kappa}U_i(C_i;\nu)\hat{\pi}(\nu)\right]}{\int_{\mathcal{V}}\exp\left[-\frac{1}{\kappa}U_i(C_i;\nu)\hat{\pi}(\nu)\right]d\nu}. \tag{31}$$

Substituting $\pi^*(\nu)$ into (30), the objective to be maximized by the regulator becomes

$$J_i = \max_{u_i(t)}\left\{-\kappa\log\int_{\mathcal{V}}\exp\left[-\frac{1}{\kappa}U_i(C_i;\nu)\hat{\pi}(\nu)\right]d\nu\right\}. \tag{32}$$

We set $\theta = 1/\kappa$ and interpret θ as the robustness parameter. When $\theta \to 0$ ($\kappa \to \infty$), the regulator optimizes using the baseline prior; when $\theta \to \infty$ ($\kappa \to 0$), the regulator optimizes by taking into account the worst case prior. Expanding (32) around $\theta = 0$ and using the cumulant generation function, we obtain the expansion

$$K_i(\theta,\nu) = \mathbb{E}_{\hat{\pi}}\left[U_i(C_i;\nu)\right] - \frac{\theta}{2}\mathrm{Var}_{\hat{\pi}}\left[U_i(C_i;\nu)\right]. \tag{33}$$

Assume for the stochastic parameter that $\nu \in \mathcal{V} = \left[\underline{\nu},\bar{\nu}\right]$ with mean μ_ν and variance σ_ν^2 in the baseline density. Expanding the $K_i(\theta,\nu)$, we obtain:

$$\mathbb{E}_{\hat{\pi}}\left[U_i(C_i;\nu)\right] \approx U_i(C_i;\mu_\nu) + \frac{U_i''(C_i;\mu_\nu)}{2}\sigma_\nu^2 \tag{34}$$

$$\mathrm{Var}_{\hat{\pi}}\left[U_i(C_i;\nu)\right] \approx \left(U_i'(C_i;\mu_\nu)\right)^2\sigma_\nu^2, \tag{35}$$

where the derivatives are taken with respect to the stochastic parameter ν. Then the maximization problem for the regulator in region i becomes

$$J_i = \max_{u_i(t)}\left\{U_i(C_i;\mu_\nu) + \frac{U_i''(C_i;\mu_\nu)}{2}\sigma_\nu^2 - \frac{\theta}{2}\left(U_i'(C_i;\mu_\nu)\right)^2\sigma_\nu^2\right\}. \tag{36}$$

If we disregard second-order terms, the optimization problem described by (36) suggests that the utility of the decision maker is penalized by a term defined by the marginal utility of a small change in the mean of the ambiguous parameter by the variance of the baseline prior and the robustness parameter θ. When $\theta \to 0$, the decision maker is an expected utility maximizer and uses the baseline prior.

4.2 Regulation under aversion to ambiguity and model misspecification

Keeping regional T_i and R_i fixed, we study the impact of increasing the robustness parameter θ on the optimal choice of controls by comparative statics. Increasing the robustness parameter θ means that regulation takes into account distorted priors which deviate from the baseline and, at the limit as $\theta \to \infty$, they tend to the worst case scenario.

Proposition 1. *Consider the epi-econ model (16) and assume that the parameter b_i, which reflects the effectiveness of the containment control, is uncertain with a baseline prior $\hat{\pi}(b_i)$. Then the Nash equilibrium under ambiguity can be defined, while an increase in the robustness parameter θ will reduce containment policy in region i.*

For the proof, see the Appendix.

Since the ambiguous parameter is on the effectiveness of control efforts against the emerging ID (that is, b_i), if the worst case value of b_i is zero, then when it costs zero for the adversarial agent to harm the regulator through the ambiguous parameter b_i, the best reply of the regulator in the zero sum game is to set $v_i^* = 0$. The intuition is that as θ increases and the aversion of the regulator induces him/her to consider distorted priors regarding the effectiveness or the cost of the containment policy which are worse relative to the baseline, less control is exercised, since its effectiveness tends to zero in the worst case scenario. Since the setup can be generalized to a vector of controls represented by a linear combination of specific controls determining containment policy (that is, $b_i v_i = \sum_{j=1}^{J} b_{ij} v_{ij}$, $i = 1, 2$), Proposition 1 suggests that high aversion to ambiguity regarding the effectiveness of a specific control will reduce the use of this control and will potentially increase the use of other controls which are less ambiguous.

4.3 Strong preferences for robustness and ambiguity-adjusted Nash equilibrium

Optimal containment policies can be obtained by maximizing (70) and using first-order condition (71) for the optimal choice of v. To simplify, assume that the baseline prior for the effectiveness of parameter b_i is a uniform distribution with

$$\begin{aligned} b_i &\in [m_{b_i}, M_{b_i}], m_{b_i} < b_i < M_{b_i} \\ \hat{\mu}_{b_i} &= \frac{m_{b_i} + M_{b_i}}{2}, \hat{\sigma}^2_{b_i} = \frac{(M_{b_i} - m_{b_i})^2}{12}. \end{aligned}$$

Using this assumption in (70) and the moment-generating function of the uniform distribution, we obtain

$$\frac{-1}{\theta} \ln \left(\mathbb{E} \exp \left[(-\theta) \varphi_{1i} b_i v_i \right] \right) =$$
$$\frac{-1}{\theta} \log \left(\frac{\exp \left[(-\theta) \varphi_{1i} \zeta_i M_{b_i} v_i \right] - \exp \left[(-\theta) \varphi_{1i} \zeta_i m_{b_i} v_i \right]}{\theta \varphi_{1i} M_{b_i} v_i - \theta \varphi_{1i} m_{b_i} v_i} \right) = h(\theta, v_i)$$

with

$$\lim_{\theta \to \infty} h(\theta, v_i) = \varphi_{1i} \zeta_i m_{b_i} v_i \ , \ \lim_{\theta \to 0} h(\theta, v_i) = \varphi_{1i} \zeta_i \hat{\mu}_{b_i} v_i.$$

