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Impact of inequalities on Brown to Green transition in financial markets: an agent-based approach

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1 Internship

1.1 Abstract (fr)

La chaire d'éconophysique entre EconophysiX et CFM à l'École polytechnique explore les intersections entre la physique et l'économie. Cette chaire, inaugurée en février 2019 en partenariat avec Capital Fund Management (CFM), se consacre à l'étude des marchés financiers et de l'économie à travers des approches issues de la physique des systèmes complexes.

Depuis quelques années, les enjeux macroéconomiques prennent une part de plus en plus importante dans les projets de recherche de la chaire, notamment ceux liés à la transition climatique.

L'étude de l'impact du changement climatique sur la société et l'économie est cruciale pour formuler des politiques qui soutiennent la transition énergétique. Les économistes ont développé des modèles d'évaluation intégrée (IAMs) pour relier le changement climatique aux stratégies économiques, mais ces modèles sont critiqués pour leur complexité, leur manque d'hétérogénéité et l'inclusion inadéquate du système financier.

Pour résoudre ces problèmes, divers modèles basés sur des agents (ABMs) ont été créés, se concentrant sur la consommation d'énergie et de biens par les ménages et les entreprises. Parmi les exemples notables, citons le modèle "Dystopian Schumpeter meets Keynes" (DSK) et sa version intégrée au système financier, DSK-FIN.

D'autres modèles intégrés basés sur des agents (ABIAMs) proposent des approches similaires avec des implémentations différentes. Cependant, ces modèles adoptent souvent une perspective macroéconomique, négligeant l'hétérogénéité des richesses et son impact sur la vulnérabilité climatique.

Les inégalités sociales exacerbent les impacts climatiques en créant des déséquilibres de pouvoir qui entravent les politiques climatiques. Par conséquent, nous suggérons, à travers ce stage, de développer un modèle multi-agents multi-niveaux plus simple que les modèles d'agents existants, qui met l'accent sur les perspectives sociales et financières afin d'explorer les liens entre l'inégalité sociale et les défis climatiques.

1.2 Abstract (en)

The econophysics chair at École polytechnique between EconophysiX and CFM, explores the intersections between physics and economics. This chair, inaugurated in February 2019 in partnership with Capital Fund Management (CFM), is dedicated to the study of financial markets and economics using approaches derived from the physics of complex systems.

In recent years, macroeconomic issues have become an increasingly important part of the Chair's research projects, particularly those relating to the climate transition.

Studying the impact of climate change on society and the economy is crucial to formulating policies that support the energy transition. Economists have developed Inegrated Assessment Models (IAMs) to link climate change to economic strategies, but these models are criticised for their complexity, lack of heterogeneity and inadequate inclusion of the financial system.

To solve these problems, various Agent-Based Models (ABMs) have been created, focusing on the consumption of energy and goods by households and businesses. Notable examples include the Dystopian Schumpeter meets Keynes (DSK) model and its version integrated with the financial system, DSK-FIN.

Other Agent-based integrated assessment models (ABIAMs) offer similar approaches with different implementations. However, these models often adopt a macroeconomic perspective, neglecting the heterogeneity of wealths and its impact on climate vulnerability.

Social inequalities exacerbate climate impacts by creating power imbalances that hamper climate policies. Therefore, we suggest through this internship to develop a multi-level multi-agent model simpler than existing agent models, which focuses on social and financial perspectives in order to explore the links between social inequality and climate challenges.

2 Introduction

Studying the impacts of climate change on society and the economy is essential for establishing policies to help businesses, politicians and households adapt to the ongoing energy transition. It is in this context that economists have developed Integrated Assessment Models (IAMs) to establish the links between climate change and the economy, and the start-up strategies to be adopted.

Nevertheless, these models are criticized for their complexity, their lack of heterogeneity (Diffenbaugh and Burke, 2019 [2]) and the partial or total absence of the financial system (Monasterolo 2020 [11]). The assumptions of these models are also criticized by limitating the risks and the impacts of climate change on the economy, thus leading to optimistic results (Stern and Stiglitz, 2023 [13])

To overcome these problems, a number of agent-based models have been developed, focusing mainly on energy and goods consumption between households and companies. An agent-based model (ABM) is a type of computational model used to simulate the interactions of agents within a defined environment. These agents can represent individuals, groups, or entities such as companies, governments, or even biological cells, each with their own set of rules and behaviors. ABMs can provide insights into the dynamics of systems and help in understanding how changes at the micro-level can lead to macro-level outcomes.

In the specific cases we study, the ABMs that have been developed includes: the Dystopian Schumpeter meets Keynes model (DSK, Lamperti 2018 [9], Lamperti 2020 [10]), with further integration of the financial system in another version (DSK-FIN, Lamperti 2019 [7], Lamperti 2021 [8]). Other Agent-Based IAM (ABMIAM) models (see Safarzynska and van den Bergh (2022) [12], Czupryna (2020) [1], Gerdes (2022) [3]) offer versions similar to the DSK model in their chosen modules (companies types, company/household links, economic impact of climate change), although they differ in their implementation, with different methods and greater detail on certain modules.

However, these models always approach the transition from a very macro-economic point of view with a lot of parameters and interactions, neglecting the influence of the heterogeneity wealth or introducing it via some financial industry and a credit limitation for investments via bank loans (DSK Lamperti (2018) [9] and (2020) [10], Safarzynska and van den Bergh (2022) [12], Gerdes (2022) [3]) or household investments (Czupryna (2020) [1]).

