# Climate Action in a World of Complex Ties

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## Resumo

Num ponto onde o mundo está a mergulhar precipitadamente no colapso climático, a persistência de inércia global e de vazios políticos torna-se num cenário inaceitável. Perceber os requisitos necessários para que a cooperação prevaleça em acordos climáticos é essencial, onde é imperativo reconhecer a heterogeneidade e desigualdade em que os países se encontram e como estas influenciam as suas contribuições. Com este objetivo, formulamos acordos climáticos como um Dilema de Risco Coletivo, que reconhece o risco inerente ao desastre climático e requer um mínimo de contribuições para que haja efeito da ação coletiva. Neste trabalho pretendemos perceber o impacto de conjugar diversidade no risco, desigualdade de riqueza e heterogeneidade social no dilema, recorrendo a uma abordagem evolucionária e a redes complexas.

Este estudo demonstra que a heterogeneidade pode ter diferentes impactos, dependendo da forma como é distribuída na rede. Os nossos resultados indicam que diversidade no risco pode promover significativamente a cooperação se os indivíduos centrais da rede tiverem uma elevada percepção de risco. Em particular, correlacionar positivamente o risco, a riqueza e o grau é a melhor configuração para que os acordos climáticos sejam cumpridos. Observámos também que os indivíduos e grupos mais ricos devem ser os que mais contribuem para maximizar a cooperação. Em concordância, verificámos que se os requirimentos para os diferentes grupos forem adaptados com base na capacidade dos mesmos, a cooperação é amplificada. As nossas conclusões podem influenciar elaborações de medidas governamentais e sugerem que o curso deste dilema está fortemente dependente dos líderes climáticos.



**Palavras-chave:** Ação Climática, Desigualdade Social, Cooperação, Teoria de Jogos Evolutiva, Redes Complexas

## Abstract

At a point where the world is diving precipitously into climate collapse, the persistence of global inertia and political voids becomes unacceptable. Understanding what can promote global cooperation to reach climate agreements is essential, where it is imperative to recognize the heterogeneity and inequality that characterize countries and how these can influence their willingness to contribute. For this purpose, we formulate climate agreements with a game-theoretical metaphor denoted as the Collective-Risk Dilemma. This dilemma recognizes the inherent risk associated with climate disaster and requires a minimum number of contributors to guarantee the effect of collective action. Here we investigate the impact of incorporating heterogeneity in social ties, risk diversity and wealth inequality in the dilemma, resorting to the tools of evolutionary game theory and complex networks.

This study shows that heterogeneity can have different impacts depending on how it is distributed in the network. Our results indicate that risk diversity can significantly enhance cooperation if the central individuals of the network have a high perception of risk. Positively correlating risk, wealth, and centrality is the best arrangement for targets in climate agreements to be met. We further observe that richer individuals and groups should contribute more to maximize cooperation. Accordingly, if the requirements for the different groups are adapted to their capacity, cooperation is improved. Our findings may have implications for policy-making and suggest that the course of the dilemma is strongly dependent on the climate leaders.

**Keywords:** Climate Action, Social Inequality, Cooperation, Evolutionary Game Theory, Complex Networks

# Contents

# List of tables

# List of figures

# List of acronyms

**CRD** Collective-Risk Dilemma

**ESS** Evolutionary Stable Strategy

**PGG** Public Goods Game

**NE** Nash Equilibrium

# Chapter 1

# Introduction

Climate change stands as a challenge without precedents in history. It will exacerbate all the threats that humanity already has in its hands. From social inequalities to economic hardship, innumerable problems will be severely aggravated.

There is an urgent need for climate action, and this action requires local and national responses, anchored in a logic of global cooperation. However, in a world full of complex ties, where the environmental aspects are articulated with the social ones, various factors make cooperation difficult to emerge.

It is important to emphasize that climate change takes form as environmental injustice. The historical responsibility for emissions is not evenly distributed around the world. It is known that the carbon emissions of the world's richest 1% are more than double the emissions of the poorest half of the world. More precisely, the process of industrialization, which is at the origins of global warming, has enriched the North, to the detriment of the South. Furthermore, the repercussions and exposure to global heating vary significantly, as not everyone is affected in the same way. The highest-income countries of Global North will suffer fewer consequences, while the Global South, which has historically contributed the least to global warming, bears a disproportionate share of the burden of environmental damage. In fact, the poorest zones of the Global South, with more marginalized communities, are already facing the most drastic effects of this climate crisis [1].

Recognizing the heterogeneity and inequality that characterize countries, which will be worsened with global warming, is fundamental to push for change on climate justice and to a better understanding of how countries can self-organize to reach large-scale cooperation. Several fields, such as political science, economics, sociology, or computer science, have been striving to understand this influence.

The focus of this thesis is to capture the key features of the climate change problem, through the lens of a model capable of analyzing the impact of asymmetries between countries in cooperation dynamics. In particular, we are interested in including heterogeneity in social ties, risk diversity and wealth inequality in the climate change dilemma. With this, we aim to contribute to a better comprehension of the conditions under which cooperation in climate settings can flourish.

## 1.1 What is Cooperation?

Following the Method of Doubt of Descartes, in the hope of achieving some certainties, it is recommendable to return to the notions we know with absolute assurance. Based on the vast literature about cooperation, there is a common notion that it occurs when an individual concedes a benefit to another, paying an associated cost [2]. In the context of communities, it happens when a group works for a common benefit, rather than adopting an antagonistic behavior for individual profit.

Notwithstanding, understanding how cooperation can prevail in large populations through evolution is still an unclear path. Until the 1960s evolutionary theorists neglected the role that cooperation could play in improving reproductive success [3]. Darwin's theory of natural selection created the assumption that the world is intrinsically competitive and evolution is merely based on a ferocious struggle between individuals. With this postulation, selfishness can be perceived as a virtue, as individuals best adapted to their environments are more likely to survive and reproduce [2]. By contrast, other scholars, as Peter Kropotkin, considered the work of Darwin to provide contributions that were a catalyst for the study of cooperation in evolution. In the book *Mutual Aid*, Kropotkin opposed the idea that evolution is only based on competition, arguing that *"the progressive development of the animal kingdom, and especially of mankind, is favoured much more by mutual support than by mutual struggle"*. Through biological and sociological evidence, he mentions: *"I saw mutual aid and mutual support carried on to an extent which made me suspect in it a feature of the greatest importance for the maintenance of life, the preservation of each species, and its further evolution"* [4]. Accordingly, one can find cooperation to shape the preservation of life in all scales of complexity. Cooperation between genes to form cells. Cells coordination in an effort to preserve health and avoid the appearance of diseases [5]. Social insects as cooperative colonies, efficiently dividing labor and helping each other find resources [6]. Collective action among humans in the emergence of cultural inheritance as language [7], or the large-scale cooperation involved in human rights organizations. From simple organisms as cells to very complex models as humans, cooperation seems to be ubiquitous and profoundly interlaced with the evolution of humanity.

The coexistence of mutual struggle and mutual aid in evolution represents a universal paradox. To understand this interdisciplinary challenge, one may resort to the tools of Game Theory. Game-theoretical models are capable of grasping the essence of social dilemmas, where even though cooperation can be looked upon as an irrational decision to the individual - as it needs to incur a cost -, it is the path that conducts the population to the best possible outcome. Nevertheless, as the prominent economist Herbert Simon introduced [8], it is relevant to consider bounded rationality in decision-making, as it may be reductive to assume that individuals always take decisions based on a fully rational process of finding an optimal choice. Therefore, and in order to consider more pragmatic scenarios, transitioning to a framework that studies the ecology of cooperation in large populations, not purely based on rational strategic decisions, is necessary. Citing the philosopher Peter Singer, we should *"take seriously the fact that we are evolved animals, and that we bear the evidence of our inheritance, not only in our anatomy and our DNA but in our behavior too. (...) an understanding of human nature in the light of evolution-*

*ary theory can help us to identify the means by which we may achieve some of our social and political goals"* [3]. With this purpose, the framework designated as Evolutionary Game Theory captures the adaptive behavior of populations, adding the recognition of complex dynamics to the Classical Game Theory [9].

## 1.2 The Difficulties to Cooperate on Climate Settings

In a decade where we are surrounded by news constantly alerting us of the immanent irreversibility of climate change, it may appear incomprehensible why global inaction is so prevalent.

The expectations around climate agreements are progressively growing. Although it is necessary to combat political alienation, it is also inevitable to question these agreements, since the contributions until now are albeit from sufficient. As Greta Thunberg stated in an interview in the Austrian World Summit: *"2021 is currently forecasted to be the year with the second-highest emission rise ever (...) The gap between your actions and words is becoming more impossible to ignore while more and more extreme weather events are raging all around us"*.

Thousands of climate activists demand greater action and ambition, which requires effective coordination to reach global cooperation. Nevertheless, the current difficulties are numerous. The benefits of lowering emissions are not exclusively felt by those who bear the costs of reducing the emissions, as everyone shares the profits. Consequently, individuals may be tempted to free-ride on the effort of others. On the other hand, even with the growth of social mobilizations, educational campaigns, or local temperatures getting warmer, the low perception of the risk disaster that remains present was already conceived as one of the Achilles' heels of cooperation [10]. Moreover, the fact that we are contributing in the present to a future with an underlying uncertainty was proved to be one of the main barriers [11]. Related to what was mentioned above, since the burden of climate change is not equal to everyone, fairness principles recurring to historical responsibility for emissions, vulnerability to climate change, and economic capacity are also essential to take into account [12]. Consequently, conflict dynamics between rich and poor parties in these agreements need to be unraveled [13]. Additionally, the lack of monitorization in who fulfills the requirements of green policies agreements is also considered as one of the principal impediments [14].

Creating mechanisms that focus on the cooperative relationships between humans in a climate that is in constant mutation is imperative. According to the IPCC (Intergovernmental Panel of Climate Change), we only have less than ten years to save the planet from irreversible damages, which implies that the carbon emissions need to be reduced by half [15]. We are the last generation capable of avoiding climate collapse. It is critical to understand what can foster cooperation in such a demanding problem.

## 1.3 Objectives

As we previously referred, countries are characterized by different risk perceptions, wealth levels and can interact preferentially with specific sets of other countries. For instance, rich countries may have more interactions/ties than poor countries. Poor countries may have a higher perception of risk disaster than rich. The impact of combining risk, wealth and heterogeneity in social ties in reaching cooperative agreements remains astray. In this thesis, we resort to computer simulations, evolutionary game theory and complex networks to understand how cooperation and collective success in a non-linear public goods game - representing the climate change dilemma - is impacted by risk, wealth and network heterogeneity.

Specifically, the aim of this thesis is to answer the following questions, regarding the climate change dilemma:

1. What is the impact of correlations between risk perception and network connectivity?
2. What is the effect of correlations between wealth and network centrality?
3. How can information about network heterogeneity, risk diversity and wealth inequality be combined to leverage cooperation in climate settings?
4. Regarding the distinct classes of wealth, how should the cost of cooperating be distributed?

## 1.4 Document Outline

The document is organized as follows.

In order to understand the problem in question and our proposal, we present some relevant background theory, regarding evolutionary game theory and complex networks, in Chapter 2. Subsequently, in Chapter 3, we review literature that is primarily concerned with heterogeneity and the climate change dilemma. In Chapter 4, we describe in detail the computational model that is used to perform simulations, capable of answering our proposed research questions. The results and discussion of the simulations are described in Chapter 5. Finally, in Chapter 6, we provide our more significant conclusions, along with a description of possible future directions that may emerge from this thesis.

# Chapter 2

# Background Theory

In this chapter, we present some background theory that is relevant to understand the problem in question and our contributions. We introduce some of the principal notions of Game Theory. Following that, we shall define certain Evolutionary Game Theory concepts. Finally, we specify complex networks definitions and properties that we consider in the performed computer simulations.

## 2.1 Game Theory

Game theory represents the mathematical framework capable of formalizing conflict of interests between individuals. Correspondingly, it studies the interaction of agents and the outcomes of their rational strategic decisions, helping to identify the potential barriers to cooperation and to determine in which ways cooperative behavior can be enhanced [16].

### 2.1.1 Prisoner's Dilemma

Prisoner's Dilemma is one of the most famous illustrations of conflict in Game Theory. It constitutes an abstract metaphor that captures the essence of a general cooperation dilemma that occurs between two players.

In this game, players can take one of two actions: Cooperate and Defect. The payoffs of one player associated with these actions are presented in Table 2.1.

| | **Cooperate** | **Defect** |
|---|---|---|
| **Cooperate** | $benefit - cost$ | $-cost$ |
| **Defect** | $benefit$ | $0$ |

Table 2.1: Payoff matrix of one player in a Prisoner's Dilemma between two individuals, where $benefit > cost$.

In order to predict the strategies and the behavior of the rational agents, it is important to define the general stability concept designated as Nash Equilibrium [17]. Nash Equilibrium (NE) occurs when no player benefits from changing the set of strategies that constitutes the equilibrium. Based on this notion, one can perceive that Defect reflects this property, as it provides a higher payoff than the other alternatives, independently of the choice of the opponent. Therefore, the best course of action for each self-interested individual is selecting Defect.

However, despite defecting being the only rational strategy, the best outcome for both players would be mutual cooperation. To understand this cooperation paradox, it is useful to resort to the efficiency concept, designated as Pareto Optimality. A situation is defined as Pareto Efficient when the circumstances of one individual can not improve without disfavoring another individual. As one can observe, this does not apply to the Defect strategy.

### 2.1.2 Public Goods Game

Expanding this conflict to a group of $N$ individuals, we are in the presence of an N-Person Prisoner's Dilemma, also known in the literature as Public Goods Game. In this game, each individual has an initial endowment $b$, contributing a fraction $c$ of their endowment to a common pot. Subsequently, the contributions are multiplied by a factor $m$, which can be perceived as the enhancement factor, meaning that higher factors produce higher proportions of contribution. Finally, the public good will be equally divided by all the players.

In this game, the NE occurs when each player makes zero contributions, receiving the benefits at no cost (a rational strategy also known as free-riding). However, and analogously to what was mentioned above, the best possible outcome would be that all individuals cooperate, contributing the maximum possible amount to the pot.