Thus when $\theta \to \infty$, the regulator is infinitely robust and uses the worst case scenario, while when $\theta \to 0$, the regulator uses the baseline prior. With b-ambiguity, the optimal control for the worst case is

$$v_i^{a,w}(t) = \frac{\varphi_i \zeta_i m_{b_i}}{c_i} = \frac{\varphi_i m_{b_i}}{c_i} \frac{B_i}{S_i}. \tag{37}$$

Since $m_{b_i} < \hat{\mu}_{b_i}$, the worst case prior for the policy effectiveness implies less control relative to the baseline prior. Considering the b-ambiguity case, the best response function at a fixed time t is defined as:

$$S_i = \Omega_i^a + q_j S_j, i, j = 1, 2, i \neq j \tag{38}$$
$$\Omega_i^a = \varphi_{0i} \left(\bar{R} \right) + \varphi_{1i} \left[b_i v_i^{a,w} - q_j \right]. \tag{39}$$

Since $v_i^{a,w}$ is less – relative to the deterministic or the baseline case – the impact of increased aversion to ambiguity regarding the effectiveness of containment policies is a shift of the best response function towards the origin in figure 1 which implies an increase in the Nash equilibrium share of infected.

Thus ambiguity regarding the effectiveness of containment measures leads, in a Nash equilibrium, to an increase in the share of infected. The effectiveness of containment measures could be related to technical characteristics such as weak effectiveness of vaccines but also to social characteristics such as opposition to social distancing or vaccination. Reduced vaccinations and opposition to containment measures in parts of the world during the COVID pandemic could suggest increased ambiguity regarding the vaccinations associated with the containment policy v.

Consider now the case where the regulator of a region expresses aversion to ambiguity regarding $\bar{\varphi}_{0i}$, the part of the contact number that does not depend on short-run policies. Then from (70) the regulator's problem for region i can be written as

$$J_i = \max_{u_i(t)} \left\{ \log C_i - \frac{1}{\theta} \ln \left(\mathbb{E} \exp \left[\left(-\theta_i \zeta_i \bar{\varphi}_{0i} \right) \right] \right) \right\}.$$

Assume that the baseline prior for the policy-independent part of the contact number is a uniform distribution with the worst case being $\bar{\varphi}_{0i} = 0$, and parameteres in the following intervals:

$$\begin{aligned} \bar{\varphi}_{0i} &\in [0, M_i], 0 \leq \bar{\varphi}_{0i} \leq M_i \\ \hat{\mu}_i &= \frac{M_i}{2}, \hat{\sigma}_i^2 = \frac{(M_i)^2}{12}. \end{aligned}$$

Then, using the moment-generating function for the uniform distribution,

$$h_i(\theta) = -\frac{1}{\theta} \log \left(\mathbb{E} \exp \left[\left(-\theta \bar{\varphi}_{0i} \right) \right] \right) = -\frac{1}{\theta} \log \left(\frac{\exp \left[(-\theta) \zeta_i M_i \right] - 1}{\theta \zeta_i M_i} \right).$$

If the regulator in region i is infinitely robust, then $\lim_{\theta \to \infty} h(\theta) = 0$. This means that if aversion to ambiguity regarding the effectiveness of the short-run containment measures b_i tends also to infinity and the worst case is associated with $m_{b_i} = 0$, then $v_i^{a,w}(t) = 0$. In this case the the inverse of the contact number

$$\hat{S}_i = \frac{1}{\sigma_i} = \bar{\varphi}_{0i} + \varphi_{1i} \left[b_i v_i - q_j (1 - S_j) \right] \to 0,$$

which implies that at the limit the whole population will be infected in the Nash equilibrium. This observation leads to the following proposition:

Proposition 2. *When the ambiguity of the regulator about the the policy-independent, in the short-run, component of the contact number is very high* $(\theta \to \infty)$, *the only route for reducing the contact number is to reduce ambiguity about the effectiveness of the short-run containment policy. When this short-run ambiguity cannot be reduced for voluntary-based containment* *policies, strong command-and-control policies might be necessary.*

Consider now the case in which in region i, say $i = 2$, the worst cases for $\bar{\varphi}_{02}$ and b_2 imply at the limit that $\hat{S}_2 \to 0$. In this case optimizing region $j = 1$ will not respond to region 2's choices but will unilaterally adopt containment control policies. The optimal containment policy for this region will be:

$$v_j^{a,w} = \frac{\varphi_{1j}\hat{\mu}_{b_j}}{c_j}\frac{B_j}{S_j}.$$

From (38) and (39), setting $\varphi_{01} = 0$, we obtain for $j = 2$:

$$S_j = \varphi_{1j}\frac{\varphi_{1j}\hat{\mu}_{b_j}}{c_j}\frac{B_j}{S_j} \Rightarrow S_j = \sqrt{\frac{\varphi_{1j}^2\hat{\mu}_{b_j}B_j}{c_j}}.$$

This result could explain differences in infection and policy effectiveness across regions observed during the COVID-19 pandemic.