On the one hand, social inequalities within countries imply an unequal proportion of damages among agents: exposure to climate change hazards, susceptibility to damages, and ability to cope and recover. This can resume in one sentence: the richest is the agent, the less is the impact on its wealth (Islam, 2017 [6]). Those mechanisms induce an increase in inequalities, by favorizing even more richest wealth.

On the other hand, inequalities are an engine of climate change by creating power imbalances that enable capital interests to expand carbon-intensive production and obstruct climate policies (Green, 2022 [4]). That suggests including carbon-centered policies in a wider social and economic program of reforms to achieve the climate transition with more efficacy.

Proposal: In this context, we propose to develop a new and simpler multi-level multi-agent based model centered on a social and financial view. It aims to understand the deep connections that link social inequality and the climate challenge in a first time, and act as a tool for policy-making by regulators and institutions.

3 The Doomsday Model

The Doomsday model introduces a set of heterogenous agents with different initial wealths, linked by non-linear climate feedback loops. We use the term *Doomsday*, but we don't consider that a single event can wipe out all wealth. We prefered recurrent medium-intensity climate shocks that are a realistic way of modeling *Doomsday*, in the sense that global warming increases the frequency of extreme weather events.

Each agent has part of its wealth invested in Brown (**B**) assets -i.e. that damage our planet and contribute to the climate challenge- the other part in Green (**G**) assets by opposition. Wealths produce interests each year that are functions of time and that are dependant of the total wealth invested in **B** or **G** assets. Each agent searches to maximize its own wealth and rank in the society, but knowing the consequences of investing in **B** assets that can lead to economic losses. They so have a puzzle to solve between: (1) trying to be the richest to save themselves -which initially implies staying in a **B** strategy-, and (2) incrase the probability of economic shocks if they invest in **B**-with **B** returns initially more important than **G**. At each timestep, agents then chose a strategy according to their *Utility Function*, on the basis of the previous state of the system. When agents choose their strategy, they choose it depending on a rationality parameter. The computation ends when the max number of iterations has been reached.

3.1 Agents

Each citizen is represented by an agent i, with a wealth $W_{i,s}(t)$ divided in 2 parts: Green assets ($s = \mathbf{G}$) and Brown assets ($s = \mathbf{B}$). The ensemble of wealth $\big(W_{i,G+B}(t)\big)_{i\in[1,N]}$ of the N agents, is distributed according to a log-normal law and an initial Gini coefficient. To be able to associate an initial Gini coefficient with the initial wealth distribution, we chose to eliminate the stochasticity of the distribution by using the quantile function of the log-normal distribution:

$$W_{i,G+B}(t_0) = \exp\left(\mu + \sqrt{2}\sigma \cdot \mathrm{erf}^{-1}\left(\frac{2i}{N} - 1\right)\right), \tag{1}$$

where μ and σ are respectively fixed and numerically fitted with the desired Gini coefficient.

Each type of Wealth (**B** or **G**) represents financial assets but also more usual ones like a car, a house or even some equipment. In the spirit of finance, each wealth owns a returns that permits it to grow. Due to lobbying effects, returns have a dynamic that directly depend of the total wealth invested in **B** or in **G**, following the update rule:

$$r_G(t) = r_0 + \left(\mathrm{EMA}\left(\frac{W_G(t)}{W_G(t) + W_B(t)}, \tau_{lob}\right) - \frac{1}{2}\right) \times 2I, \tag{2}$$

$$r_B(t) = r_0 + \left(\mathrm{EMA}\left(\frac{W_B(t)}{W_G(t) + W_B(t)}, \tau_{lob}\right) - \frac{1}{2}\right) \times 2I, \tag{3}$$

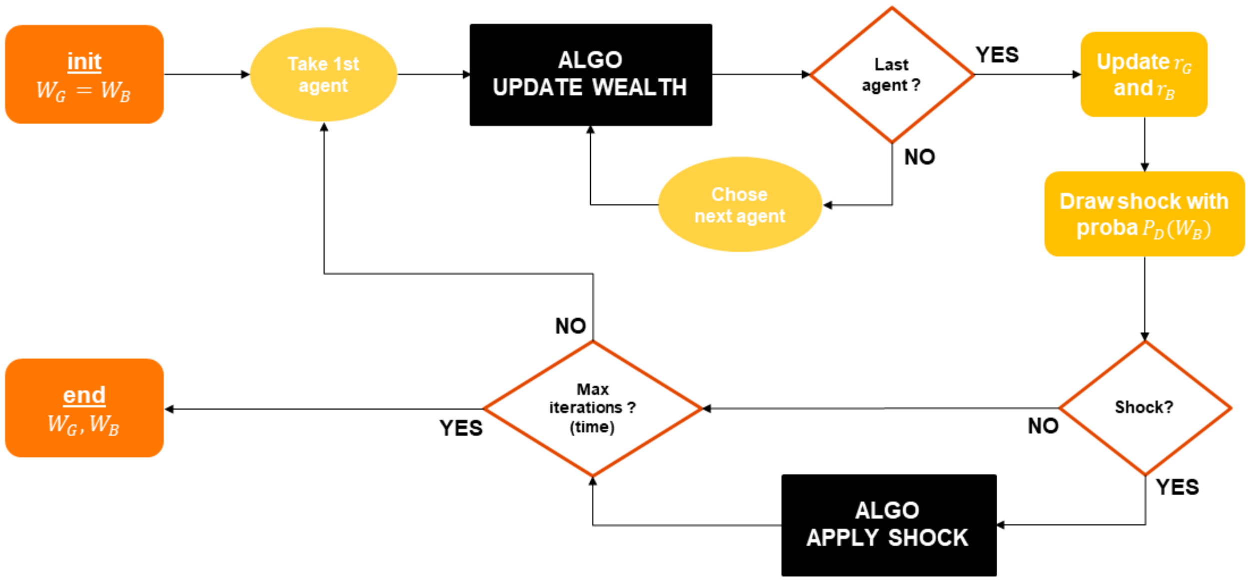


Figure 1: Global scheme of the model

with τ_{lob} a timescale factor of the Exponential Moving Average linked to the lobbying, and I is the max impact[1] that can be applied on returns.