Considering this dilemma in a shared-resource setting, one can observe that cooperation is needed to avoid collective damages, while at the same time, the incentives to defect are present. In parallel with the climate change problem, one can realize that all countries would benefit if all reduce carbon emissions, nevertheless, a country will individually profit by not reducing. If countries continue to act individually according to their self-interest, the tragedy of the commons will occur, which in this case will lead to climate collapse. In a general setting, the tragedy of the commons is the situation where a group of individuals ends up depleting the shared resource through their collective antagonistic behavior [18].

## 2.2 Evolutionary Game Theory

As aforementioned, Evolutionary Game Theory merges population ecology at a large scale to Classical Game Theory [9]. Instead of considering purely rational individuals, it focuses on behavior dynamics. With this representation, individual preferences are in constant adaptation, as individuals are persistently revising their strategy by imitating others. Based on Darwinian Evolution, it adopts mechanisms of Natural Selection, where strategies that do well are propagated faster. Namely, payoff turns into individual fitness, from which social success can be derived. Individuals with higher fitness will be more frequently imitated, a phenomenon also known as social learning.

Similar to the Nash Equilibrium defined in Game Theory, to understand which strategies will remain stable in a population in this framework, one can recur to the concept of Evolutionary Stable Strategy (ESS). A strategy is called an ESS if it will never be invaded by any other strategy through natural selection [19]. In other words, ESS is a strategy which, if adopted by a population, cannot be invaded by any different strategy that is initially rare.

Next, we present two different methods of studying population dynamics in evolution.

### 2.2.1 Infinite and Well-mixed Populations

First, consider an infinite and unstructured population, where individuals are equally likely to interact (well-mixed). To understand the evolution of strategies in such a setting, imitation is typically modeled with the replicator equation. This equation describes the fraction of the population that adopts a pure strategy, assuming a deterministic update. Analogously to Natural Selection, it recognizes that a strategy that benefits an individual will spread in the population, as it will be imitated more often. Therefore, it favors strategies that adapt better in the population during evolution.

In particular, considering the strategies cooperating (*C*) and defecting (*D*), the evolution of the fraction $x$ of *Cs* (thus, $1-x$ of *Ds*) is governed by the gradient of selection associated with the replicator dynamics equation:

$$\dot{x} = x(1-x)[f_C(x) - f_D(x)], \tag{2.1}$$

where $f_C(x)$ and $f_D(x)$ represent the fitness of cooperators and defectors, respectively. According to this equation, the fraction of *Cs* (*Ds*) will increase in the population whenever $\dot{x} > 0$ ( $\dot{x} < 0$).

### 2.2.2 Finite and Structured Populations

In the previous subsection, we introduced an analytical method to study deterministic dynamics on infinite populations. However, any real population is finite. In particular, considering the context of this thesis, the number of countries that take part in climate negotiations is finite and not large enough to be approximated by an infinite population model. This limitation requires us to transition from infinite to finite populations, and thus, deterministic methods are no longer sufficient to be applied. It is further necessary to consider the emergence of stochastic effects that are prevalent in evolution [20].

For this purpose, and to study all possible structures in populations, one can consider a simple form of social learning, where an individual decides to change its strategy, after being influenced by other. In this pair-wise comparison rule [20], one individual ($i$) will choose to adopt its randomly selected neighbor's ($j$) strategy, with a probability given by the following statistical function:

$$p = \frac{1}{1 + e^{-\beta(f_j - f_i)}}, \tag{2.2}$$

where $f_i$ corresponds to the fitness of individual $i$, and $f_j$ to the fitness of individual $j$. Consequently, imitation will happen with a probability proportional to the fitness difference. In this formula, $\beta$ can be perceived as a measure of error that defines the intensity of selection. Specifically, if $\beta \ll 1$, there is a weak selection, and imitation will occur independently of fitness differences. On the opposite situation, if $\beta$ assumes large values, the process will become more deterministic, strongly depending on the fitness difference.

In contrast to Classical Game Theory, both tools mentioned above confer complexity to the simple rational description offered by the Prisoner's Dilemma. However, the problem was still shown to converge to defection when using this framework. For instance, in [21], the authors inferred that defection is the only stable point where the system is in equilibrium. To surpass this result, studies with heterogeneous graphs were formulated [22] through the lens of network science. For this reason and in order to understand our contributions, complex networks will be introduced next.

## 2.3 Complex Networks

As Albert Barabási mentions in [23], networks are at the heart of complexity. To fully understand this sentence, it is necessary to primarily understand what complexity is. A system can be defined as complex if it is difficult to derive its complex behavior from a knowledge of the system's component [23]. From microscopic interactions as connections between genes to collective phenomena as cooperation between individuals, the world is shaped by complexity - and beyond each complex system, there is a network capable of interconnecting all of its components.

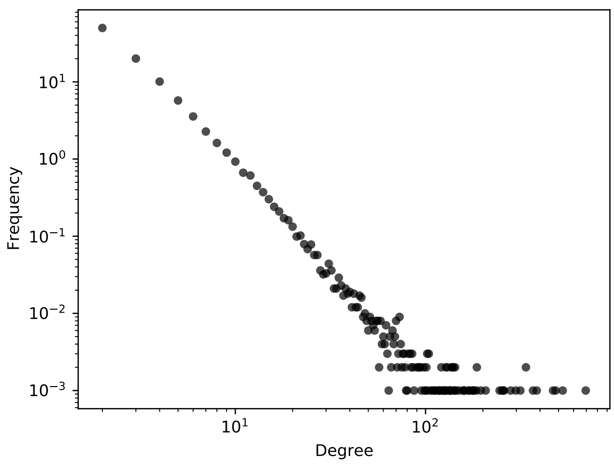
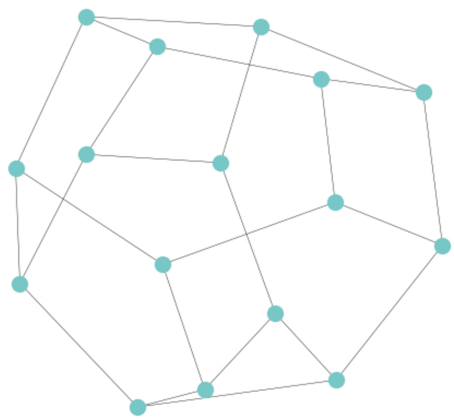


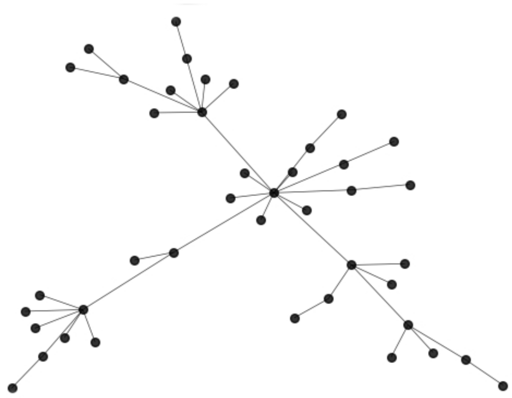

Figure 2.1: Degree distribution of a scale-free network on a log-log scale. The network was generated with the Barabási-Albert model of growth and preferential attachment, with $1000$ nodes and average degree of $4$. The distribution follows a power-law $k^{-\gamma}$ with $\gamma \approx 3$. It portrays that the frequency of low degree nodes is significantly high, whereas the frequency of high degree nodes is low.

Although such networks vary substantially in size, origin, or field, they are often governed by the same rules. Regarding the topology of networks, there are many scenarios, ranging from citation networks to astrophysical ones, that follow a scale-free distribution. To comprehend what is a scale-free network, one must introduce the common notions of a graph. In the context of this thesis, nodes represent individuals, and links define their interactions. Each node has a degree that corresponds to the connectivity in the network, which can be translated to the number of links that the node has. Consequently, the degree distribution represents the organization of these degrees over the whole network. In particular, in a scale-free network, the degree distribution is determined by a power-law [24]. It follows the form $k^{-\gamma}$, where $k$ corresponds to the degree, as depicted in Figure 2.1. This property illustrates that most individuals only have a few connections, while a minority interacts with many. These minorities are often designated as hubs, stemming from the fact that they represent highly connected nodes. Or in other words, that they have a high centrality. Hence, the heterogeneity present in networks can be understood, where some nodes have a degree much higher than others, as it is noticeable in the scale-free network depicted in Figure 2.2b. This topology contrasts with a simplified homogeneous regular network [25], where it is considered that all nodes have the same degree, as illustrated in 2.2a.

It is noteworthy that the development of large networks is ruled by self-organizing phenomena through evolution. For instance, the Barbási-Albert model, one of the most famous models to generate scale-free networks, tries to model properties of real networks that are translated into two generic mechanisms: growth and preferential attachment. Growth recognizes that networks are not static, they are constantly expanding in time, since we are continuously adding new nodes. Preferential Attachment is typically in the genesis of scale-free networks. In a colloquial sense, it recognizes that popularity is engaging, considering that new nodes attach preferentially to already highly connected nodes [24].



(a) homogeneous regular network



(b) scale-free network

Figure 2.2: Plot of two networks generated with the library: *networkx* [26]. **a)** homogeneous network, represented by a regular graph, where all nodes have the same number of neighbors **b)** scale-free network, generated by the Barabási-Albert model, where only a few nodes have a lot of connections (which represent the hubs) and the majority of the nodes have few connections.

# Chapter 3

# Related work

In this chapter, we review previous work that seeks to understand the self-organization of cooperation across societies. We start by referring to the most known mechanisms capable of enhancing cooperative behavior. Subsequently, we discuss social heterogeneity, where we highlight the growing importance of realistically modeling the predominant differences between individuals. Afterward, we focus on the climate change dilemma, also from a heterogeneous perspective.

## 3.1 Mechanisms for the Evolution of Cooperation

In this section, we introduce five rules discussed by Nowak in [2] to explain the evolution of cooperation. Understanding these mechanisms is essential, as they constitute important means for most of the studies that seek to explain how cooperative behavior can prevail in a plethora of scenarios.

- Kin Selection: Firstly proposed by Hamilton [27], it considers the gene as the unit selection, with cooperation happening between genetic relatives. Assuming that is relevant for individuals to propagate their genes, one will cooperate with their relatives, as all will benefit by engaging in this relationship. In particular, the mechanism considers that the probability of individuals sharing a gene (also known as relatedness) must be higher than the cost/benefit ratio of taking an altruistic action.

- Direct Reciprocity: Considering that cooperation occurs not only between genetically related individuals, kin selection is not sufficient. To surpass these constraints, Trivers proposed a mechanism designated as direct reciprocity [28]. It recognizes that in the context of more complex societies, there are repeated encounters between individuals. Thus, they elaborate strategies that are more complex cognitively in memory. Accordingly, the future behavior of one individual might be influenced by the decisions taken by others in the past. The rationale is straightforward: if one decides to cooperate, in the next meeting the other will probably cooperate as well, where reciprocity consists in establishing a beneficial mutual exchange.

- Indirect Reciprocity: There are several situations where help is asymmetric and uneven. Consider the example of one helping a stranger, there is no possibility for direct reciprocity. Nonetheless, cooperation also happens with persons that will never interact again. To explain this, Nowak and Sigmund [29] proposed the mechanism of indirect reciprocity, based on reputation. More precisely, the possible consequences for our reputation are considered when making a decision. Helping someone increases our reputation, and, consequently, will be compensated by others. This mechanism requires cognitive complexity, as it is not only necessary to remember the past but also to keep track of the social network that is in constant mutation. In this process, language is an important key to fostering the spread of information. Namely, anchoring language and indirect reciprocity help cultural evolution thrive, which is essential to our adaptability as a species.
- Structured Populations: Another important contribution to understand the appearance of cooperation was the realization that the outcome of evolutionary games can be improved with structured populations, in comparison with well-mixed ones. Nowak and May [30] showed that the introduction of spatial structure via nearest-neighbor interactions enhances the formation of cooperative clusters on a squared lattice, which confers protection to cooperators against the exploitation by defectors. Therefore, it illustrates the spatial reciprocity that is intrinsic to complex networks, as connected individuals in a social network tend to help one another. Notwithstanding, the structure used in this study is not realistic, as it considers that each node has the same number of links. Given the importance that this mechanism has in our work, following studies with more complex topologies will be further discussed in Section 3.2.1.
- Group Selection: The pioneering work [31] considered that selection does not only happen in individuals, as competition can also occur between groups. In this setting, individuals can work for the greater good. Correspondingly, reaching success can be easily achieved in groups of individuals that assume cooperative behavior, as it can increase the fitness of the group. As a result, groups with higher fitness will grow and reproduce faster than the other groups.

## 3.2 Social Heterogeneity

Most of the previous models in Evolutionary Game Theory assume that individuals are sufficiently equal in the relevant aspects that this framework can grasp. However, this assumption is highly unrealistic, as heterogeneity is ubiquitous around the world. Unraveling symmetries is fundamental to understand the emergence of cooperation.

Motivated by this, a general framework to study direct reciprocity among unequal individuals was proposed in [32]. This was modeled by giving individual properties to each player, in contrast to what is typically assumed, where all players have the same endowment and the contributions to the public goods are multiplied by a common productivity factor. Therefore, inequality can be reflected in their endowments, productivities, and how much they can benefit from public goods.

This evolutionary analysis provided insights into the influence of combining different dimensions of heterogeneity in cooperation. Specifically, they showed that extreme inequality is always detrimental to cooperation. However, an intricate balance between productivity and endowment heterogeneity can favor pro-social behavior. Additionally, they concluded that if higher endowments are received from more productive individuals, group success is augmented, whereas misaligning these two sources decreases the chances of achieving cooperation.

### 3.2.1 Complex Networks

Although the preceding analysis considers unequal individuals, it makes the assumption that they interact with an equal probability. Yet, this modeling disregards the diversity present in their ties, where distinct roles persist in social communities.