4.3.1 A generalization

To more clearly provide a picture of the non-cooperative equilibrium between the two regions for more general baseline priors, we use approximations (33)-(36) and consider ambiguity in the effectiveness of the containment policy, b_i, $i = 1, 2$. Applying (33)-(36), we consider the problem:

$$J_i = \max_{u_i(t)} \left\{ \log C_i - \frac{\theta}{2}\hat{\sigma}_{b_i}^2 \left(\zeta_i \varphi_{1i} v_i\right)^2 \right\},$$

subject to the constraints of problem (16) where ζ_i is the Lagrangian multiplier of constraint (17). The optimality condition implies

$$v_i^{*a} = \frac{\zeta_i \varphi_{1i}\hat{\mu}_{b_i}}{c_i + \theta_{b_i}\left(\zeta_i^2 \hat{\sigma}_{b_i}\varphi_{1i}\right)^2}, \ \zeta_i = \frac{B_i}{S_i}, \tag{40}$$

where $\hat{\mu}_{b_i}, \hat{\sigma}_{b_i}^2$ are the mean and variance of the baseline prior for ambiguous parameters corresponding to the effectiveness of the containment policy. If we assume that the baseline prior is uniform with $b_i \in [m_{b_i}, M_{b_i}]$, $0 \leq m_{b_i} \leq M_{b_i}$, then (40) can be further simplified by setting $\hat{\mu}_{b_i} = \frac{m_{b_i}+M_{b_i}}{2}, \hat{\sigma}_{b_i}^2 = \frac{\left(M_{b_i}-m_{b_i}\right)^2}{12}$.

Along the lines of Proposition 1, differences across regions in concerns regarding the effectiveness of instruments in reducing the contact number differentiate the optimal values for the containment instruments. The region for which ambiguity about the effectiveness of a costly instrument is stronger will use less of this instrument relative to a region in which ambiguity about the effectiveness of the instrument is relatively smaller. This result can differentiate between containment policies which are based on voluntary behavior versus command-and-control policies. If the effectiveness of command-and-control policy is characterized by less ambiguity, it will be used more relative to voluntary containment policies. Thus ambiguity differentials differentiate the optimal intensity of use of the containment policies and introduce policy trade-offs. Furthermore, in line with the theory, as $\theta \to 0$ the optimal controls are designed on the baseline prior, while if regulation is designed on the basis of the worst case regarding the effectiveness of the control and $\theta \to \infty$, then no control is undertaken.

5 Disease prevention in the long run: climate change and natural world preservation

In the previous section we studied disease containment in the short run by assuming that the disease has already emerged and that the infected-susceptible dynamics move fast towards their steady-state values. In the short run, the allocation of the regional land use among agricultural and human activities, and temperature anomalies (T_1, T_2)), were treated as exogenous parameters. In a long-run perspective, land use can change, while temperature will evolve as a slow variable responding to the use of energy. Changes in land use which might reduce the natural world (R_1, R_2) and bring human activities closer to disease reservoirs, along with an increase in regional average temperatures, will affect the long-run path of the contact rate, φ_{0i}, which is independent of short-term containment.

5.1 Non-cooperative long-run prevention

To study non-cooperative solutions in the long run, we assume that each region takes as given the initial temperature anomaly and commits to the emission path that optimizes own welfare function, given the best response of the other region. The solution of this problem will characterize an open loop Nash equilibrium (OLNE). The consumption flow for the slow time scale problem is obtained by substituting the fast-time (short-run) optimal controls for containment v_i^* into $\hat{S}_i$ and the short-run Nash equilibrium levels of susceptibles S_i^N. Then the control problem for region i in the time scale of the climate change can be written as:

$$J_i^N = \max_{\{u_i(t),R_i(t\}} \int_0^\infty \mathrm{e}^{-\rho t} \left[\log C_i(t) + \psi_i \log R_i(t)\right] dt, \tag{41}$$

subject to (5)-(7) and (17)-(20), with $\rho > 0$ the utility discount rate and controls

$$u_i\left(t\right) = \left(l_{c,i}(t), l_{LI,i}(t), l_{H,i}(t), L_{LI,i}(t), L_{H,i}(t), E_{c,i}(t), E_{LI,i}(t), E_{H,i}(t)\right), R_i(t)\,,\ i = 1, 2.$$

In this optimization problem, after dropping t to ease notation, the following conditions apply:

$$\hat{S}_i = \varphi_{0i}\left(R_i, T_i\right) + \varphi_{1i}\left[b_i v_i^*\left(S_i^N\right) - q_j\left(1 - S_j^N\left(t\right)\right)\right] \tag{42}$$

$$S_i = \min\left\{\hat{S}_i, 1\right\} \tag{43}$$

$$\varphi_{0i}\left(R_i, T_i\right) = \frac{\phi_{it}\left(R_i, T_i\right)}{1 + \phi_{1i} m_i}, \varphi_{1i} = \frac{\phi_i}{1 + \varphi_{1i} m_i} \tag{44}$$

$$\bar{L_i} = R_i + L_{LI,i} + L_{H,i} \tag{45}$$

$$S_i = l_{c,i} + l_{LI,i} + l_{H,i} \tag{46}$$

$$E_i = E_{c,i} + E_{LI,i} + E_{H,i} \tag{47}$$

$$T_i\left(t\right) = \Lambda_i X\left(t\right), \tag{48}$$

where $\varphi_{1i}\left[b_i v_i^*\left(S_i^N\right) - q_j\left(1 - S_j^N\left(t\right)\right)\right] = \bar{\varphi_{1i}}$ is fixed at the solution of the short-run problem and aggregate regional energy or, equivalently, use of GHGs is $E_i = E_{c,i} + E_{LI,i} + E_{H,i}$. Each region takes the action paths of the other region as fixed and solves problem (41). The current value Lagrangian (or generalized Hamiltonian) for the problem is:

$$\begin{aligned} \mathcal{L}_i &= \mathcal{H}_i + \mu_i\left[\bar{L_i} - R_i - L_{LI,i} - L_{H,i}\right] \\ &\quad \kappa_i\left[S_i - l_{c,i} - l_{LI,i} - l_{H,i}\right] \\ \mathcal{H}_i &= \left[\log C_i + \psi_i \log R_i\right] + \lambda_i\left[E_1\left(t\right) + E_2\left(t\right) - dX\right], \end{aligned}$$

where $\mathcal{H}_i$ is the current value Hamiltonian. The Lagrangian multipliers (μ_i, κ_i) should be interpreted as the sensitivity of the optimal solution to changes in the constrained constants $\left(\bar{L}_i, \bar{\varphi_{1i}}\right)$, while the costate variable λ_i has the usual interpretation as the shadow cost of the GHGs accumulation or the regional social cost of carbon (SCC). This is an optimal control problem with mixed constraints and the optimality conditions (e.g., Seierstad and Sydsaeter 1986, chapter 4) can be written as:

$$\frac{a_{c,i}\beta_{l,c,i}}{l_{c,i}} = \frac{a_{LI,i}\beta_{l,LI,i}}{l_{LI,i}} = \frac{a_{H,i}\beta_{l,H,i}}{l_{H,i}} = \kappa_i \tag{49}$$

$$\frac{a_{c,i}\beta_{c,E,i}}{E_{c,i}} = \frac{a_{LI,i}\beta_{LI,E,i}}{E_{LI,i}} = \frac{a_{H,i}\beta_{H,E,i}}{E_{H,i}} = c_{E_i} + \lambda_i \tag{50}$$

$$\frac{a_{LI,i}\beta_{L,LI,i}}{L_{LI,i}} = \frac{a_{H,i}\beta_{L,H,i}}{L_{H,i}} = \mu_i \tag{51}$$

$$\frac{\psi_i}{R_i} + \kappa_i \frac{\partial \varphi_{oi}(R_i, T_i)}{\partial R_i} = \mu_i \tag{52}$$

$$\dot{\lambda}_i = (\rho + d)\,\lambda_i + \omega_i \Lambda_i X - \kappa_i \frac{\partial \varphi_{oi}(R_i, X_i)}{\partial X} \tag{53}$$

$$\dot{X} = E_1^* + E_2^* - dX \tag{54}$$

$$E_i^* = \frac{\Gamma_i}{c_{E_i} + \lambda_i}\,,\ \Gamma_\iota = a_{c,i}\beta_{c,E,i} + a_{LI,i}\beta_{LI,E,i} + a_{H,i}\beta_{H,E,i}. \tag{55}$$

Conditions (49)-(52) characterize demand for inputs $u_i(t)$ and "natural world" R_i as functions of the regional climate change $T_i(t)$ and the SCC $\lambda_i(t)$ along with the regional overall land availability $\bar{L}_i$ and the short-term optimized containment parameter $\bar{\varphi_{1i}}$. Proposition 3 follows directly from the above conditions regarding the overall land allocation among agricultural activities and natural world preservation.

Proposition 3. *Conditions (51) and (52) indicate that the overall land allocation between land-intensive agriculture, L_{LI}, hydroponic/greenhouse high energy intensity agriculture and natural world preservation should be determined such that the marginal product of each type of agriculture and marginal existence values plus the marginal contribution of the natural world to reduction of the contact number are equated. Thus an additional positive externality – over and above existence values – emerges for the natural world. This positive externality which is given by $\kappa_i\left(R_i, T_i; B_i, \bar{\varphi_{1i}}\right)\frac{\partial \varphi_{oi}(R_i,T_i)}{\partial R_i}$ evaluated at $R_i = h_i^R\left(T_i, \mu_i\right), \mu_i = \mu_i\left(T_i; \Delta_i, \bar{L}_i\right)$ should be accounted for in cost-benefit analysis regarding land allocation decisions. This positive externality depends on the evolution of temperature and the labor productivity (B_i) and productivity in agriculture (Δ_i) of the regional economies. The overall* *land allocation between agriculture and preserved natural world depends also on climate change.*

For the proof, see the Appendix.

Given the interpretation of the Lagrangian multipliers (κ_i, μ_i), Proposition 3 makes clear the quantitative link of the natural world's social value, in the context of an emerging ID, with climate change. The path of climate change at the OLNE is determined by the Hamiltonian system (53)-(54).

5.1.1 The OLNE steady state

To study the Hamiltonian system (53)-(54) that determines the OLNE, we first define the optimal controls as functions of the state variable T_i and the costate variable λ_i.

From (50), (51), (52), (49) and Proposition 3, we obtain respectively :

$$E^*_{h,i} = \frac{a_{h,i}\beta_{h,E,i}}{c_{E_i} + \lambda_i}, h = c, LI, H \tag{56}$$

$$L^*_{h.i} = \frac{a_{h,i}\beta_{L,h,i}}{\mu_i\left(T_i; \Delta_i, \bar{L}_i\right)}, h = LI, H \tag{57}$$

$$R^*_i = h^R_i\left(T_i, \mu_i\left(T_i; \Delta_i, \bar{L}_i\right)\right) \tag{58}$$

$$l^*_{h.i} = \frac{a_{h,i}\beta_{l,h,i}}{\kappa_i\left(R^*_i, T_i; B_i, \bar{\varphi_{1i}}\right)}. \tag{59}$$

These are optimal feedback controls since they depend on the state-costate paths (T_i, λ_i). To make clear the impact of climate change on the natural world preservation at an OLNE, we consider a simplified example in which

$$\varphi_{0i}\left(R_i, T_i\right) = b_{0i} + b_{R_i}R_i - b_{T_i}T_i. \tag{60}$$

Then the following proposition can be stated when temperature is regarded as exogenous at any point in time.