Once agents chose their strategy, they reallocate an exact fraction δ of their total wealth in their wealth **G** or **B** -according to the strategy-, and update their two wealth with the returns $r_G(t)$ and $r_B(t)$:

$$W_{i,s}(t+1) = (W_{i,s}(t) \pm \delta W_i) \times (1 + r_s(t)) \,. \tag{4}$$

At the end of the iterations the wealth can undergo an economic shock, thus modifying the real wealth at time $t+1$. The mechanism and it's implications will be detailed further in the *Climate shocks module* section. A global scheme of the model is presented in Figure 1.

The initial wealth aren't equally divided into **B** and **G**: instead we assume that **B** assets are far more important compared to **G** assets. This strong imbalance cause the initial $r_B(0)$ to be bigger than the initial $r_B(0)$, and thus the solution of the strategy puzzle isn't trivial.

3.2 Utility function

In order to chose a strategy, agents needs to have a quantitative indicator that makes the balance between the desire to increase your wealth in order to escape doomsday with the desire not to increase the probability of doomsday happening. In this matter, agents make their choice according to the following Utility Function:

$$\Delta x_i(t) = a(1 - \lambda_D)\Delta w + b\lambda_D F \Delta P_D, \tag{5}$$

[1]That implies that if $I = 3\%$ and $r_0 = 8\%$, r_G and $r_B \in [5\%, 11\%]$. This choice permits to have good dynamics with a speed controlled by τ_{lob} and limit the impact of lobbying on returns.

where a and b are fixed normalizing constants that initally gives an order 1 to $a\Delta w$ and $bF\Delta P_D$. λ_D is the weight agents gives to the doomsday compared to the increase of their wealth. Δw is an approximation[2] of the difference of the wealth's increase between strategies **B** and **G**, which is then normalized by the total wealth $W_{TOT}(t)$:

$$\Delta w = (r_G(t) - r_B(t))\frac{W_{i,G}(t) + W_{i,B}(t)}{W_{TOT}(t)}. \tag{6}$$

In the Doomsday part, we have 2 functions that balance each other: F is the rank of the agent (the higher the wealth, the lowest the rank) and ΔP_D is the difference of the impact of agent i on the Doomsday indicator P_D. In detail we have the following:

$$F = \frac{RANK_i(t)}{N}, \tag{7}$$

$$\Delta P_D = \frac{\text{EMA}(W_B(t) + 2\delta W_i(t), \tau)}{W_{MAX}}, \tag{8}$$

where W_{MAX} can be seen as the maximum **B** wealth Earth can absorb, τ is the timescale of the impact of the addition or deletion of **B** wealth.
One must note that F and ΔP_D are two terms that balances each other: an agent with a high wealth will have a little F but a huge impact on W_B and thus a high ΔP_D. The equilibrium between the two terms will lead to different strategy dynamics between agents, with wealth and inequality in the system being the overriding factors. The final element in the strategy choice process is the rationality of the agents. The utility function is multiplied by a rationality factor $\beta \in [0, +\infty[$, which traduces the extent to which an agent will choose the strategy it chose. A β close to 0 means a total irrationality and $\beta \to +\infty$ means a total rationality. Knowing that the agent chose the strategy **G** according to the following probability:

$$P(G) = \frac{e^{\beta \Delta x_i}}{e^{\beta \Delta x_i} + e^{-\beta \Delta x_i}}. \tag{9}$$

Irrationality can also play a role of inertia by pushing the system to stay in its previous state, limiting evolution (the more irrationality, the more agents choose their strategy randomly). Details of the full process strategy selection are presented in a scheme in Figure 2, which corresponds to the Algo Update Wealth hidden part presented in the global scheme in Figure 1

3.3 Climate shocks module

For the moment, agents are making choices that take their impact on the climate into account, with a different level depending on certain factors as . Nevertheless, these effects on the economy are real and have an impact on global wealth. We therefore introduce a climate shock module to our model, which will randomly reduce the wealth of certain agents.

[2] We make an approximation here in order for an agent not to give too much power to a strategy: if its wealth is a full **B** or full **G** state, the gain of the other would then be 0. Instead, agents look what their increase could be if they were full **B** or full **G**, and make the difference.