To keep unraveling symmetries, transitioning to evolutionary games on heterogeneous structures provided influential contributions. This is the example of the work done in [22], with inherent network reciprocity and framed as a spatial Public Goods Game (PGG). In this study, individuals interact with their direct neighbors, and, consequently, the number of games they participate in is proportional to the number of connections they have. As individuals are structured in a scale-free network, there is variety in the number and size of PGG that each individual engages in. The results of this paper suggest that considering diversity in the interactions enhances cooperation. In particular, it was observed that cooperation becomes the dominant strategy on heterogeneous networks significantly earlier than on homogeneous ones.

Moreover, they explored two opposite limits for the amount contributed by one individual in each group that they participate in. One in which the contribution is fixed, and the other where the amount is equally divided between all games in which they engage. In the latter, there is additional diversity arising from the different contributions that each individual makes in a game. The authors inferred that this diversification in the investments can also foster cooperation.

Understanding the impact of connectivity in the network stands as an important factor in this analysis. Considering that in this model the connectivity confers an increase in the relative fitness, hubs (highly connected nodes) are shown to be the nodes that can more rapidly evolve into cooperators. Accordingly, they can foster the spread of cooperative behavior through the whole social network.

Besides the network degree, following studies with other network properties were made on top of scale-free graphs. For instance, the impact of highly clustered networks was explored in [33]. The authors derived that cooperative behavior becomes easier to expand in this setting, as it promotes the emergence and support of cooperative clusters, which as mentioned in [30], is known to strengthen cooperation.

Furthermore, given the increased complexity introduced through scale-free networks, the influence of correlations is acquiring importance in understanding the evolution of cooperation. Correlations between degree and investment levels were introduced in [34]. The authors showed that assuming that endowments grow proportionally with the degree can restrain cooperation. In particular, if cooperative hubs have a higher investment capability, the cooperators' frequency decreases. By contrast, cooperation is enhanced when low degree nodes are those investing the most. In this thread of research, correlations between degree and unequal payoff were also investigated in [35]. Their results suggested that considering an appropriate degree of diversity in the payoff allocation among individuals can help in understanding the emergence of cooperation. Both [34] and [35] give insights into the unequal wealth allocation that is present in the world, by assigning different investments or payoffs to the players, and converge on the idea that hubs play a fundamental role in the evolution of cooperation, which also intersects with the conclusions in [22].

#### From Networks to HyperGraphs

The previous works make a significant assumption considering the interaction between groups. This assumption relies on the fact that the interactions only involve two individuals at a time. To provide a more realistic description, and to transcend the pairwise modeling, hypergraphs confer a mathematical representation capable of transitioning from interactions between pairs to larger groups. With this topology, higher-order interactions can be represented, where more than two entities may participate together in one interaction. The recent study [36] analyzes the influence of hypergraphs in the evolution of cooperation in structured populations, framed in terms of PGG. They showed that group (higher-order) interactions are able to sustain cooperation, similar to network reciprocity. In particular, they derived that reciprocity grows with the increasing order of the interactions, where hubs are crucial to this result.

## 3.3 Cooperation in Climate Change Dilemmas

The typical approach of public goods games focuses on providing a collective benefit. However, the climate change problem is concerned with avoiding collective damage, with an inherent uncertainty associated with it. To depict this, the pioneering experiment [10] showed that the essential keys of the global climate change issue can be formalized in terms of a Collective-Risk Dilemma (CRD). This dilemma represents a threshold public goods game, where it is required a minimum number of contributors to avoid a probabilistic loss. As a result, collective results vary non-linearly with the number of cooperators. Correspondingly, imposing a threshold portrays international environmental agreements, where a minimum number of countries are necessary to sign and ratify. In this class of games, people have to contribute sequentially to a public good which value they do not know, and if the target sum is not met, all individuals lose their investments with a certain probability. With this framework, the authors concluded that the individual's investments are risk-averse, as one may expect. They showed that contributions are shadowed by risk and uncertainty, where under a high perception of risk disaster the chance of groups reaching the target sum was fostered.

In the following work [21], the authors proposed an evolutionary approach to a vast plethora of collective action problems in which the risk of failure is a key issue. Like the previous study, they modeled the setting of a climate change dilemma by applying a non-linear public goods game, where some contributions may have a higher impact than others, due to the imposed threshold. For this, they introduced a non-linear payoff function, in contrast with a standard public goods game. It differs from the preceding approach, as instead of modeling the behavioral adaptation process with a repeated game, the authors used an evolutionary game-theoretical formulation. With this representation, individuals imitate those who seem more successful, seeking to improve themselves. Nevertheless, both studies reach the same conclusion: increasing risk perception enhances global cooperation. Namely, it was observable that when the risk was absent, the tragedy of the commons was always verified. Increasing the perception of risk changed the nature of the dilemma, turning cooperation into a sustainable strategy. Moreover, they demonstrated that questioning the scale at which this social dilemma is best resolved is fundamental. Their results indicated that when decisions occur mostly between small groups, cooperation is more feasible. Combining local agreements among considerable small groups maximizes the chances of accomplishing success, which is in line with the polycentric approach discussed in [37].

The study in [21] also included a component of complex networks. The authors explored the impact of various group sizes in scale-free networks. The heterogeneity present in climate settings was reflected, where individuals are already based on a network with economic and political ties. In particular, they illustrated the scale-free property, where a minority of individuals participate in a significant number of agreements, while the rest participate only in a few. Their results suggested that integrating the abound diversity inherent to social networks is a further influencing factor in prospering cooperation. Regarding this conclusion, they observed that hubs play an important role, which converges with the conclusions discussed in the above Section 3.2.1.

### 3.3.1 Wealth Inequality

In order to add realism to the previous approaches, new variations were introduced in the CRD formulation. In particular, to understand the impact of wealth inequality in reaching climate agreements, experiments formulated as a CRD presented a dichotomy on the endowments of the participants [13, 38]. For this purpose, they considered two wealth classes representing rich and poor nations. Although the approaches and assumptions of their models differ, both concluded that the avoidance of disastrous climate change is strongly dependent on the rich's initiative to cooperate. Specifically, [38] provided contributions showing that the poor are not willing to compensate for the lack of the rich's contributions, and although inequality may increase the incentives for the rich, it may also have the opposite effect on the poor. Therefore, they inferred that inequality seems to hamper cooperation, whereas communication and introducing coordination-promoting institutions are fundamental to reach success. From another perspective, the authors in [13] concluded that the chances of avoiding climate collapse are improved by meeting intermediate targets.

The impact of wealth inequality and the behavior dynamics among both wealth classes was further explored in [39]. By contrast with the previous works, the authors recurred to Evolutionary Game Theory (with an unstructured population). The distribution of unequal endowment present in this study recognizes that just 20% of the richest countries produce approximately the same gross domestic product as the remaining fraction of the poorest. Therefore, it portrays that 20% of the population represents the wealthier countries and 80% the poorest, where countries contribute an amount proportional to their wealth.

In the work [39], the authors also analyzed the repercussions of homophily in the behavior dynamics, i.e, the tendency of agents to imitate those with equivalent wealth status. As the proverbial expression quoted in [40] encapsulates: "birds of a feather flock together". Accordingly, homophily seems to be a basic organizing principle in societies that is observed empirically. It is a prevalent pattern in individual relationships that has an underlying influence on their interactions. The authors in [39] concluded that in well-mixed populations without homophily, heterogeneity in wealth can promote group success. This happens as in this scenario there is cooperative feedback between the two wealth classes, where the poor influence the rich to cooperate, which in turn, feeds back into the poor. On the other side, when the pattern of homophily is reflected, wealth inequality decreases the feasibility of achieving group success. In this case, analyzing the impact of risk provided important contributions. Specifically, when there is a low perception of risk, cooperation collapses, as also observed in the previous study [21]. By contrast, with the augment of risk perception, generally the rich try to compensate for the poor, who stop contributing. As concluded in [38], inequality may encourage the rich to contribute. Notwithstanding, it leads to a lower contribution of the poor. According to [39], the contributions of the poor have a significant dependency on homophily. Hence, their results suggested that homophilic behavior between rich and poor should be averted.

A distinct approach, regarding wealth inequality, is to study the impact of mechanisms focused on the cooperative relationships between different wealth classes. Inspired by the concept of "Financial Mechanism" (as the UNFCCC describes), the recent work [41] explores the impact of implementing financial incentives. The study was performed applying both behavioral experiments and game-theoretical analysis. In this implementation, high-income subjects shall provide financial resources to low-income subjects to motivate them in order to contribute to reducing emissions. Their results suggested that as the more richer individuals invest in financial incentives, the more poorer individuals contribute to reducing the emissions. With this configuration, it was observable that the majority of mitigation comes from the poor. Overall, the study indicated that the chances of achieving environmental agreements were fostered when high-income countries transfer part of their wealth to low-income countries.

### 3.3.2 Fairness

Considering that it may not only matter to achieve a minimum number of cooperators but that it may also be of importance to achieve it in the fairest way possible, a set of fairness notions can be applied in this context. In particular, deciding which fraction of individuals should incur a cost to achieve success, results in a fairness dilemma. Countries have not yet reached an agreement on the decision of how to share the burden of mitigation amongst themselves. Correspondingly, the work in [38] concluded that a common fairness notion is a precondition to reach global coordination in climate settings.

The impact of wealth inequality was introduced in the previous section. Presumably, there is a strong connection between equality and cooperation. To analyze how individuals react towards inequality, the experiment games in [42] provided different wealth levels to the players. The authors showed that social inequality arouses negative emotions in individuals, as humans are strongly influenced by egalitarian preferences. Therefore, they concluded that egalitarian motives have a significant impact on reaching cooperation. However, more than equality, individuals seem to be moved by fairness, as the study in [43] demonstrated. People have an aversion toward unfairness, and under certain special circumstances, this leads them to reject offers.

In the context of climate change, a set of fairness principles, such as historical responsibility for emissions, vulnerability to climate change and economic capacity are decisive to reach climate agreements. For instance, from an economic perspective, the study in [38] showed that the rich individuals' fairness perceptions and willingness to redistribute are crucial to achieve global cooperation. More precisely, when the rich class was questioned if the wealthier fraction should contribute more, the responses were not unanimous. These fairness perceptions strongly hamper cooperation and require a high level of communication to be resolved. As the results in [12] suggested, to avoid continuous disagreement in negotiations, it may be inevitable that rich countries with high historical responsibility carry a larger share of the burden.

### 3.3.3 Institutions

The limited progress of existing attempts to achieve global cooperation is also related to the absence of external monitoring institutions.

Regarding the dilemma in question, the study in [14] explored the impact of reward and punishment institutions, through the means of an evolutionary approach. They realized that by introducing a threshold in a CRD, after an initial effort to leverage the emergence of cooperation, the population will naturally self-organize towards an equilibrium where cooperation may be stable. Motivated by this, they showed that rewards are an efficient mechanism to surpass the initial struggle, specially when there is a low perception of risk. To maintain cooperation, the authors showed that punishment is an influential policy.

A more challenging goal is to recognize the predominant heterogeneity in the world when considering institutions. For instance, in parallel with wealth inequality, the authors in [14] highlighted that funding institutions are acquiring extreme importance. These institutions aim to fund countries that are in a more vulnerable position, helping their mitigation capacity. On the other hand, considering heterogeneity in interactions from a network science perspective, the recent work [44], framed as a non-linear PGG with laboratory experiments on economic decision-making, sheds light on the impact of diverse monitoring networks.

## 3.4 Summary

As discussed in this chapter, there is a lot of research that seeks to understand what can catalyze cooperation. We observed that identifying the pervasive diversity that is inherent to social dilemmas is becoming increasingly relevant in this field. Breaking symmetries that are commonly assumed to simplify the complex dilemmas that abound in the world is fundamental to grasp how cooperation can be promoted.

Nonetheless, none of the previous approaches recognizes the different risk perceptions and climate change awareness that persist across the world. Moreover, the effect of combining heterogeneity in social ties, through scale-free networks, and wealth inequality in the CRD remains unexplored. In this work, we propose to combine network heterogeneity, risk diversity, and wealth inequality in the climate change dilemma, which effects remain astray. We aim to provide insights into which conditions can flourish cooperative behavior, incorporating and merging these layers in the CRD. This confers a more accurate description of this type of dilemma, while also allowing us to better understand the impact of such factors in achieving environmental agreements.

# Chapter 4

# Model and Methods

Here, we introduce the model that allows us to answer our main research questions (see Section 1.3) through computer simulations. We define the problem as a Collective-Risk Dilemma in structured populations with its variations, namely in terms of social ties, risk perception and wealth.

## 4.1 Collective-Risk Public Goods Games

We formulate our model as a Collective-Risk Dilemma, as it has been shown to capture the key features of the climate change problem [10, 21, 45]. This dilemma constitutes a non-linear Public Goods Game, which introduces a threshold on the number of cooperators, and where the contributions are influenced by the risk of future losses.

Specifically, let $Z$ be the size of the population and $N$ the size of the group where the dilemma occurs. Individuals engage with an initial endowment $b$, which can be interpreted as the asset value at stake and can contribute a fraction $c$ of their endowment. If an individual decides to contribute it is designated as a Cooperator (*C*), otherwise, it is denoted as a Defector (*D*). To reach success, a minimum number $M$ of contributors is required, where $M \leq N$. Consequently, if a group of size $N$ does not contain $M$ Cooperators, all members of that group lose their remaining endowments with a probability $r$ that represents the risk of failure (with $0 \leq r \leq 1$). Namely, by introducing a coordination threshold where it is necessary to cooperate to reach success, we are capable of mimicking climate negotiations and agreements that demand a minimum number of contributions to come into practice.

To define the payoff function, we resort to the equation applied in the evolutionary approach to a Collective-Risk Dilemma in [21]. The payoff of a defector $P_D(k)$ in a group with $k$ cooperators, $k \in \{0, 1, \ldots, N\}$, can be written as:

$$P_D(k) = b\{\Theta(k - M) + (1 - r)[1 - \Theta(k - M)]\}, \tag{4.1}$$

where $\Theta(x)$ represents the Heaviside step-function distribution, with $\Theta(x) = 0$ if $x < 0$ and $\Theta(x) = 1$ otherwise. As aforementioned, $b$ represents the endowment, $M$ the threshold and $r$ the risk of failure.