Proposition 4. *An increase in the regional temperature at a point in time should increase the preservation of the natural world in this region if optimal non-cooperative land-use policies are followed even when existence values are not taken into account.*

For the proof, see the Appendix.

Using the linear representation of $\varphi_{0i}(R_i, T_i)$, the feedback controls can be further characterized. From (45),

$$\bar{L}_i = \frac{B_i b_{R_i} + \mu_i \left(b_{0i} + \bar{\varphi_{1i}} + b_{T_i} T_i\right)}{b_{R_i} \mu_i} + \frac{\Delta_i}{\mu_i}.$$

Then, solving for μ_i, we obtain

$$\mu_i^* = \frac{B_i b_{R_i} + b_{R_i} \Delta_i}{b_{0i} + b_{R_i} \bar{L}_i - \bar{\varphi_{1i}} - b_{T_i} T_i},$$

and after substituting μ_i^* into (57) and (72), we obtain the land allocation as a function of climate change and the productivity parameters

$$L_{LI,i}^*(T_i; \Delta_i, \bar{L}_i), L_{H,i}^*(T_i; \Delta_i, \bar{L}_i), R_i^*(T_i; \Delta_i, \bar{L}_i). \tag{61}$$

Using (49) and (72) to define κ_i from Proposition 3 (see the proof of the proposition) as $\kappa_i^* = \kappa_i \left(R_i, T_i; B_i, \bar{\varphi_{1i}}\right)$, we obtain labor allocation as a function of climate change and the productivity parameters

$$l_{h,i}^* \left(T_i; B_i, \bar{\varphi_{1i}} \Delta_i, \bar{L}_i\right), h = c, LI, H, \tag{62}$$

while energy use is directly related to the SCC through (50). Conditions (61), (62) and (50) characterize the feedback controls for land-labor allocation, energy use and natural world preservation as functions of climate change, the productivity of the economy, the exogenous land availability and the short-term disease-containment parameter. By substituting these controls into (53)-(54), the evolution of the OLNE potentially towards a steady state can be studied.

Open loop Nash equilibrium The OLNE for the two regions will be characterized by the system

$$\dot{X} = \frac{\Gamma_1}{c_{E_1} + \lambda_1} + \frac{\Gamma_2}{c_{E_2} + \lambda_2} - dX \tag{63}$$

$$\dot{\lambda_1} = (\rho + d)\lambda_1 + \omega_1 \Lambda_1 X - \kappa_1^* \frac{\partial \varphi_{o1}(R_1^*, \Lambda_1 X)}{\partial X} \tag{64}$$

$$\dot{\lambda_2} = (\rho + d)\lambda_2 + \omega_2 \Lambda_2 X - \kappa_2^* \frac{\partial \varphi_{o2}(R_2^*, \Lambda_2 X)}{\partial X}. \tag{65}$$

Proposition 5. *Assume that* $\varphi_{0i}(R_i, T_i)$ *is given by (60) and*

$$\kappa_i^*(X) = \frac{B_i}{b_{0i} + b_{R_i} R_i^*(\Lambda_i X; \Delta_i, \bar{L_i}) - b_{T_i} T_i + \bar{\varphi_{1i}}} > 0,$$

$$\Theta_i(X) = \Lambda_i \left(b_{R_i} \frac{\partial R_i^*(\Lambda_i X; \Delta_i, \bar{L_i})}{\partial X} - b_{T_i} \right) < 0$$

for the relevant range of regional temperature anomalies $T_i = \Lambda_i X$, *and that a steady state for the system (63)-(65) exists. Then at this steady state, state and costates are defined as:*

$$\begin{aligned} X^\infty &= \left(\frac{\Gamma_1}{c_{E_1} + \lambda_1^\infty} + \frac{\Gamma_2}{c_{E_2} + \lambda_2^\infty} \right) \frac{1}{d} \\ \lambda_1^\infty &= \frac{-\left[\omega_1 \Lambda_1 X + \kappa_1^*(X)\,\Theta_1(X)\right]}{(\rho + d)} \\ \lambda_2^\infty &= \frac{-\left[\omega_2 \Lambda_2 X + \kappa_2^*(X)\,\Theta_2(X)\right]}{(\rho + d)}. \end{aligned}$$

Taking into account the link between climate change and the emerging ID will increase the regional steady-state SCC at an OLNE. The steady state will either be completely unstable or will exhibit saddle point stability with a one-dimensional stable manifold in the space $(X, \lambda_1, \lambda_2)$. *In the case of saddle point stability, for any initial value for the GHGs,* X_0, *in the neighborhood of this steady state, control paths can be chosen by each region so that the system will converge to the OLNE.*

For the proof, see the Appendix.

Proposition 5 suggests that the regional SCC, and therefore any climate policy based on this concept, should include an additional component related to the impact of climate change on the contact number of the emerging ID. This component is reflected in the term $\kappa_i^*(X)\,\Theta_i(X)$. The positivity of the term $\kappa_i^*(X)$ is reasonable because it implies that optimal containment policy in the very short run will improve the overall performance of the system, since this term reflects the sensitivity of the optimal solution to a small change in the short-run optimal containment parameter. The negativity of the term $\Theta_i(X)$ means that the impact of climate change on the contact number is sufficiently strong to counterbalance any positive effects on that contact number that emerge because an increase in regional temperature increases preservation incentives, which will have a favorable impact on the contact number.