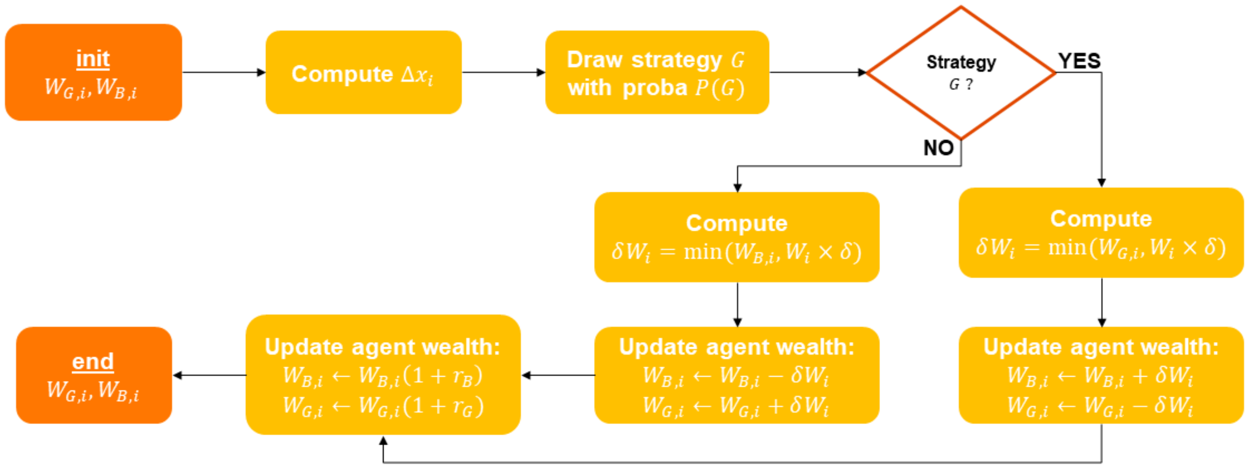


Figure 2: Scheme of the strategy choice process

In detail, at the end of a step we decide to apply an economic shock to the company with a probability:

$$P_D(t) = \frac{\text{EMA}(W_B(t), \tau)}{W_{MAX}}. \tag{10}$$

If an economic shock occurs, we chose randomly a proportion γ_B of agents and reduce their **B** wealth by factor $r_{loss,B}$, and apply a similar process with γ_G a proportion of agents who will see their **G** wealth reduced by a factor $r_{loss,G}$. An example of the process is given in Figure 3. In this specific example of 4 agents, we took $\gamma_B = 75\%$ and $\gamma_G = 25\%$ so that the algorithm draw 3 agents to apply the **B** reduction and 2 agents to apply the **G** reduction. At the end, some agents have a full impact of the economic shock (agent 2), some have a mitigated impact (agents 1, 4) and some could have no impact on their wealth (agent 3). This modelize that agents aren't impacted in the same way by climate events: a french citizen won't be affected by the floods of Dubai in 2024 whereas Dubai citizen will be totally impacted, and a rich investor from the USA could be strongly impacted on its investments.

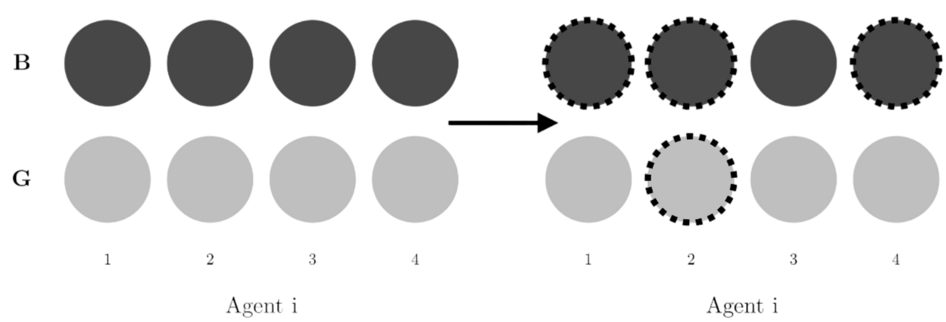


Figure 3: Example process of an economic shock in the case of 4 agents with $\gamma_B = 75\%$ and $\gamma_G = 25\%$. If an economic shock appears, 75% of agents will see their **B** wealth reduced by $r_{loss} = 50\%$, and 25% of agents will see their **G** wealth reduced.

4 Macro-economic dynamics

The *Doomsday* model permits the study of long-range effects on society in a **B**-centered economy and the parameters that influence the transition. In this section, we study the *Doomsday* model without any policy, and we fix a set of initial parameters for all the studies, which are listed in Table 1.

Parameter	**Value**	**Description**
N	100	Number of agents
W_{MAX}	10^9	Max **B** wealth earth can support
$W_{TOT}(0)$	$W_{MAX}/2$	Total initial wealth
τ	100 years	Timescale of impact of addition or deletion of **B** wealth in the total wealth
δ	5%	Percentage of wealth an agent reallocate at each step
λ_D	20%	How much agents give importance to *Doomsday* comparing to a wealth increase
r_0	5%	Fundamental base value
I	3%	Impact I, max deviation from r_0 a return can have
τ_{lob}	3 years	Timescale of lobbying impact on returns
$\frac{W_G(0)}{W_{TOT}(0)}$	10%	Fraction of initial **G** wealth in the total initial wealth
$GINI$	0.3	Initial Gini coefficient
β	10^3	Rationality factor
γ_B	10%	Percentage of agents who see their **B** wealth impacted
γ_G	10%	Percentage of agents who see their **G** wealth impacted
r_{loss}	50%	Percentage of loss on selected **B** and **G** wealth