In accordance, the payoff of a cooperator is $P_C(k) = P_D(k) - cb$, where $cb$ stands as the contribution of the cooperator (with $0 \leq c \leq 1$).

To better illustrate, an example of a possible payoff function of this dilemma is shown in Figure 4.1.

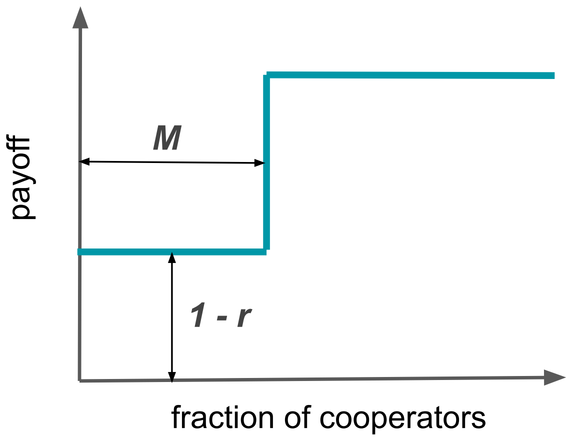



Figure 4.1: Example of a payoff function following the equation (4.1). In the figure, the costs spent by cooperators were excluded.

## 4.2 Population Structure

The population structure is defined by a graph. Nodes represent individuals and links define interaction and imitation partners.

In our study, we start by considering a population structured in a homogeneous regular network [25]. With this representation, individuals are topologically equivalent, as they have the same number of connections. Notwithstanding, as the authors in [21] emphasize, countries or regions are involved in networks of overlapping alliances or agreements that include political and economical relationships, with a prevalent diversity in their roles and positions. Accordingly, some individuals naturally participate in more agreements than others, and, consequently, are more influential in the network. To portray this diversity in the relationships and roles of the different individuals, we follow the work [21], where we introduce social heterogeneity by organizing the population in a scale-free network. As explained in Section 2.3, scale-free networks depict that the majority of individuals only interact with a few neighbors, but there is a minority (designed as hubs) that interacts with many. In these networks, the degree follows a power-law distribution (see Figure 2.1). This heterogeneity also results in a power-law distribution of the number and size of the collective dilemmas each individual participates in.

To use this heterogeneous structure we resort to the Barabási-Albert Model, one of the most famous models to generate scale-free networks, which combines growth and preferential attachment in their generation process. Precisely, the network begins with a ring of $m_0$ nodes. New nodes are added to the network one at a time. Each new node is connected via $m$ new edges with existing nodes (with $m < m_0$). To establish connections, new nodes are connected to older nodes with a probability proportional to the connectivity of the older nodes. As a result, new nodes attach preferentially to already well-connected nodes in the network. The probability $p_i$ that the new node connects to an existing node $i$ (with a connectivity of $n_i$) can be formalized as: $pi = \frac{n_i}{\sum_j n_j}$, where the sum is calculated across all pre-existing nodes. With this, the average connectivity of the network $z$ is given by $2m$ [24]. In our simulations, the networks remain unchanged after being generated.

## 4.3 Strategy evolution and population dynamics

Concerning public goods games on networked populations, the network defines how the strategy evolution occurs. All individuals engage in all possible public goods games, where the payoff is the result of their benefits and costs. The accumulated payoff of all the games is mapped onto individual fitness. Individuals participate in games with $n$ direct neighbors, therefore, the number of games that each individual engages in is $n + 1$. To illustrate, an example of a neighborhood defined by a social graph is presented in Figure 4.2, where we show the different games in which the focal individual (largest sphere) participates. One can interpret these games as the different environmental agreements/negotiations that occur in climate settings.

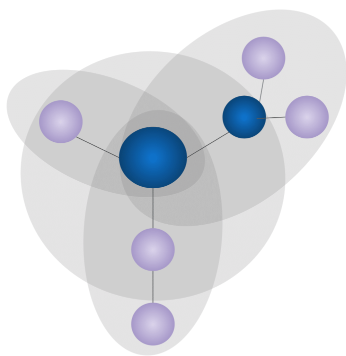


Figure 4.2: The focal individual (represented by the largest sphere) participates in distinct groups, each with its own group size. This individual has three direct neighbors ($n = 3$), therefore, it is possible to recognize four groups: one where the largest sphere is at the center and the others centered on one of the focal individual's neighbors. Individual fitness is derived from the accumulated payoff in all four groups [22].

To simulate evolution on networks, we apply Algorithm 1, based on typically used evolutionary processes. This algorithm considers social learning in finite and structured populations. Here, a dynamical approach is applied, where individuals are influenced by the decisions and success of their own neighbors.

Initially, individuals start with a strategy $s$ randomly placed on the network, with 50% of the population starting as a Cooperator (*C*) and the remaining 50% as a Defector (*D*). The strategy $s$ is set to $1$ if the individual adopts cooperative behavior, whereas it is $0$ in the case of defection. In each new generation, the population of individuals revises their strategy through peer-influence. This process of revision occurs $Z$ times in one generation, where $Z$ corresponds to the population size. Strategies are updated asynchronously, meaning that only one individual changes its strategy at a time. To simulate the revision procedure, we select a random node $i$ with strategy $s_i$, which in turn randomly selects a random neighbor $j$, whose strategy $s_j$ to imitate with a given probability. This probability is calculated using

**Algorithm 1** Evolutionary Process

**Input:** number of iterations, population

Setup of individuals and their strategies $s$ in the population
**for** number of iterations **do**
  **for** population size **do**
    $i \leftarrow$ random individual of the population
    $j \leftarrow$ random neighbor of individual $i$
    $f_i \leftarrow$ fitness of $i$
    $f_j \leftarrow$ fitness of $j$
    $prob \leftarrow$ imitation probability (2.2) between $f_i$ and $f_j$
    **if** $rand < prob$ **then**
      $s_i \leftarrow s_j$
    **end if**
  **end for**
**end for**

the imitation function typically employed for finite and structured populations, defined by Equation (2.2), with $f_i$ as the fitness of individual $i$, and $f_j$ as the fitness of individual $j$. Consequently, imitation will happen with a probability proportional to the difference between the fitness of both individuals ($f_j - f_i$). The parameter $\beta$ of the equation represents the strength of selection. As a result, when this constant increases, imitation will depend more on the fitness difference and it is expected that better-performing players will be imitated more often. For small values of $\beta$, individuals are susceptible to errors in the imitation process. In the algorithm, the imitation probability is compared with $rand$, representing a random value between $0$ and $1$, to include stochastic effects.

To consider the evolutionary process in networked populations, we reformulate the payoff function in (4.1). Namely, the payoff of an individual $y$ centered in the game of the focal individual $x$ can be written as:

$$P(x, y) = b\{\Theta(k_x - M) + (1 - r)[1 - \Theta(k_x - M)]\} - cbs_y, \tag{4.2}$$

with $k_x = \sum_{i \in \Omega_x} s_i$, where $\Omega_x$ denotes the set constituted by the nodes that are neighbors of $x$ and $x$ itself. The fitness that individual $y$ accumulates in the games can thus be formalized as:

$$f_y = \sum_{x \in \Omega_y} P(x, y). \tag{4.3}$$

## 4.4 Including Risk Heterogeneity

As we have explored in the previous chapter, unraveling symmetries is fundamental to understand what can foster cooperation. In the studies that were approached previously, the perception of risk was considered to be the same for all players. Nevertheless, some countries have a higher perception of risk than others. For instance, the exposure of climate damage is significantly more expressive in the Global South [1]. As a result, assuming that the population has the same perception of risk might be unrealistic.

In order to provide a more accurate description of climate agreements, we introduce a variation to the CRD formulation. Specifically, we consider a dichotomy in the risk levels of the population: $r_H$ and $r_L$ (where $r_H > r_L$), representing high and low risks, respectively. We thus consider that the medium risk of the population is $\bar{r}$. The population is composed of $Z$ individuals, where $Z_H$ represents the number of individuals with high risk and $Z_L$ constitutes the number of individuals with low risk (where $Z_L = Z - Z_H$).

In this scenario, the payoff of an individual $y$ centered in the game of the focal individual $x$ can be written as:

$$P_{H/L}(x, y) = b\{\Theta(k_x - M) + (1 - r_y)[1 - \Theta(k_x - M)]\} - cbs_y, \tag{4.4}$$

with $r_y \in \{r_H, r_L\}$, for individuals with high and low risk, respectively.

## 4.5 Including Wealth Inequality

Regarding wealth inequality, to portray the unequal distribution of wealth present in climate settings we follow the work [39]. We consider a population of $Z$ individuals, where $Z_R$ represent the rich (provided with an initial endowment $b_R$) and $Z_P = Z - Z_R$ constitute the poor (with an initial endowment $b_P$, where $b_P < b_R$). Rich cooperators contribute with $c_R = cb_R$, whereas poor cooperators contribute with $c_P = cb_P$.

The study we are following considered unstructured populations. To transition to networked populations, we assume that the payoff of an individual $y$ that engages in a game centered in the individual $x$ with a group constituted by $k_x^R$ rich cooperators, $k_x^P$ poor cooperators, and $N - k_x^R - k_x^P$ defectors can be defined as:

$$P_{R/P}(x, y) = b_y\{\Theta(\Delta) + (1 - r)[1 - \Theta(\Delta)]\} - cb_y s_y, \tag{4.5}$$

with $b_y \in \{b_r, b_p\}$, for rich and poor individuals, respectively. We consider $\Delta = c_R k_x^R + c_P k_x^P - Mc\bar{b}$, where $\bar{b}$ represents the average endowment ($Z\bar{b} = Z_R b_R + Z_P b_P$). In this setting, opposed to what was assumed before, to surpass the threshold it is not demanded a minimum number of cooperators, but it is necessary a minimum amount of contributions.

It is relevant to emphasize that rich and poor individuals may occupy different positions in what concerns, for instance, the network connectivity and the risk level. Our model allows us to study the impact of correlations between wealth, risk and connectivity.

## 4.6 Simulations

The use of computer simulations is advantageous to test the influence of a set of parameters in our model, as it constitutes a pragmatic way to predict the behavior or the outcomes of population dynamics in evolution. For instance, in the context of this thesis, we are interested in performing experiments capable of answering our proposed research questions, regarding network heterogeneity, risk diversity and wealth inequality.

To perform these simulations a program was written in *Python*. Using the *NetworkX* library [26], we created communities with $Z = 1000$ individuals. The average group size of the networks $\bar{N}$ is given by $z+1$, where $z$ is the average connectivity of that network. To fix some concepts in the simulations, we can consider the individuals in the network as regions/countries and contributions as emission reductions.

The success of a population is measured with the average group achievement, denoted by $\eta_G$, which represents the average fractions of groups that can successfully surpass the threshold. This metric is useful to evaluate the results of our model in comparison to the ones in related works.

In our contributions, we plot the evolution of the group achievement by averaging the results over 10 different realizations for each type of graph. Each data point corresponds to an average of over 500 runs, that is, 50 different realizations of the same class of graph. Each run starts from a population with an equal composition of *Cs* and *Ds*, which are randomly placed on the network. Each equilibrium group achievement, which represents the stationary state of one run, is obtained by averaging $2000$ generations after a transient period of $10^5$ generations.

# Chapter 5

# Results

In this chapter, we provide the results of our computer simulations, following the model described in Chapter 4, along with a discussion. We begin by presenting a Baseline Scenario without heterogeneity. Following that, we introduce heterogeneity in social ties through scale-free networks. We study the impacts of considering different thresholds $M$, changing the initial condition of the hubs, and varying the intensity of selection $\beta$. Subsequently, we introduce risk diversity in scale-free networks, where we analyze the effects of correlations between connectivity and risk. Next, we address wealth inequality and study the impacts of combining wealth, risk and network heterogeneity. Finally, concerning wealth inequality, we study the effect of considering distinct notions of fairness applicable to our model.

## 5.1 Homogeneous Networks

We first show experiments corresponding to a Baseline Scenario, where we follow the work [45]. We perform simulations of a Collective-Risk Dilemma (CRD) without considering any sort of heterogeneity. Specifically, we resort to a homogeneous network, in which all groups have the same number of participants, where we test the effects of considering different group sizes.

In Figure 5.1, we plot the average group achievement as a function of the risk of future losses, for group sizes ($N$) of $5$, $8$, and $12$ participants.

One can observe that for higher values of risk ($r > 0.6$) the group achievement becomes significantly high, having almost all groups surpassing the given threshold. On the other hand, for smaller values of risk ($r < 0.3$) the population can not escape from the full defection scenario. Thus, it is possible to infer that the risk is fundamental in this dilemma, which converges with the conclusions established in the literature. Intuitively, for lower levels of risk, even if individuals decide to not cooperate, it is possible for them to maintain their benefits. Therefore, there is a lower pressure for individuals to cooperate in settings with low risk, contrary to what happens when the risk is significant. Past studies have analytically shown that under low risks, the only predictable outcome is the tragedy of the commons. Augmenting the risk creates a coordination barrier in the dilemma, where it is necessary to collect efforts to surpass it. When this coordination barrier is surpassed, cooperation becomes sustainable. In particular, under

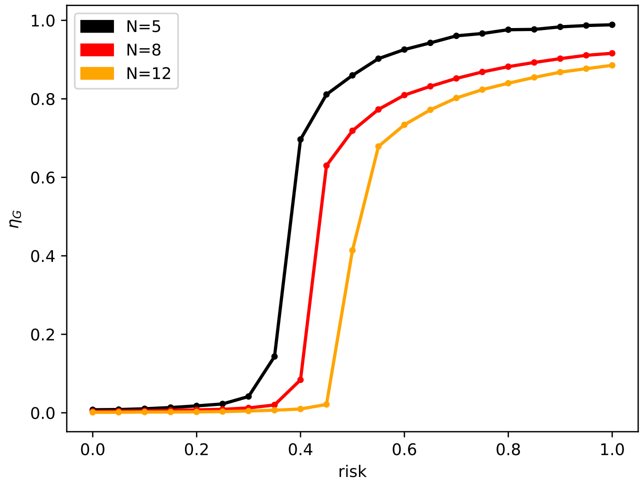


Figure 5.1: Average group achievement $\eta_G$ as a function of the risk in homogeneous networks (generated with regular graphs). In the different curves we consider distinct group sizes ($N$). Other parameters: population size $Z = 1000$, threshold $M = N/2$, fraction of contribution $c = 0.1$, endowment $b = 1$, strength of selection $\beta = 1.0$.

high risks, coordination is easier to achieve and the system self-organizes to the side of full cooperation. From Figure 5.1, we can see that cooperation becomes viable when the risk takes values near $0.5$.