As shown in the proof of Proposition 5, the saddle point stability implies that for any initial value of GHGs in the neighborhood of the steady state, the OLNE paths converging to this steady state can be approximated as:

$$X(t) = A_1 c_{11} e^{-\varrho_1 t} + X^{\infty}\,, X(0) = X_0 \tag{66}$$

$$\lambda_1(t) = A_1 c_{21} e^{-\varrho_1 t} + \lambda_1^{\infty} \tag{67}$$

$$\lambda_2(t) = A_1 c_{31} e^{-\varrho_1 t} + \lambda_2^{\infty}, \tag{68}$$

where the parameters (A, c, ϱ) are calculated at the solution. Substitution of the paths (66)-(68) into (61), (62) and (50) will determine the OLNE time paths for the controls which will drive the system to the OLNE steady state.

Optimal short-run containment In the analysis of the optimal short-term disease containment in section 3, R_i and T_i were treated as fixed exogenous parameters. The solution of the long-run problem implies that if the regions follow OLNE policies, then the fixed R_i and T_i in the short run will be determined by the corresponding OLNE paths at each point in time. Thus the short-run optimal containment policy v_i^* will follow the OLNE path $v_i^*(t)$ at the time scale of the climate change and will eventually converge to the OLNE steady state.

6 Ambiguity in the long run and robust control

The impact of ambiguity in the short run was examined in section 4. In this section we study the impact of ambiguity on the contact number of the disease which affects the evolution of the average temperature in each region. Since the impact of climate change on the emergence of IDs is an issue of current investigation, it is natural to associate ambiguity with this impact. This argument suggests that the regulator in each region is concerned about possible misspecification of the function $\phi_{0iT}(T_i(t))$. These concerns can be introduced by allowing additive distortions to this function of the form

$$\sqrt{\epsilon}\sigma_{0i}^{T}\left(\eta_i^T + z\right),$$

where σ_0 is volatility and ϵ is a small noise parameter, z is i.i.d and η represents distortions of the contact number. If we consider a multiplier robust control problem (e.g., Hansen et al. 2006, Hansen and Sargent 2011), the penalty associated with the distortion relative to the benchmark model can be expressed as

$$\frac{\left(\eta_i^j\right)^2}{2\theta_i^j(\epsilon)}.j = R, T,$$

where $\theta_i^j(\epsilon)$ is the robustness parameter. It has been shown (Campi and James 1996) that if $\theta_i^j(\epsilon) = \theta_{i0}^j\epsilon$, then as $\epsilon \to 0$, the stochastic robust control problem is reduced to a simpler deterministic robust control problem. Assume that part of the contact number which includes misspecification concerns can be specified as

$$\varphi_{0i}(R_i, T_i) = b_{0i} + b_{R_i}R_i - \left(b_{T_i} + \sigma_{0i}^T\eta_i^T\right)\Lambda_i X. \tag{69}$$

Then the regional optimal control problems can be written as

$$J_i^N = \max_{\{u_i(t),R_i(t\}}\min_{\{\eta_i^T\}}\int_0^\infty \mathrm{e}^{-\rho t}\left[\log C_i(t) + \psi_i \log R_i(t) + \frac{\theta_i^T\left(\eta_i^T\right)^2}{2}\right]dt,$$

subject to (5)-(7) and (17)-(20). The condition for the choice of the distortion η_i^T by the fictitious adversarial (or minimizing) agent is:

$$\eta_i^T = \kappa_i\frac{1}{\theta_i^T}\sigma_{0i}^T\Lambda_i X.$$

When the regional regulator is not concerned about misspecifications, $\theta_i^T \to \infty$ and $\eta_i^T \to 0$. Then from (64) and (65),

$$\lambda_i^\infty = \frac{-\left[\omega_i\Lambda_i X + \kappa_i^*(X)\hat{\Theta}_i(X)\right]}{(\rho + d)}, i = 1, 2,$$

where $\hat{\Theta}_i(X) = \left[\Lambda_i b_{R_i}\frac{\partial R_i^*(\Lambda_i X;\Delta_i,\bar{L}_i)}{\partial X} - b_{T_i} - \left(\frac{1}{\theta_i^T}\sigma_{0i}^T\Lambda_i\right)^2\right]$.

Therefore, under the assumptions of Proposition 5, misspecification concerns about the impact of climate change on the contact number will further increase the regional SCC.

7 Concluding remarks

We developed a two-region epidemic-economic model with the objective of studying short-term containment policy and long-term policies which focus on land-use changes and climate change as drivers of the emergence of IDs. The insights emerging from this model suggest that non-cooperative containment policies in the short-run, in which land use and climate change effects are considered as fixed, could lead to a Nash equilibrium outcome in the level of susceptibles. Ambiguity regarding the effectiveness of containment policies implies that increased concerns about the effectiveness of containment policies leads to weaker policies. The presence of strong ambiguity regarding the part of the containment number that depends on land use and climate change and which is exogenous in the short run could make necessary the introduction of command-and-control policies to supplement containment policies which are implemented on a voluntary basis.

In the long run the objective is to characterize an OLNE when the controls are land-use allocation between agriculture and the natural world, and carbon emissions in each region. In this equilibrium an additional positive externality – over and above existence values – emerges for the natural world while the SCC should be increased relative to the case when the emerging IDs are not taken into account. These adjustments result from the link between land use and climate change and the contact number of the emerging ID and should be taken into account in cost-benefit analysis. Ambiguity and concerns about model misspecification lead to further increase in the SCC.