Table 1: Base parameters used in the simulations

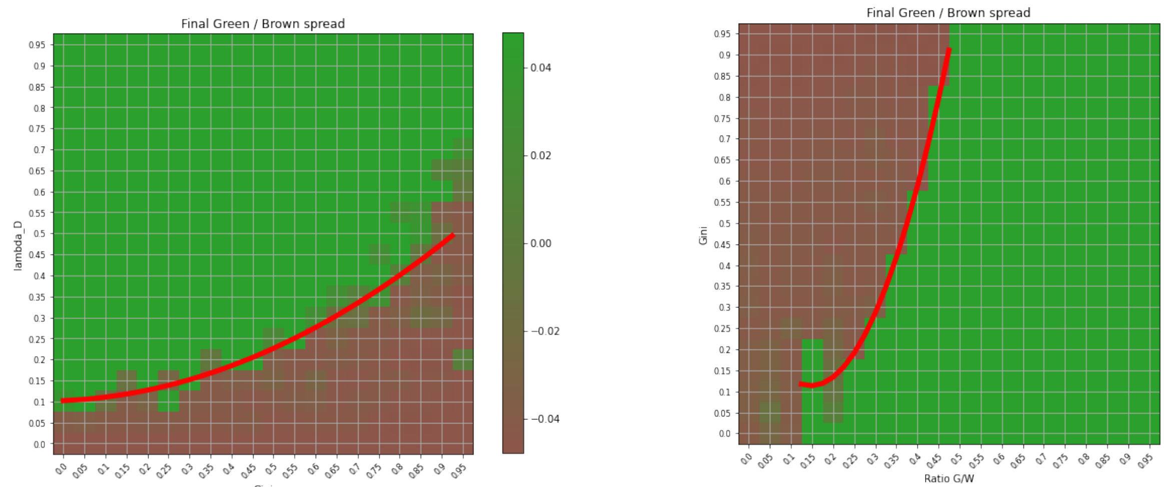
All the simulations will be averaged over 20 runs for a fixed set of parameters. When we study the effect of one or more parameters we assume the others are those given in Table 1. We first analyze the influence of inequalities in the *Doomsday* model, which is the central part of this model.

4.1 Influence of social inequality on climate change

To study the impact of social inequality on climate change in the Doomsday model, we simulated different dynamics by adjusting the initial Gini coefficient ($GINI$). The Gini coefficient measures the inequality of wealth distribution within a population, with a higher coefficient indicating greater inequality.

The $GINI$ phase transition simulations presented in Figure 4 show that social inequalities significantly affect agents' ability to adapt to climate shocks and make the **G** transition. In these graphs, we chose to plot the final spread between returns, which is directly linked to the total wealth ratio according to our definition of return dynamics. Within a high inequality society (initial $GINI > 0.4$), agents have more difficulties undergoing their climate transition, which could never happen if they don't give sufficient importance to *Doomsday* (for initial $GINI = 0.4$, **G** transition occurs if $\lambda_D > 0.15$).

The initial ratio of **G** wealth to the total wealth is also a strong initial condition (see Figure 4), as it results in lobbying that creates a higher return for **B** assets (in case of $ratio < 0.5$). Moreover, it takes more time for agents who want to change their strategy to effectively change their wealth. During this period, extreme events can occur that can actually change the $GINI$ coefficient and the final state of the system.



(a) λ_D vs $GINI$

(b) $GINI$ vs $\frac{W_G(0)}{W_{TOT}(0)}$

Figure 4: Phase diagrams showing the $r_G(t_{final}) - r_B(t_{final})$ varying different parameters. 5 simulations are computed and averaged for each set of parameters.

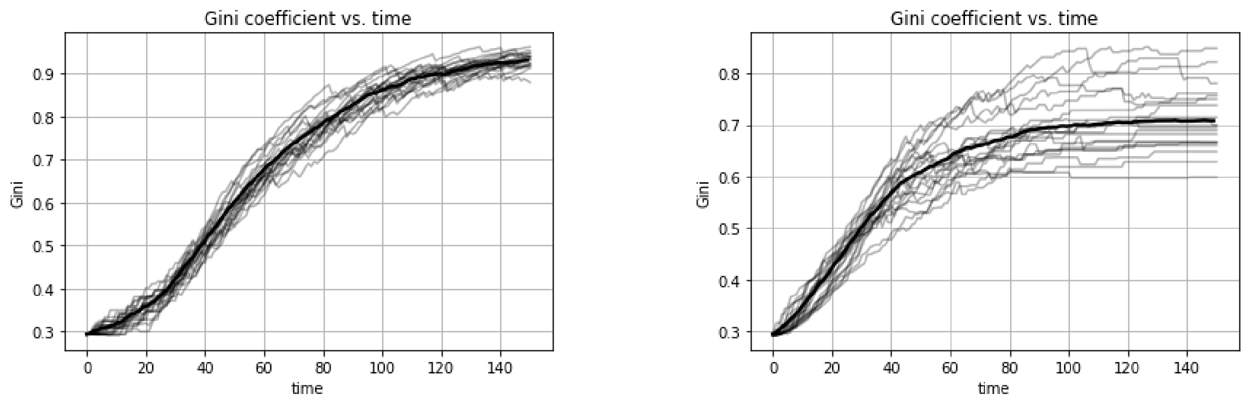
By looking at the shape of the curves, we can deduce the importance agents give to *Doomsday* (i.e., λ_D) and the initial proportion of **G** wealth in the system have more influence than the initial level of inequalities. Indeed, given a fixed λ_D or $ratio$, we can always find a $GINI$ that permits the climate transition, whereas the contrary isn't fully true.

If we look at the evolution of inequalities near the criticality ($GINI = 0.3$ and $\lambda_D = 0.15$), results shown in Figure 5 indicate that in the **B** phase (i.e., $\lambda_D = 0.1$), society becomes completely unequal, with a ratio between the final maximum and minimum wealth of $\approx o(10^3)$.