Studying the effect that different group sizes can have in climate agreements is important, as it is fundamental to determine the scale at which these negotiations should be established to maximize cooperation. In accordance with the conclusions in the literature, the results of Figure 5.1 suggest that population success is more feasible within small groups. Specifically, when the group size $N$ becomes closer to the population size $Z$, cooperation is more difficult to achieve. Therefore, instead of a global climate summit where all countries are participating at once, we should aim for multiple small-scale agreements. This reasoning is in line with the conclusions of Elinor Ostrom [37], who mentions that thinking globally while acting locally may seem the responsible way to foster cooperation in climate settings. This polycentric approach recognizes the relevance of local interactions, which leads to a better self-organization of the population.

To summarize, Figure 5.1 indicates that we should combine various small-scale agreements with a high perception of risk. These results extend the conclusions taken in [45] for a well-mixed scenario, where individuals interact with an equal probability, to our more realistic setting, where the dilemma occurs in a structured population and individuals only interact with a subset of the population.

## 5.2 Heterogeneous Networks

In the previous section, we mentioned that the aim should be on establishing climate agreements following a polycentric approach. To put this approach in practice, it is fundamental to understand how small-scale agreements should be established. That is, how groups should be organized in the population to promote cooperation.

It is relevant to emphasize that climate agreements are embedded in already complex networks of economical and political ties, where some countries/regions are much more influential than others for these agreements to come into practice. Therefore, instead of organizing the population in a homogeneous structure, where all individuals are topologically identical, we should consider a more realistic and heterogeneous structure. To depict this, we follow the work in [21], where we test the effects of considering the CRD in scale-free networks, as they portray the ubiquitous diversity in the relationships and roles of the different players. We thus consider that groups are organized into overlapping agreements in a heterogeneous graph, where each neighborhood defines a group (as explained in Chapter 4).

Until this point we have considered a fixed and equal threshold for all groups, meaning that every group should contribute the same amount. However, given the complexity introduced with scale-free networks, where some groups are much bigger than others, this might not be a fair assumption. For instance, let us interpret the network as a distributed system of agreements to coordinate efforts in order to reduce the emissions of CO2. Larger groups might require a larger reduction of emissions. With this said, we introduce a new threshold that is dependent on the number of individuals that take part in the different groups. Specifically, instead of considering $M$ as a fixed value, it is an increasing function of $N$. In this setting, we are assuming that there is a notion of fairness in the definition of population success, in which success is achieved if groups contribute an amount proportional to their group size.

Figure 5.2a shows the effects of considering scale-free networks with the two distinct thresholds just described above. Both networks have an average group size of $7$. Therefore, to maintain the average threshold value in both settings, we consider $M = 3$ in the scenario where the threshold is fixed and $M = 3N/7$ in the scenario where the threshold varies.

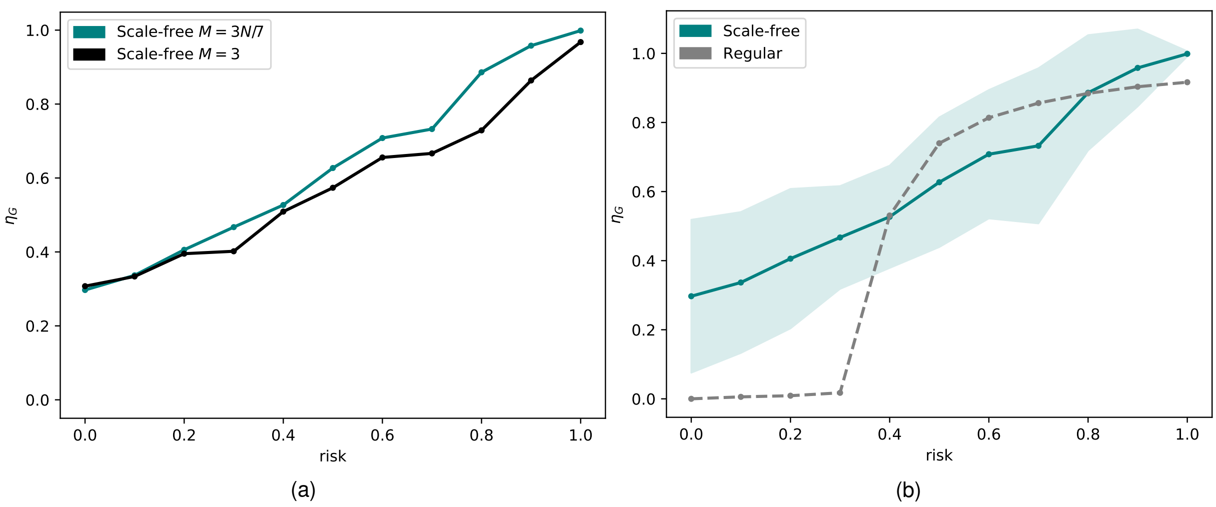



Figure 5.2: Average group achievement $\eta_G$ as a function of the risk, considering different networks and distinct thresholds. **(a)** Represents scale-free networks with two different types of thresholds. The blue line corresponds to a threshold that increases linearly with the group size ($N$): $M = 3N/7$, that is, we require a fraction of $3/7$ of group members cooperating. The black line corresponds to a threshold that is fixed for all groups: $M = 3$, that is, we require $3$ group members cooperating. With $M = 3N/7$ we make sure that the average value of $M$ is the same in both scenarios. **(b)** Comparison between homogeneous regular networks (with $M = 3$) and scale-free networks (with $M = 3N/7$). The shaded area illustrates the uncertainty between different simulations that is only present in scale-free networks. Other parameters: population size $Z = 1000$, average group size $\bar{N} = 7$, fraction of contribution $c = 0.1$, endowment $b = 1$, strength of selection $\beta = 6.0$.

We can observe that considering $M = 3N/7$ has a slightly larger average group achievement, especially for larger risk values. However, the results suggest that the difference between the two threshold scenarios is not significant. In line with the conclusions in [21], when $M$ is fixed, it is easier for large groups to surpass the threshold than when $M$ varies. Consequently, the highly connected players that are in the center of these groups will have higher fitness, as it increases when the threshold is achieved. Since these players are very influential in the network - given the high number of connections they have, which causes them to be imitated more often - they can influence the members of smaller groups to assume cooperative behavior. By contrast, when $M$ depends on $N$, it is harder for large groups to surpass the threshold and to spread cooperation to the rest of the network. Notwithstanding, as the majority of the groups in the network are small (given the scale-free network properties), cooperation is compensated for the fact that in this scenario it is easier for smaller groups to obtain group success.

The results for experiments with different population structures, namely, homogeneous regular networks (with $M = 3$) and scale-free networks (with the introduced threshold $M = 3N/7$) are provided in Figure 5.2b. The curves show the average results of the simulations, and the shaded blue area corresponds to the standard deviation derived from the different simulations, which reflects the uncertainty that only emerges in scale-free networks. It is possible to observe that, even with the high uncertainty present in the heterogeneous scenario, scale-free networks can open a window of opportunity to cooperation. This is particularly true when the risk is low ($r < 0.4$) or high ($r > 0.8$). Additionally, we experimentally observed that the variance for the fixed threshold was similar and close to the variance of the threshold that varies in Figure 5.2b.

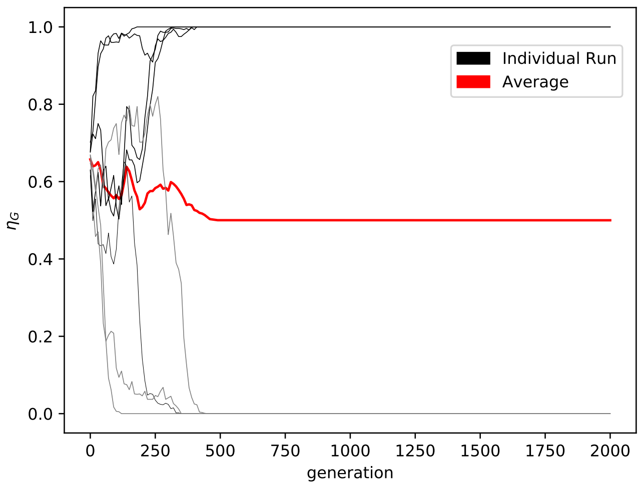



Figure 5.3: Time evolution of the group achievement through generations for 10 runs in scale-free networks. The black and grey curves represent individual runs and the red curve corresponds to the average of these 10 runs. The plot was generated considering successive equally spaced points in time (5 to 5 generations). In each run we wait $10^4$ generations. Other parameters: population size $Z = 1000$, average group size $\bar{N} = 7$, threshold $M = 3N/7$, risk perception $r = 0.5$, fraction of contribution $c = 0.1$, endowment $b = 1$, strength of selection $\beta = 6.0$.

To better understand the uncertainty that occurs in the heterogeneous case, in Figure 5.3 we show a time series of the evolution of the group achievement through generations. We present the runs of ten scale-free networks and their average (the red curve), assuming the perception of risk of the population as $r = 0.5$. As one can notice, the system never converges to the average of the simulations. Instead, it is clear the coordination that occurs, where the system always converges to $0$ or to $1$. This is consistent with the conclusions in [46], where the authors show that homogeneous networks promote the coexistence between cooperators and defectors, while heterogeneous networks promote their coordination - where the system always ends on the side of full cooperation or full defection. Hence, in these coordination problems, there is a typical variance in the results.

Intuitively, the reason why this uncertainty is present only in heterogeneous networks is due to the crucial role of the hubs in the evolution of cooperation. In our simulations, their initial strategy is randomly assigned. Therefore, it is natural that when most hubs start as cooperators, they can foster the evolution towards fully cooperative populations. However, when these hubs happen to be occupied by defectors, the opposite scenario occurs, leading the population to full defection.

To verify this reasoning, we change the setup of the hub's strategies in the evolutionary process. Let us consider that the hubs have a connectivity $n$ in the network of: $\frac{n_{max}}{3} \leq n \leq n_{max}$, where $n_{max}$ is the maximum connectivity of that network (as formulated in [22]). We test the effects of initializing the hub's strategy with two extreme limits: one with all hubs as cooperators, and the other with all hubs as defectors, maintaining the population with 50% *Cs* and 50% *Ds*.

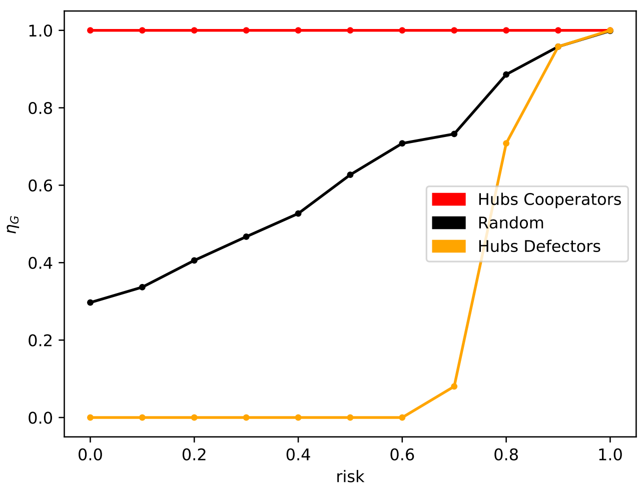



Figure 5.4: Group achievement as a function of the risk, considering different setups of the hub's strategies in the evolutionary process. Namely, we test the effects of initializing all hubs as *Cs* (in the red curve), all hubs as *Ds* (orange curve), and randomly assigning the strategy in the hubs (black curve). Other parameters: population size $Z = 1000$, average group size $\bar{N} = 7$, threshold $M = 3N/7$, fraction of contribution $c = 0.1$, endowment $b = 1$, strength of selection $\beta = 6.0$.

In Figure 5.4, we present the average group achievement as a function of the risk, considering the two aforementioned setups, and the previous setup that is being considered in our experiments, where the strategy of the hubs is randomly assigned.

One can observe from Figure 5.4 that when all hubs start as cooperators, global cooperation can be achieved, independently of the risk. Contrastingly, when all hubs start as defectors, global cooperation is only feasible in the presence of elevated risks (when $r > 0.8$).

To understand this outcome, it is important to stress that hubs are able to accumulate a considerably higher fitness than other nodes, as our model considers accumulated payoffs (see Equation (4.3)) and they take part in the majority of the games. Hence, hubs will be imitated more effectively and seen as preferential role models, which is in accordance with what was observed in [47].

It is thus possible to confirm that the initial strategy of the hubs can have an extreme impact on the population dynamics. As a result, our outcomes have a natural degree of uncertainty.

Anticipating the next sections, it is noteworthy that this uncertainty can give an interesting political message. Namely, if the results are strongly dependent on the individuals with a higher centrality that take part in more groups, we should aim to circumvent this uncertainty by making an intervention in these same individuals. This idea that some positions in the network can be more important to leverage cooperation is a type of analysis that does not exist in homogeneous populations. Considering that heterogeneous networks confer a more realistic description of how climate accords are established, thereafter we will organize the population in scale-free networks. This enables us to explore more complex components that are unique to these structures.