Further elaboration of the model could analyze productivity differences as well as differences in the quality of aggregate land endowments among regions and the associated impacts on regional policies, while a calibration of the model can be based on the parameters defined in Appendix 8.2. Introduction of accumulation of produced capital into the economic model is another area of further research.

8 Appendix

8.1 Proofs of Propositions

Proposition 1

Proof. Disregarding $\bar{e}_{it}$ and R_t which are constants in the short run and using (32) after replacing κ with $1/\theta$, the objective of the regulator in region $i = 1, 2$ for the noncooperative case becomes

$$J_i = \max_{u_i(t)} \left\{ \log C_i - \frac{1}{\theta} \ln \left(\mathbb{E} \exp \left[(-\theta) \zeta_i \varphi_{1i} b_i v_i \right] \right) \right\}, \tag{70}$$

subject the constraints of problem (16). The first-order conditions for the optimal containment policy v_i imply

$$v_i^* = \frac{1}{c_i} \frac{\mathbb{E} \exp \left[(-\theta) \zeta_i \varphi_{1i} b_i v_i \right] \zeta_i \varphi_{1i} b_i}{\mathbb{E} \exp \left[(-\theta) \zeta_i \varphi_{1i} b_i v_i \right]} = g \left(\theta, v_i ; \zeta_i \right). \tag{71}$$

Since $\zeta_i = \frac{B}{Si}$, the Nash equilibrium under ambiguity can be defined by substituting (71) into (25).

Assume that a Nash equilibrium for a given value of the robustness parameter θ exists. Taking the total derivative of both sides of (71) with respect to v and θ, we obtain

$$\begin{aligned} c_i dv_i &= g_\theta d\theta + g_{v_{it}} dv_i \Rightarrow \left(c_i - g_{v_{it}} \right) \frac{dv_i}{d\theta} = g_\theta \text{ ,with} \\ g_\theta &= \frac{\partial \left[\frac{\mathbb{E} \exp[(-\theta)\zeta_i \varphi_{1i} b_i v_i] \varphi_{1i} b_i}{\mathbb{E} \exp[(-\theta)\zeta_i \varphi_{1i} b_i v_i]} \right]}{\partial \theta} = -\varphi_{1i} \zeta_i v_i \hat{\sigma}^2_{b_i} \\ g_{v_i} &= -\varphi_{1i} \theta \hat{\sigma}^2_{b_i}. \end{aligned}$$

Then it follows that

$$\frac{dv_i}{d\theta} = \frac{-\varphi_{1i} v_i \hat{\sigma}^2_{b_i}}{\left(c_i + \varphi_{1i} \zeta_i \theta \hat{\sigma}^2_{b_i} \right)} < 0.$$

■

Proposition 3

Proof. From (42) and (46),

$$\varphi_{0i}(R_i, T_i) + \bar{\varphi_{1i}} - \frac{B_i}{\kappa_i} = 0 \Rightarrow \kappa_i = \frac{B_i}{\varphi_{0i}(R_i, T_i) + \bar{\varphi_{1i}}} = \kappa_i\left(R_i, T_i; B_i, \bar{\varphi_{1i}}\right).$$

From (51), (52) and (45),

$$\begin{aligned}
\frac{a_{LI,i}\beta_{L,LI,i}}{\mu_i} &= L_{LI,i}\,, \quad \frac{a_{H,i}\beta_{L,H,i}}{\mu_i} = L_{H,i} \\
R_i &= h_i^R(T_i, \mu_i) \\
\bar{L}_i &= h_i^R(T_i, \mu_i) + \frac{\Delta_i}{\mu_i} \Rightarrow \\
\mu_i &= \mu_i\left(T_i; \Delta_i, \bar{L}_i\right) \\
\Delta_i &= a_{LI,i}\beta_{L,LI,i} + a_{H,i}\beta_{L,H,i}.
\end{aligned}$$

Then the result follows. ∎

Proposition 4

Proof. From the proof of Proposition 3 it follows that

$$\begin{aligned}
b_{0i} + b_{R_i}R_i - b_{T_i}T_i + \bar{\varphi_{1i}} - \frac{B_i}{\kappa_i} &= 0 \Rightarrow \\
\kappa_i &= \frac{B_i}{b_{0i} + b_{R_i}R_i - b_{T_i}T_i + \bar{\varphi_{1i}}}.
\end{aligned}$$

From (52)

$$\frac{\psi_i}{R_i} + \left(\frac{B_i b_{R_i}}{b_{0i} + b_{R_i}R_i - b_{T_i}T_i + \bar{\varphi_{1i}}}\right) = \mu_i.$$

Assuming no existence values in order to simplify and focus on the impact of climate change, then

$$R_i = \frac{B_i b_{R_i} + \mu_i\left(b_{0i} + \bar{\varphi_{1i}} + b_{T_i}T_i\right)}{b_{R_i}\mu_i} \tag{72}$$

$$\frac{\partial R_i}{\partial T_i} = \frac{b_{T_i}}{b_{R_i}} > 0. \tag{73}$$

∎

Proposition 5

Proof. A steady state for system (63)-(65) will be the solution of

$$\begin{aligned} X^{\infty} &= \left(\frac{\Gamma_1}{c_{E_1} + \lambda_1^{\infty}} + \frac{\Gamma_2}{c_{E_2} + \lambda_2^{\infty}} \right) \frac{1}{d} \\ \lambda_1^{\infty} &= \frac{-\left[\omega_1 \Lambda_1 X + \kappa_1^* (X) \Theta_1 (X)\right]}{(\rho + d)} \\ \lambda_2^{\infty} &= \frac{-\left[\omega_2 \Lambda_2 X + \kappa_2^* (X) \Theta_2 (X)\right]}{(\rho + d)}. \end{aligned}$$