In the case where the system ends in a **G** phase the increase of inequality is strong but moderated, with an average increase of 0.4 points of the $GINI$.

In any case, the $GINI$ coefficient has an influence and is influenced by the state of the system, with a strong link between inequalities and a **B** state.

[2] As a reference the Gini coefficient of Eurozone is about 0.3 in 2022



(a) **B**-end state phase for $\lambda_D = 0.1$

(b) **G**-end state phase for $\lambda_D = 0.2$

Figure 5: Evolution of the $GINI$ coefficient for different simulations within a **B** of **G** final state phase. The black line is the average of the 20 simulations.

4.2 Dynamics of climate transition

The dynamics of the climate transition in the *Doomsday* model are influenced by several key parameters, including the agents' initial wealth distribution, the level of inequality, and their responsiveness to climate risks. In this section, we explore these dynamics in more detail, focusing on how different initial conditions affect the transition to a greener economy.

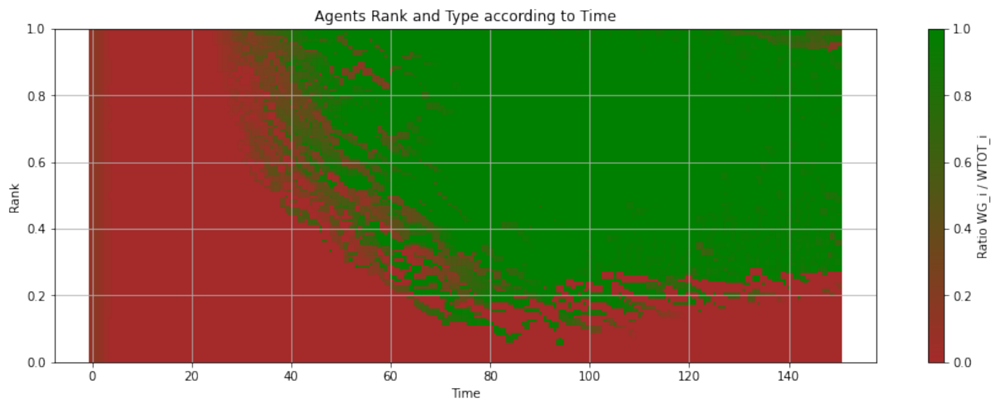
We've seen that when agents lead to a collective behavior to make their climate transition, it still results in an increase in inequalities. This increase in inequality is exacerbated when the transition never happens. In this matter, we plot the "spatio-temporal" dynamics of a transition from a **B** economy to a **G** one by looking at the ratio of **G** wealth over their total wealth as a function of their rank (i.e., their position in the system) and time. We used the standard parameters for the **G** transition and fixed $\lambda_D = 0.1$ for the **B** case. The plot is shown in Figure 6.

We can see that the richest agents aren't making the transition; it's the collective behavior of the poorest that propagates through the richest and permits the transition. This also explains the increase in inequalities: as the poorest agents are the first to choose to transition to **G** wealth, they have the lowest returns compared to the wealthiest ones. At the end, the richest agents turn to **G** if they see that the spread between r_B and r_G is sufficiently advantageous for **G**.

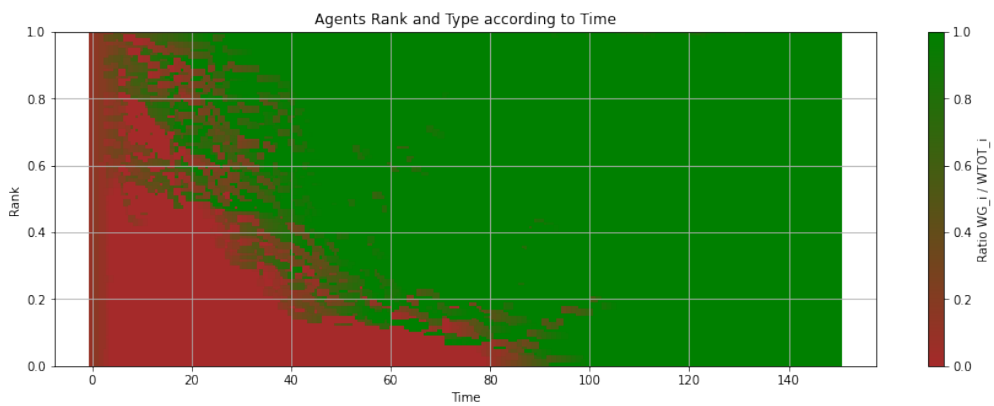
In the specific case of a **B** final state, only rich agents remains **B**, which leads to the rise of the $GINI$ coefficient we've seen in Figure 5.

Spread dynamics is a good indicator to study the final state of a system, as it permits us to describe a globally **G** or **B** society and the way it evolves over time. Some dynamics are shown in Figure 7, where the prominent line represents the average over the 20 simulations.