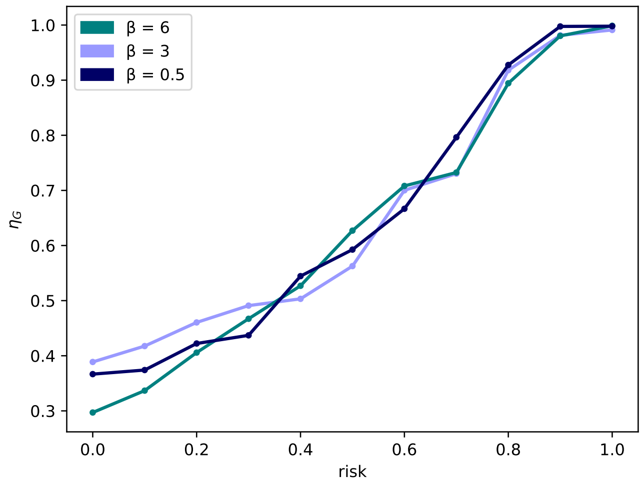



Figure 5.5: Average group achievement $\eta_G$ as a function of the risk, considering distinct values of the intensity of selection $\beta$ in scale-free networks. Other parameters: population size $Z = 1000$, average group size $\bar{N} = 7$, threshold $M = 3N/7$, fraction of contribution $c = 0.1$, endowment $b = 1$.

In the previous results, we consider the intensity of selection as $\beta = 6$. Here we investigate the impact of varying this variable. Correspondingly, in Figure 5.5, we show the average group achievement as a function of risk, considering different $\beta$ values: $0.5$, $3$, $6$.

As one can observe from Figure 5.5, the results are robust with respect to changes in the intensity of selection $\beta$. Specifically, even when one assumes low values of $\beta$, and, consequently, there are errors in the social learning process and imitation does not strongly depend on the fitness difference (see Equation (2.2)).

The observed robustness may be a result of the diversity of the network, as we are considering a game with accumulated payoffs in a strongly heterogeneous setting. Accordingly, even with low values of $\beta$, the difference between the fitness of the players can vary substantially. As we mentioned before, this is particularly true in the case of the hubs since they take part in more games. Therefore, even when $\beta$ is low (and errors in the imitation can occur), it is more probable that players with higher fitness will be imitated more often. This is the same outcome that a high value of $\beta$ produces, as it makes the imitation process strongly dependent on the fitness difference. Consequently, it is natural that high and low values of $\beta$ confer similar results.

Our results are consistent with the findings in the study [47], which infers that heterogeneous networks exhibit resiliency to the intensity of selection.

## 5.3 Risk Diversity

In the preceding sections, we confirmed that the perception of risk is a key factor in the climate change dilemma. Nevertheless, it was assumed that the risk was a global property of the network, where all individuals had an equal perception of risk. This assumption, however, does not take into account that the levels of climate change perception vary greatly across the world. Therefore, to transition to a more realistic description of climate agreements, we consider two distinct levels of risk in the population: high risk ($r_H$) and low risk ($r_L$), as detailed in Section 4.4.

Moreover, it was also concluded that in heterogeneous networks some positions in the network - the positions with higher centrality - can have a crucial role in the emergence of cooperation. For this reason, it is relevant to analyze the impact that manipulating the initial condition of highly connected nodes can have in the evolutionary process. Motivated by this, in this section we study the effects of correlating network connectivity with risk.

To introduce the correlations, we divide the population into two halves: one half with high risk, and the other half with low risk. We introduce a measure of heterogeneity between high and low risk, denoted by $\delta$. Specifically, we assume that the population has a medium risk $\bar{r}$, where the class with high risk has $\bar{r}+\delta$, and the class with low risk has $\bar{r}-\delta$. This implies that the higher the $\delta$, the more diverse is the population. We perform experiments varying $\delta$ between $0$ and $0.4$, considering that the medium risk in the population $\bar{r}$ is $0.5$. Therefore, when $\delta$ is $0$ we are in the presence of the homogeneous case, where all individuals in the population have a risk equal to $0.5$. On the other hand, when $\delta$ is equal to $0.4$, we have the maximum heterogeneity in the risk levels of our simulations.

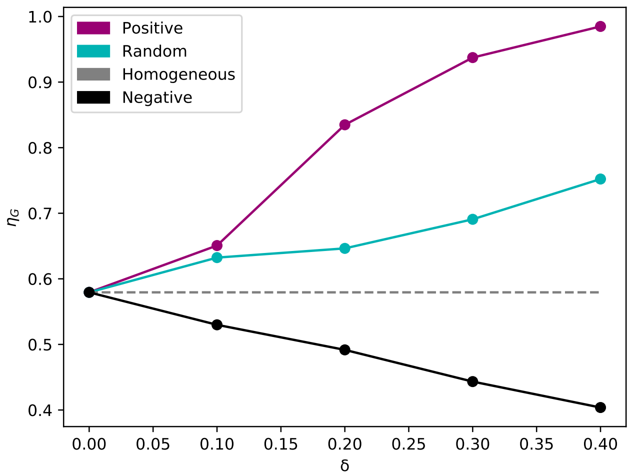
Regarding the different correlations, we consider three distinct configurations:

- Positive: the half of the population with high risk corresponds to the nodes with the highest degree, whereas the half with low risk corresponds to the nodes with the lowest degree;

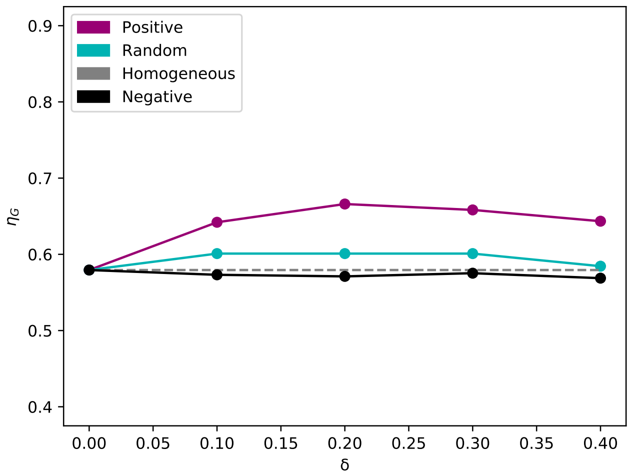
- Negative: the half of the population with high risk corresponds to the nodes with the lowest degree, while the half with low risk corresponds to the nodes with the highest degree;

- Random: individuals are randomly assigned to the high or low risk half.

First, we consider the risk to be an individual property of the players, following the methods described in Section 4.4. By portraying this heterogeneity, even if individuals are in the same group, the costs and benefits of participating in the games will be individual. This is explicit in their payoffs, as the payoffs for different individuals will have different risks (see Equation (4.4)). For instance, if the threshold is not achieved in a group, there will be members of the group who will suffer far greater losses than others. Analogously, when a group successfully surpasses the threshold, the benefit will depend on the individual in question.




(a)




(b)

Figure 5.6: Group achievement as a function of $\delta$ (which represents a measure of heterogeneity between high risk and low risk), considering different correlations between risk and connectivity in scale-free networks. **(a)** Heterogeneity in the individual risk, where the risk is considered to be an individual propriety in the network. **(b)** Heterogeneity in the risk at the level of the games, where the risk of all individuals participating in a given game is the risk of the focal individual of that game. Other parameters: population size $Z = 1000$, average group size $\bar{N} = 7$, threshold $M = 3N/7$, fraction of contribution $c = 0.1$, endowment $b = 1$, average risk $\bar{r} = 0.5$, strength of selection $\beta = 6.0$.

In Figure 5.6a, we evidence the impacts of assuming different correlations between risk and connectivity. Precisely, we show the group achievement as a function of $\delta$ considering the three aforementioned correlations. Besides, we present a reference scenario without risk heterogeneity in scale-free networks (the dashed grey line), where individuals have the same level of risk that is equal to $0.5$.

Figure 5.6a shows that assuming a positive correlation between connectivity and risk leads to an impressive boost of cooperation. Namely, it confers the highest levels of group achievement in this experiment, with the group achievement becoming $1$ when $\delta = 0.4$. Conversely, assuming a negative correlation significantly decreases the levels of cooperation, providing the lowest levels of group achievement. On the other hand, in comparison with the reference scenario, randomly attributing the different risk levels can marginally improve cooperation.

To understand the striking enhancement of cooperation in the positive correlation, notice that, in this scenario, hubs are associated with a high risk. As we have seen before and as it is well-established in the literature, an elevated perception of risk is fundamental to turn players into cooperators in climate settings. Consequently, hubs will easily cooperate. As hubs will be imitated more often - due to their number of connections - they will spread cooperative behavior through their neighbors, which allows them to easily achieve group success. Considering that the fitness of players increases when they are more successful, this confers a significant increase in the hub's fitness. Additionally, as imitation is determined by the fitness difference, hubs will serve as a model for other players to learn that cooperation leads to success, fostering the evolutionary process towards a fully cooperative population.

Analogously, when individuals have a low perception of risk, there is a lower pressure for individuals to cooperate (as discussed previously). Consequently, it is reasonable that when we assume a negative correlation between connectivity and risk - where hubs face a low perception of risk - the influential role that hubs have in the network reverts to the scenario where defection prevails, as defective behavior will be imitated more frequently. Notwithstanding, the increase in the hub's fitness conferred by surpassing the threshold in their groups will not be verified in this setting. This might explain the bigger impact in the positive correlation in comparison with the negative one.

Regarding the random correlation, there is an increase in the group achievement. As we have already discussed, when hubs have a high risk the levels of cooperation considerably increase. Therefore, the effect of the random correlation turns out to be positive, as it is only necessary to have a few runs in which some hubs are associated with high risk for having a large impact on the average result.

### 5.3.1 Risk at Different Scales

It is worth emphasizing that diversity in risk can emerge in distinct ways. Consequently, it is possible to map risk heterogeneity in the network from different perspectives that naturally depend on the interpretation of the network. In Figure 5.6a, we embraced diversity as a whole, as we considered the risk to be an individual property of the players. Nevertheless, it is also reasonable to consider risk heterogeneity at other scales.

Taking this into consideration, we explore other possibilities by assuming the risk at the level of the games. Considering that a node defines the game centered in itself (see Figure 4.2), we can interpret the risk of a certain game to be the risk of the node that defines that specific game. In particular, we consider the risk that an individual $y$ faces by participating in the game centered in individual $x$ to be $r_x$ in the payoff function (4.4), instead of $r_y$. In this case, by contrast with setting 5.6a, all members of a certain game face the same consequences by participating in that game.

One possible interpretation for the risk heterogeneity in the setting 5.6b is to consider the network of agreements as the geographical location where the agreements are being established. Namely, if we assume that a specific area has a certain risk of failure, all members that are establishing an agreement focused on that area share that same risk. For example, an agreement to manage fishery resources in the North of the Atlantic, or a negotiation that occurs around the Pacific coast match this idea. On the other hand, in the scenario 5.6a, we can interpret that the different games are agreements/negotiations established by social and political ties that transcend geography, as it is expected that many real-life agreements are formed between countries that do not necessarily share the same risk.

Notwithstanding, notice that scale-free networks are usually characterized for having interconnected hubs [48]. Given that we are correlating the risk with connectivity, hubs with the same level of risk are connected. Consequently, in setting 5.6a, there is also a tendency for participants in the same group to share the same risk, to a lesser extent than in 5.6b. This tendency is observed empirically, as neighboring nations tend to experience more similarities in climate change awareness and risk perception (as suggested in [49]).

Considering the plethora of options in this dilemma, it is plausible that climate agreements may fall somewhere between these two scenarios, as the agreements can be established focused both on specific areas and other characteristics that exceed geography.

In Figure 5.6b, we assume the heterogeneity at the level of the games. It is clear that the impact of considering risk heterogeneity in the games is not so evident as when the risk is an individual property, as in Figure 5.6a. Nevertheless, it is possible to observe that the variation of the two scenarios goes in the same direction, as the positive correlation confers the best arrangement in this experiment, whereas the negative correlation provides the worst. This allows us to conclude that there is consistency in the results between both figures.

To grasp the remarkable boost of cooperation in the former scenario in comparison with the latter, it is important to analyze the effective risk in the different schemes. For this, let us consider the star-graph example of Figure 5.7. In the figure, we assume a positive correlation between risk and connectivity, with the blue spheres representing highly connected nodes and purple spheres low-degree nodes. Accordingly, blue lines indicate that the hub engages in the game defined by that neighbor with high risk and purple lines with low risk. To illustrate our reasoning, we calculate the average risk that the focal hub (the blue sphere in the center) faces in its games.

As it is observable in 5.7a, when we consider the risk as an individual property, the hub always participates in the agreements with a risk of $\bar{r}+\delta$, independently of the pattern of connection. Contrastingly, when we consider the risk at the level of games in 5.7b, the risk that the hub faces in the games depends

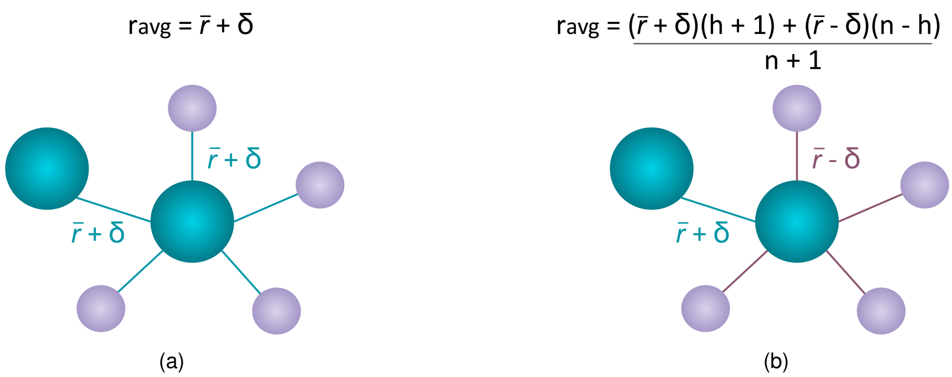



Figure 5.7: Comparison between the average risk $r_{avg}$ that the focal hub (the blue sphere in the center) faces in its games, in a star-graph. Here, we consider a positive correlation between risk and connectivity. Blue spheres represent highly connected nodes and purple spheres low degree nodes. Accordingly, blue lines portray that the hub engages in the game defined by that neighbor with high risk and purple lines with low risk. We consider that the hub is connected to $h$ other hubs and to $n - h$ leaves (where $n$ is the connectivity of the hub). **(a)** Heterogeneity in the individual risk. In this setting, the hub faces an average risk of $\bar{r} + \delta$. **(b)** Heterogeneity in the risk at the level of the games. In this scenario, the hub participates in the games with an average risk that depends on the corresponding focal individual of those games.

on the connectivity of the focal individual of those games, and, consequently, on the risk that those individuals have. In particular, when the focal individual of the game has a high degree, the risk of that game is $\bar{r} + \delta$ (the blue line). By contrast, when it has a low degree, the risk of that game is $\bar{r} - \delta$ (the purple lines).