Assume that such a steady state exists. The Jacobean matrix for system (63)-(65), evaluated at the steady state, will be

$$J = \begin{bmatrix} -d & \frac{\Gamma_1}{\left(c_{E_1} + \lambda_1^{\infty}\right)^2} & \frac{\Gamma_2}{\left(c_{E_2} + \lambda_2^{\infty}\right)^2} \\ \left(-\omega_1 \Lambda_1 + \frac{\partial\left[\kappa_1^*(X^{\infty})\Theta_1(X^{\infty})\right]}{\partial X} \right) & \rho + d & 0 \\ \left(-\omega_2 \Lambda_2 + \frac{\partial\left[\kappa_2^*(X^{\infty})\Theta_2(X^{\infty})\right]}{\partial X} \right) & 0 & \rho + d \end{bmatrix}.$$

The eigenvalues for this system are

$$\left\{ \rho + d, \frac{1}{2} \left(\rho \pm \sqrt{4d^2 - 4\left(J_{21}J_{12} + J_{31}J_{13}\right) + 4d\rho + \rho^2} \right) \right\},$$

where J_{ij} are the corresponding elements of the Jacobean matrix. Thus, the system could have at the most one negative real eigenvalue.

If such a negative eigenvalue, ϱ_1, exists, then linearizing the system at the steady state and setting the constants of the positive eigenvalues equal to zero, we obtain for an initial value X_0 for the GHG concentration:

$$\begin{aligned} X(t) &= A_1 c_{11} e^{-\varrho_1 t} + X^{\infty}, X(0) = X_0 \\ \lambda_1(t) &= A_1 c_{21} e^{-\varrho_1 t} + \lambda_1^{\infty} \\ \lambda_2(t) &= A_1 c_{31} e^{-\varrho_1 t} + \lambda_2^{\infty}, \end{aligned}$$

where (c_{11}, c_{21}, c_{31}) is the eigenvector associated with the negative eigenvalue. Given X_0, the constant A_1 and the initial values for (λ_1, λ_2) can be determined. The paths for $(X, \lambda_1, \lambda_2)$ can be used to obtain the optimal paths for the control toward the OLNE steady state. Note the these paths are valid in the neighborhood of the steady state, since they correspond to the the linear manifold which is tangent to the nonlinear true stable manifold at the steady state. ■

8.2 Model parameters

1. Consumption Composite

$$C_i = \left[\left(l_{c,i}^{\beta_{l,c,i}} E_{ci}^{\beta_{c,E,i}}\right)^{\alpha_{c,i}}\right] \times \left[\left(l_{LI,i}^{\beta_{l,LI,i}} \left(\gamma_{LI,i} L_{LI,i}\right)^{\beta_{L,LI,i}} E_{LI,i}^{\beta_{E,LI,i}}\right)^{\alpha_{LI,i}}\right] \times \left[\left(l_{H,i}^{\beta_{l,H,i}} \left(\gamma_{H,i} L_{LI,i}\right)^{\beta_{L,H,i}} E_{H,i}^{\beta_{E,H,i}}\right)^{\alpha_{H,i}}\right] \times \exp\left[-\left(\sum_h c_{h,E,i} E_{hi}\right)\right] \times \exp\left[-c_{vi}(v_i^2/2\right] \times \exp\left(-\omega_i T_i^2/2\right)$$

Parameter	Description	Value Region 1	Value Region 2
$\alpha_{c,i}$	Elasticity of Consumption Composite (ECC)		
$\beta_{l,c,i}$	ECC		
$\beta_{c,E,i}$	ECC		
$\alpha_{LI,i}$	ECC		
$\beta_{l,LI,i}$	ECC		
$\beta_{L,LI,i}$	ECC		
$\beta_{E,LI,i}$	ECC		
$\alpha_{H,i}$	ECC		
$\beta_{l,H,i}$	ECC		
$\beta_{L,H,i}$	ECC		
$\beta_{E,H,i}$	ECC		
$c_{h,E,i}$	cost of energy $h = c, LI, H$		
c_{vi}	cost of containment		
ω_i	climate damages		
$\bar{L}$	natural world in each region		
$\psi_i R^{\psi_i}$	exponent of existence values in R^{ψ_i}		

2. The SIS model

$$S_i(t)) \equiv \frac{1}{\sigma_i(t))} = \phi_{0i}\left(R(t), T(t)\right) + \phi_{1i}\left[b_i v(t)) - m_i S_i(t)) - q_j\left(1 - S_{jt}\right)\right]$$

Parameter	Description	Value Region 1	Value Region 2
ϕ_1	short-run impact on contact number		
b	effectiveness of containment policy		
m	infected asymptomatic		
q	regional flow infected		

$$\phi_{0i}\left(R_i(t), T_i(t)\right) = b_{0i} + b_{R_i} R_i - b_{T_i} T_i$$

Parameter	Description	Value Region 1	Value Region 2
b_{0i}	exogenous component		
b_{R_i}	natural world impact		
b_{T_i}	climate change impact		
θ_i	robustness parameter		

3. Climate model

$\dot{X}(t) = E_1(t) + E_2(t) - dX(t)\ , X(0) = X_{preindustrial}$

$T_i = \Lambda_i X$

Parameter	Description	Value Region 1	Value Region 2
Λ_i	regional TCRE		
d	GHG depreciation		

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