When a **G** transition occurs, we can see that not all societies are making it at the same time. This explains the strong differences we saw in the $GINI$ coefficient (Figure 5):



(a) **B**-end state phase for $\lambda_D = 0.1$



(b) **G**-end state phase for $\lambda_D = 0.2$

Figure 6: Evolution of the proportion of $W_G(t)_i$ for each rank through time in 1 simulation for each graph

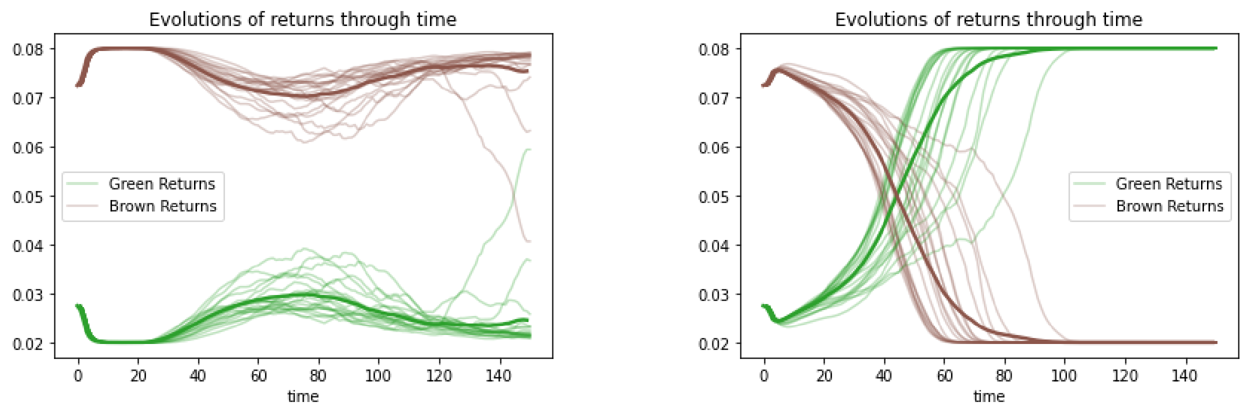
the systems in which the transition appears the fastest are those that limit the increase of inequalities. Inversely, in the **B** graph we can see an attempt of reverse which ends in the decades after (although 2 systems reach to make their transition, due to stochasticity). One can suppose that with more time each system will end by making its transition: it's actually wrong in the sense that the longer in a **B** state, the more inequalities. Without any **G** policy, it became quite impossible for a system with sufficient inequalities to spontaneously make its reversion.

Because of inequalities, even if a majority of agents made their **G** transition, the entire society can't make it until the richest agents decided to do same.

Another phenomenon is the spontaneous reversal from **G** to **B** wealth at certain ranks. This can be explained by **B** agents who suffer from a climate shock on their **B** wealth and lose rank. They then take some time to convert their **B**-oriented wealth into a **G** one.

4.3 Impact of climate shocks on the economy

Understanding the impact of climate shocks on the economy is essential to formulating policies that can mitigate these effects and promote resilience. In this section, we analyze

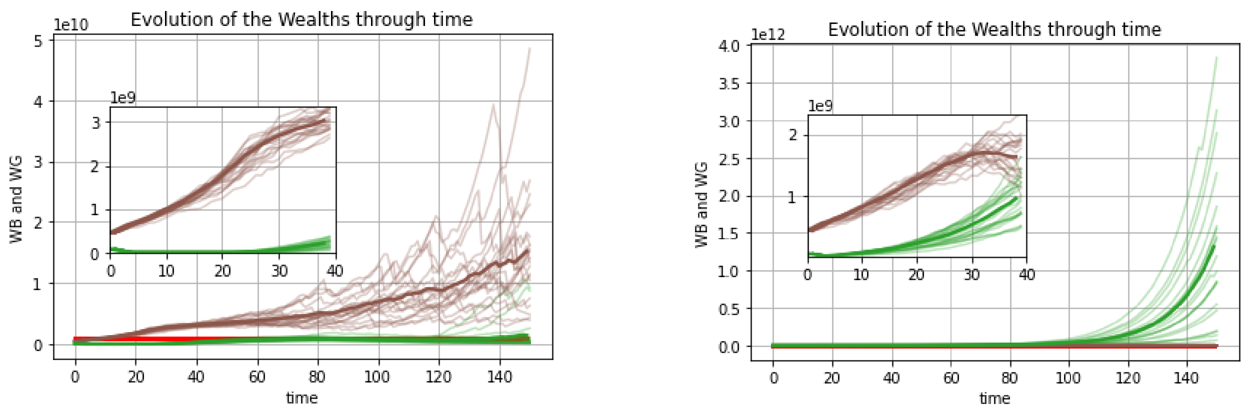


(a) **B**-end state phase for $\lambda_D = 0.1$ (b) **G**-end state phase for $\lambda_D = 0.2$

Figure 7: Dynamics of $r_B(t)$ (brown) and $r_G(t)$ (green), for 20 simulations in each graph. The prominent lines represents the average of the simulations.

the effects of climate shocks through simulations of our agent-based model, examining the evolution of wealth in different scenarios, the role of inequalities, and the critical indicators of economic stability.

We begin by examining the evolution of wealth in the two distinct scenarios: one where the system ends in a **B** state and another in a **G** state. Figures 8 show the total wealth evolution for both scenarios. In the **B** state, wealth initially grows rapidly due to high returns