For instance, let us suppose that a hub is connected to $h$ hubs and to $n - h$ leaves (where $n$ is the connectivity of the hub). In 5.7b, the hub participates in the games with an average risk that can be calculated as: $r_{avg} = \frac{(\bar{r}+\delta)(h+1)+(\bar{r}-\delta)(n-h)}{n+1}$, whereas in 5.7a the average risk is $\bar{r} + \delta$. Given that in 5.7b, $h$ is always less than $n$, as hubs are connected to the majority of the individuals and scale-free networks have significantly more low-degree nodes, it is possible to infer that the effective risk of the hubs in the agreements will always be higher when the risk is individual. This confers an advantage for hubs to cooperate in the evolutionary process, which significantly enhances the chances for global cooperation for that scenario.

Similarly, when we assume a negative correlation, the difference between the two scenarios follows the reasoning explained above: In 5.7b, the hubs engage in the games with an average risk that will be composed of high and low risks. By contrast, in 5.7a, it will be constituted only by low risks, and, consequently, will amplify the deteriorating effect that a low risk has on the evolution of cooperation.

It is noteworthy that the impact of $\delta$ is also different in the two schemes. As one can observe in 5.6a, when we assume a positive correlation, the group achievement increases when $\delta$ also increases. By contrast, when the correlation is negative, the group achievement decreases with $\delta$. Accordingly, in 5.6a, it is noticeable that the effect of increasing the risk heterogeneity enhances the effect of the correlations. On the other hand, in 5.6b, the influence of this variable does not seem as significant. To interpret these results it is also useful to consider the example of Figure 5.7. Naturally, when one considers the individual risk, increasing $\delta$, and, consequently, increasing the risk in the hubs, directly increases the average risk that hubs confront in their games - as it depends entirely on their own risks. Conversely, when the risk is at the level of games, increasing $\delta$ does not increase the average risk that hubs face in their agreements. Particularly, by increasing the risk heterogeneity, although we are increasing the risk of the games centered in highly connected nodes, we are also decreasing the risk of games centered in low-degree nodes. As a result, the impact of $\delta$ is not considerable.

We may thus infer that cooperation can be remarkably promoted by the diversity associated with considering the risk as an individual property. Nevertheless, it is relevant to stress that diversity can have different effects depending on the correlations between risk and centrality that we consider.

For simplicity, when we include risk heterogeneity thereafter, we assume the setting in which the risk is individual in the network.

### 5.3.2 The Impact of Major Hubs

The previous results indicate that hubs and their perception of risk are crucial in the course of this dilemma. When their perception of risk is high, they can unleash a wave of cooperation across the network. Yet, it is particularly dangerous if they have a low perception of risk. Translating these outcomes into a realistic perspective, we can interpret the hubs as the climate leaders of environmental agreements, given their high centrality and significance in the network. Hence, to achieve global cooperation, it is fundamental that leaders have a high perception of risk.

Now, we investigate how many hubs with high risk are necessary for cooperation to thrive in the population. To do this, we assign a high risk ($r_H$) to $Z_H$ top connected hubs. A risk $x$ is assigned to the remaining nodes to maintain the same average risk per individual in the network (we set $\bar{r} = 0.5$). The value for $x$ can be calculated as follows:

$$x = \frac{\bar{r}Z - r_H Z_H}{Z - Z_H}, \tag{5.1}$$

where $Z_H < \frac{\bar{r}}{r_H} Z$.

In Figure 5.8, we plot the group achievement as a function of the number of hubs, ordered by descent connectivity, which were assigned with a high risk. The different curves correspond to distinct values of high risk that we consider. The dashed line represents the reference scenario with all individuals having the same risk ($r = 0.5$).

We show that cooperation becomes viable when assigning a high risk to only a few major hubs. This is especially notable in the case where $r_H$ is the highest in our simulations ($r_H = 0.9$), with the group achievement becoming near $1$ by only assigning a high risk to two major hubs. Hence, the results of Figure 5.8 suggest that, even when the medium risk on the population is not significant (as $\bar{r} = 0.5$), it is only necessary to adjust the perception of risk on some few individuals that have higher connectivity to turn cooperation into the dominant strategy.

It is important to remember that in scale-free networks the degree follows a power-law, as shown in Figure 2.1. We have seen that highly connected nodes have a degree much higher than the majority of the other nodes, nevertheless, it is notable that even some of these highly connected nodes have

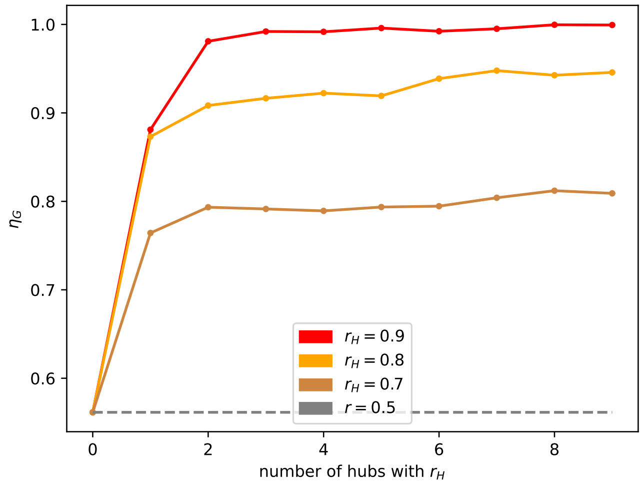



Figure 5.8: Group achievement as a function of the number of high-risk hubs, for several high-risk levels. The hubs are ordered by descent connectivity. Other parameters: population size $Z = 1000$, average group size $\bar{N} = 7$, threshold $M = 3N/7$, fraction of contribution $c = 0.1$, endowment $b = 1$, average risk $\bar{r} = 0.5$, strength of selection $\beta = 6.0$.

significantly more connections than others. There is a hierarchy in the degree, to which major hubs are closely followed by smaller ones, which in turn, are followed by nodes with a smaller degree, and so forth. Correspondingly, there are some major hubs with a degree that greatly exceeds the smaller hubs. Consequently, these major hubs will have an extreme impact on the network, as they can accumulate more fitness and influence considerably more individuals.

As we have concluded before, when the perception of risk in the hubs is high, they easily turn into cooperators and influence the rest of the network to cooperate. We may thus infer that it is only necessary to have a few major hubs with high risk, so they can disseminate the cooperative strategy to the whole network.

### 5.3.3 Discussion of the Correlations

Given these results, it is natural to ask how risk and connectivity are correlated in the real world. Are the hubs of climate agreements those with a higher perception of risk or is the scenario the opposite?

To explore this question, it is necessary to make a distinction between the terms "risk" and "perception of risk". So far, we are using both terms interchangeably, as these concepts are intimately connected. Accordingly, the meaning of the risk ($r$) is open to both interpretations, as our model is a simplification of the reality, in which we can not grasp the whole complexity that the climate change dilemma involves. Notwithstanding, to better understand the problem in question, these concepts should be defined more precisely. The concept of risk, as the Intergovernmental Panel on Climate Change (IPCC) defines [50], is the potential for adverse consequences for human or ecological systems that strongly depends on vulnerability and exposure to climate change. On the other hand, the perception of risk requires awareness of climate change (the recognition that the problem exists) and the realization of the severity of the impacts of environmental damage [49]. Nevertheless, both terms are related as risk leads to the perception of risk. The perception of risk of a certain area can derive from the exposure to climate change that occurs in that area. For example, in [49], it was demonstrated that local temperature change is the strongest predictor of risk perceptions in many countries.

Taking a look at how climate agreements are concretely being established in the real world, it is important to realize which are the hubs of the network, that is, which are the countries leading the environmental negotiations. As the results in [51] suggest, the European Union, the United States, and China are undoubtedly the climate change leaders, which we can interpret as the major hubs of the network. Moreover, we can also consider as hubs the Group of Seven (G7) - that wield significant international influence - composed of Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States. To discuss how realistic the correlations are, we will essentially analyze the risk and perception of risk of these countries.

Regarding the risk itself, it is known that the Global South will suffer the vast majority of the consequences [1]. Therefore, it is likely that the correlation should be negative in this case, as the hubs are mostly considered to be at Global North.

On the other hand, the largest cross-sectional survey of climate change perceptions [49] concludes that the lowest levels of awareness of climate change were reported in some countries of Africa, the Middle East, and Asia. By contrast, the highest levels were present in the so-called developed countries, in particular, in North America, Europe, and Japan - the hubs of the network. It is thus reasonable to ask: Why are the leaders not addressing climate change if they realize the seriousness of the problem? To understand this incongruity, in [52] the authors explain the paradox in the USA risk perceptions of climate change. They concluded that even if the majority of Americans believe climate change is a serious threat, it remains an issue with low priority, as Americans consider that it is more likely to impact people and places far distant in space and time. In other words, they are aware of climate change, but they lack an adequate perception of risk, as they have a low exposure/risk to damage. Consistently, in [49], the authors demonstrate that among the countries who were aware of global warming, those in the Global South have a higher risk perception, as they saw climate change as a far bigger threat to themselves than in Global North. Having said that, it is hard to grasp how the correlation should be regarding the perception of risk. Notwithstanding, hubs usually have a low perception of risk.

As our findings demonstrated, if hubs have a low $r$, defection is expected to prevail in the population. This can shed some light on understanding why cooperation in climate agreements is far from sufficient.

According to [49], to increase public awareness worldwide, it is critical to improve basic education, climate literacy, and public understanding of climate change. Regarding the countries which are aware that climate change is a threat, but are not at the frontline of the climate crisis, the aim should also be directed on these principles. It should be noted that even if climate damage is not impacting a country directly, there are dependent relationships in the network that already affect everyone. Take the example of a global supply chain - the majority of the world's economic production revolves around a complex network of interconnected supply chains. Supply networks, for example, are responsible for producing food, water, and medication. As extreme weather events are getting more frequent, the probability of supply-chain disruptions is also growing, which can affect everyone in multiple ways [53]. This means that, materially, the relationship exists - the risk is shared -, however, it is the recognition of this risk that may not exist.

As [49, 52] suggest, efforts to describe the potential national, regional, and local impacts of climate change, communicate these impacts and unravel fundamental misconceptions - considering the unique context of each country - are fundamental to face the problem with the urgency that it implies.

## 5.4 Wealth Inequality

Until now we have assumed that the wealth is uniformly distributed among all players. However, as discussed in Section 3.3.1, the distribution of wealth in the real world is far from being homogeneous. Hence, to portray the disparities of wealth that persist worldwide, we consider two distinct wealth classes: rich and poor. For this, rich individuals have an endowment $b_r$, and poor have an endowment $b_p$, as detailed in Section 4.5.

We follow the work in [39], where the authors recognized that 20% of the wealthier countries produce approximately the same gross domestic product as the poorest 80%. Therefore, we consider the rich to constitute 20% of the population and the remaining 80% represent the poor. Moreover, we consider that the contributions of the players are proportional to their wealth class. In this setting, the dilemma comprises a new layer: Rich players are the ones who possess the most. Nevertheless, they are also the ones with the most to lose (see Equation (4.5)).

In this section, we focus on understanding the impacts of correlating wealth with connectivity. For this, we consider three distinct correlations:

- Positive: the 20% rich will be constituted by the 20% nodes with the highest degree, and the 80% poor will be composed by the remaining nodes;
- Negative: the 20% rich will be formed by the 20% nodes with the lowest degree, and the 80% poor will be composed by the remaining nodes;
- Random: we randomly attribute the wealth levels in the network, maintaining the 20%-80% distribution of wealth.

Note that, in the previous study [39], homophily was a striking factor to analyze the impact of wealth inequality (as referred in Section 3.3.1). Namely, according to [54], a remarkable feature of global economic activity is the extent to which it is spatially correlated: poor countries tend to be near other poor countries, analogously, rich countries also tend to be clustered together. Furthermore, regarding behavior dynamics, the tendency of individuals to imitate those with equivalent wealth status is observed empirically [40]. When one assumes correlations that involve connectivity in scale-free networks, the pattern of homophily emerges implicitly. Specifically, the tendency for nodes with the same degree to be connected stems from the fact that the individuals with the highest connectivity are presumably those who have been in the network for the longest time [24], regarding the construction of the network (detailed in Section 4.2). Consequently, these nodes tend to be connected. In other words, scale-free networks exhibit a tendency for having interconnected hubs. Hence, if we correlate wealth with connectivity, hubs with the same level of wealth also tend to be connected.

We perform experiments to analyze the impact of considering the three different correlations previously described, varying the endowment of the rich ($b_r$). To assure that the average endowment per individual is equal to the scenario with no wealth inequality ($\bar{b} = 1$), we define the endowment of the poor as: $b_p = \frac{Z - Z_r b_r}{Z_p}$.

In Figure 5.9, we show the group achievement as a function of the endowment of the rich, considering the correlations between risk and connectivity described above. Observe that, along the x-axis, the wealth inequality increases, with the rich becoming richer and the poor becoming poorer. Additionally, we also show a reference scenario without wealth inequality in scale-free networks (i.e, all players have the same endowment $b = 1$), represented by the dashed grey line.