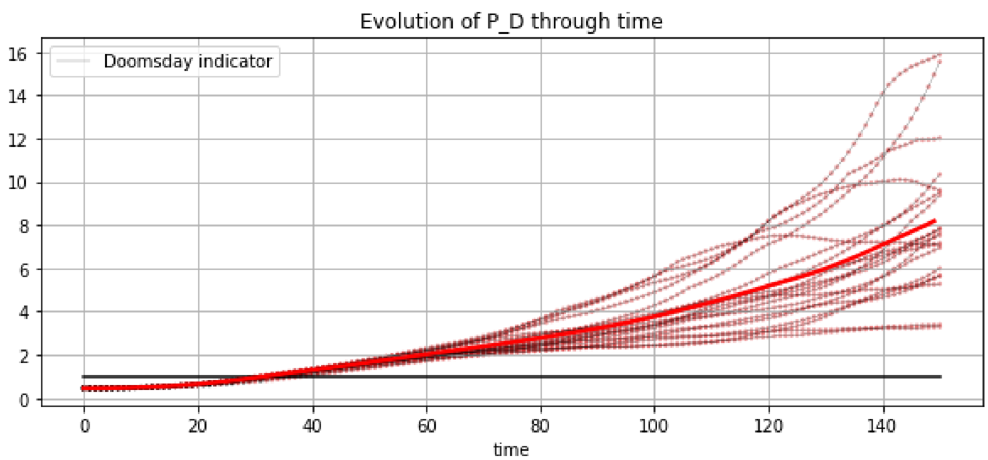
(a) **B**-end state phase for $\lambda_D = 0.1$ (b) **G**-end state phase for $\lambda_D = 0.2$

Figure 8: Dynamics of $W_B(t)$ (brown) and $W_G(t)$ (green) for 20 simulations in each graph. The prominent lines represents the average of the simulations.

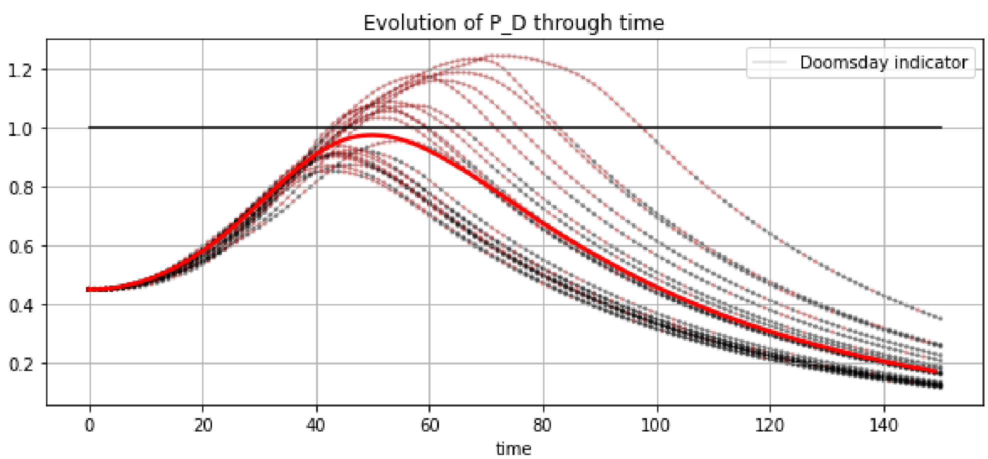
from **B** investments. However, frequent climate shocks eventually cause significant wealth losses proportional to the wealth of agents. One notable observation is the occurrence of frequent and sharp declines in wealth due to economic shocks. This can be seen from the first decade where simulations start to have different scenarios.

In the **G** state, the transition to greener investments initially results in lower returns as in the **B** state, but from year 40, the system undergoes a trend reversal of wealth, with fewer and less severe climate shocks. This leads to long-term and stable economic growth of the system. This corresponds to the reversing of the dynamics of the returns we already see in Figure 7. Notably, over time the maximum wealth in the **G** state is significantly higher than in the **B** state, indicating that even the wealthiest agents benefit more in a greener economy.

The *Doomsday* Indicator (P_D) is a critical metric for assessing the risk of a catastrophic economic collapse due to climate shocks. It quantifies the rate of severe economic downturns based on the accumulated effects of the previous states of the economy.



(a) **B**-end state phase for $\lambda_D = 0.1$



(b) **G**-end state phase for $\lambda_D = 0.2$

Figure 9: *Doomsday* indicator P_D for 20 different simulations in each graph. A black dot means no climate shock whereas a red one means a climate shock happened. The red curve is the average of the P_D curve and the black horizontal line corresponds to the cross of W_{MAX}

On Figure 9, we plot the results of the simulations for the **B** and **G** final end cases. In the **G** simulations, half of the simulations cross the W_{MAX} limit. This means that during this period, severe climate shocks (marked by red dots) occur each year with a probability of 1. In the case of the **B** simulations, the average *Doomsday* indicator grows above the W_{MAX}

limit. This implies a strong cost for the economy and society. We note that this exceeding of W_{MAX} can be limited by increasing the parameters γ and r_{loss}.

5 Conclusion

This study explored the impact of social inequalities on the transition from Brown to Green financial assets using an agent-based model. Our findings reveal that high levels of inequality significantly hinder the ability of agents to adapt to climate shocks and transition to greener investments. Societies with greater inequality struggle more with this transition, unless there is a strong emphasis on the risks of inaction.

The simulations show that poorer agents often initiate the green transition, but wealthier agents delay their shift to green assets, exacerbating inequality. Climate shocks further disrupt the economy, making it harder for a transition to occur. The initial ratio of green wealth to total wealth, and the collective behavior of agents are critical factors influencing the transition's success.

We have also not tested the policies that could help transition from brown to green: we have only built a laboratory for conducting experiments. This paper, serving as an internship report and a mid-term conclusion for this internship, describes the foundations of this model and the stylized effects that emerge from it. It is necessary to formulate hypotheses and process ideas, and study their effects on the various presented diagrams. In future work, it will be essential to search for measures that aim to reduce inequalities while promoting the green transition and minimizing the impact on the economy.

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