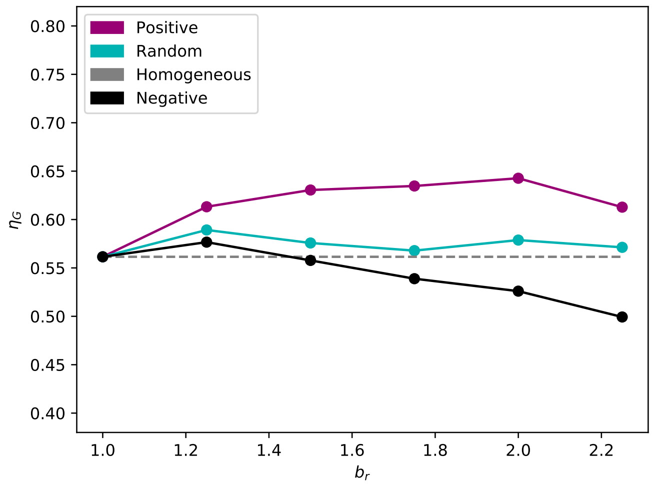



Figure 5.9: Group achievement as a function of the endowment of the rich $b_r$, considering different correlations between wealth and connectivity. We define $b_p = \frac{Z - Z_r b_r}{Z_p}$, to maintain the average endowment of the population $\bar{b} = 1$. Consequently, as the rich get richer, the poor get poorer. The grey dashed line is the homogeneous case, without heterogeneity in wealth in scale-free networks. Other parameters: population size $Z = 1000$, average group size $\bar{N} = 7$, threshold factor $M = 4N/7$, fraction of contribution $c = 0.1$, average risk $\bar{r} = 0.5$, strength of selection $\beta = 6.0$.

Subsequently, to introduce risk diversity with wealth inequality and network heterogeneity, we adjust the risk of a few hubs, considering distinct correlations between wealth and connectivity. In particular, inspired by the idea of the international influence of the Group of Seven (G7) in climate agreements, we arrange the risk in the seven major hubs of the network. The chosen $\delta$ was $0.2$ to portray an appropriate degree of risk heterogeneity. To assure that the average risk in the population maintains as $\bar{r} = 0.5$ when changing the risk in the hubs, we follow Equation (5.1) with $Z_H = 7$.

Figure 5.10 illustrates the effects of combining wealth inequality, risk diversity and connectivity. Specifically, we assume two distinct scenarios regarding the risk: one where we consider the seven

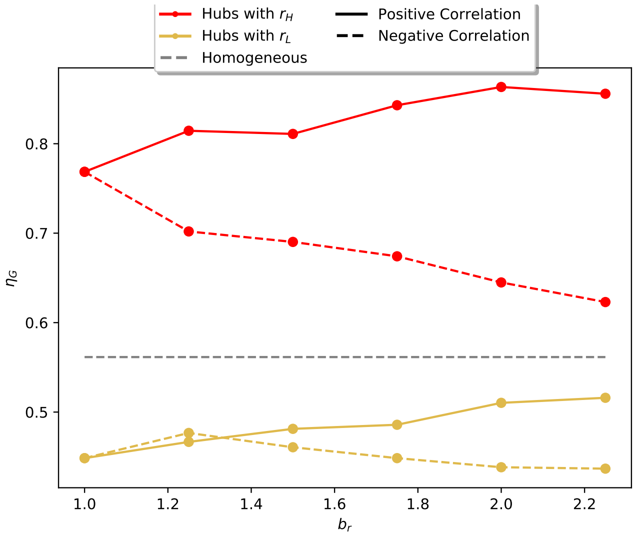



Figure 5.10: Group achievement as a function of the endowment of the rich $b_r$, combining risk, wealth and connectivity. We define $b_p = \frac{Z - Z_r b_r}{Z_p}$, to maintain the average endowment of the population $\bar{b} = 1$. We adjust the risk in 7 hubs, considering distinct correlations between wealth and connectivity. The red curves correspond to 7 hubs with $r_H = 0.7$, and the yellow curves represent 7 hubs with $r_L = 0.3$. The solid curves correspond to a positive correlation between wealth and connectivity, whereas the dashed colored curves represent a negative correlation. The grey dashed line is the homogeneous case, without heterogeneity in risk or wealth in scale-free networks. Other parameters: population size $Z = 1000$, average group size $\bar{N} = 7$, threshold factor $M = 4N/7$, fraction of contribution $c = 0.1$, heterogeneity between risks $\delta = 0.2$, average risk $\bar{r} = 0.5$, strength of selection $\beta = 6.0$.

major hubs to have $r_H = 0.7$ (in the red curves), and the other where the seven major hubs have $r_L = 0.3$ (in the yellow curves). Concerning the correlations between wealth and connectivity, the solid curves correspond to assuming a positive correlation, and the dashed colored curves to assuming a negative correlation. Further, we also show a reference scenario without heterogeneity in wealth or risk (the dashed grey line).

We can observe that assuming a positive correlation between wealth and connectivity confers the highest values of group achievement in Figure 5.9. Contrarily, assuming a negative correlation shows the lowest values of group success. Additionally, the same behavior is observable in Figure 5.10, where the solid curves (that represent a positive correlation between wealth and connectivity) also show an increase in the cooperation levels, whereas the dashed colored curves (that correspond to a negative correlation) confer a decrease. Therefore, the results of Figure 5.9 and Figure 5.10 suggest that when we include wealth inequality (with individuals contributing proportionally to their wealth), assuming a positive correlation between wealth and connectivity can marginally thrive cooperation. Contrastingly, the cooperation marginally decreases when we assume a negative correlation and the rich take part in just a few agreements. On the other hand, randomly assigning wealth levels in the population does not seem to have a significant improvement, as shown in Figure 5.9.

Notice that, even if we are guaranteeing that the average endowment per individual is constant in comparison to the homogeneous case ($\bar{b} = 1$), as nodes are distributed heterogeneously in the network, the wealth available per game is modified. This can have a significant impact on the population dynamics, which may help us understand our results. To demonstrate this reasoning, let us consider a simple example of a star-graph, as shown in Figure 5.11, in two distinct configurations:

*a)* Suppose that the hub, the central individual, is rich (purple circles) and the remaining leaves are poor (yellow circles). Here we assume a positive correlation between wealth and connectivity;

*b)* Suppose that one of the leaves is rich and the remaining nodes are poor, assuming a negative correlation between wealth and connectivity.

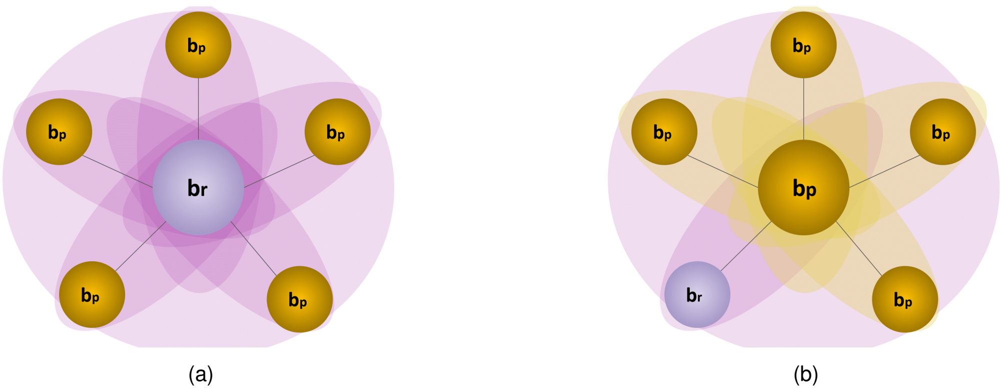



Figure 5.11: Star-graph with different dynamics regarding the distribution of wealth per group. Purple circles represent rich individuals and yellow circles poor individuals. Accordingly, purple games portray that a rich individual takes part in that game. **(a)** The hub (the central circle) is rich and the remaining leaves are poor. As a result, the endowment of the rich is considered in all games. **(b)** One of the leaves is rich and the remaining nodes are poor, where the endowment of the rich is only considered in two games.

In Figure 5.11, the purple games are those where the rich player participates. When we calculate the average endowment available per game in 5.11a, we are adding the endowment of the rich ($b_r$) in all games, as the hub takes part in all games. Conversely, in 5.11b, we only add the endowment of the rich in two games: the game centered in the rich node and the game centered in the hub (the only two purple games in Figure 5.11b). Consequently, in 5.11a, the average endowment available per game will be considerably larger than in 5.11b. Furthermore, given that the hubs tend to be connected, the average endowment available in 5.11a is further enhanced in the central games of the network. Therefore, the chances of having the demanded amount of contributions to surpass the threshold in the groups are improved in 5.11a. Having said that, it is reasonable that the positive correlation provides better results than a negative one.

Regarding the random correlation, considering that we are randomly assigning the wealth levels, there will be some runs of our simulations where hubs will be rich. Hence, is also understandable that the random correlation confers a slight improvement in the group achievement.

To better grasp the effect that increasing wealth disparities has on the budget available to the population, in Figure 5.12 we illustrate the impact of increasing $b_r$ (and, consequently, decreasing $b_p$) in the average endowment available per group. We perform this experiment considering a positive and a negative correlation between wealth and connectivity.

From Figure 5.12, one can notice that the difference between the average endowment available in both correlations is more significant as $b_r$ increases. That is, when $b_r$ increases, the amount available per group on average increases in setting 5.11a (positive correlation) and decreases in 5.11b (nega-

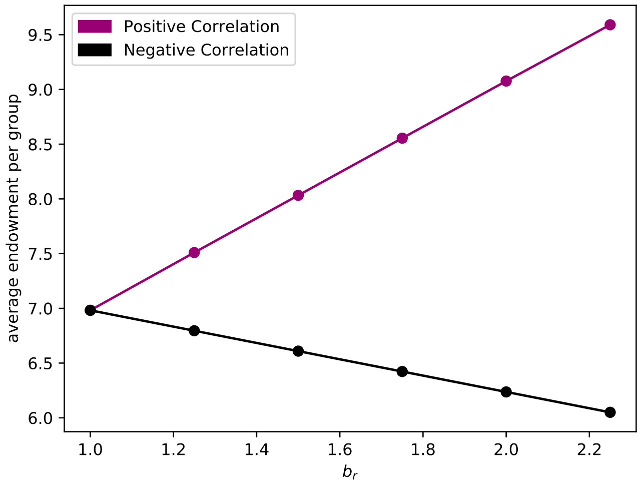



Figure 5.12: Average endowment available per group in the network as a function of the endowment of the rich (with rich becoming richer and poor becoming poorer), considering distinct correlations between wealth and connectivity. Each data point is the average of 10 different scale-free networks. Other parameters: population size $Z = 1000$, average group size $\bar{N} = 7$, average endowment per individual $\bar{b} = 1$.

tive correlation). This might explain why there is a tendency for more expressive values in the group achievement when $b_r$ increases in Figure 5.9 and Figure 5.10.

Hence, our results indicate that scale-free networks and the way that wealth is distributed among the different games - that is a direct consequence of the network - provides greater diversity in the investments available to the population, which naturally depends on how the individuals are placed in the network. In other words, inequality can have opposite effects depending on the position where rich and poor are in the network.

This conclusion is similar to the one obtained in the prior section, regarding the impact of risk diversity. Nevertheless, it is noteworthy that if one compares Figure 5.9 (where we only consider wealth inequality), the highest value of group achievement is around $0.65$, whereas in Figure 5.6a (where only risk heterogeneity was analyzed), there is a significant improvement, with the group achievement reaching a value of $1$. This indicates that risk heterogeneity may be more impactful than wealth inequality.

It remains to explain the role of risk heterogeneity combined with wealth inequality in Figure 5.10. To analyze it, let us compare, for instance, the purple curve of Figure 5.9 to the solid curves of Figure 5.10. In these curves we are assuming that hubs are rich, however, only in Figure 5.10 risk heterogeneity is introduced. Namely, the curves of Figure 5.10 correspond to the transposition of the purple curve by increasing the perception of risk in the hubs (the red solid curve) or decreasing it (the yellow solid curve). As one can observe, without risk heterogeneity, the maximum value of group achievement is near $0.65$. When we assume that hubs have a high risk, the group success significantly increases, achieving values close to $0.9$. On the opposite, decreasing the risk of the hubs decreases the levels of the group achievement to values near $0.5$. This confirms that the perception of risk in the hubs is essential. Accordingly, even if hubs are rich, the chances of achieving global cooperation are reduced if some of the major hubs have a low perception of risk.

Analogously, we can see that risk has a similar effect when hubs are poor in the black curve of Figure 5.9 and the dashed colored curves of Figure 5.10.

Besides, in Figure 5.10, it is possible to observe that when hubs have a high risk, the impact of the correlations between wealth and connectivity are more notable than when they have a low risk. As we have seen before, when hubs face a low risk they influence the network towards defective behavior. Therefore, there is not much difference between hubs having a large available amount (as in the positive correlation) or a small amount (as in the negative correlation), as it is most likely that many individuals will not cooperate in both correlations. Conversely, when hubs have a high perception of risk and influence the population to cooperate, surpassing the threshold strongly depends on the amount available to contribute.

Lastly, the results of Figure 5.10 indicate that cooperation increases when centrality is positively correlated with risk. This effect is enhanced whenever risk and centrality are positively correlated with individuals' wealth (in the red solid curve). Overall, we can infer that the best alignment between the multiple sources of heterogeneity is to positively correlate centrality, risk and wealth.

### 5.4.1 Discussion of the Correlations

Analogously to the discussion in Section 5.3.3, it is important to realize how countries are correlated with wealth realistically to push for climate action.

In real environmental agreements, the hubs - the climate leaders - actually tend to be rich. For instance, the G7 is considered to be composed of the seven wealthiest advanced countries. In particular, they account for more than 62% of the global net wealth. Moreover, United Europe and China also possess a significant part of the world's net wealth [55]. On the other hand, the Global South has the poorest countries worldwide. With this said, it is reasonable to assume that the correlation of wealth and connectivity in the real world must be nearly positive.

Following our results, this correlation opens a window of opportunity for cooperation when individuals contribute proportionally to their wealth. Nevertheless, as debated previously, the sense of urgency in the hubs seems vastly insufficient. Correspondingly, since the covid pandemic, it is known that the G7 has committed billions more to fossil fuel than green energy [56]. Having said that, it is likely that the most realistic combination between centrality, wealth and risk is the one where hubs are rich but have a low perception of risk. In Figure 5.10, it is observable that in this setting (the yellow solid curve) group success is not feasible.

The course of this demanding problem seems to essentially depend on the hubs and their perception of risk. It is crucial that the leaders recognize their profound responsibility and act in accordance, otherwise, the tragedy of the commons is inevitable.

### 5.4.2 Including Fairness Notions

It is known that one of the causes for previous failures to reach climate agreements has been attributed to conflicting policies between rich and poor. Understanding how the cooperation cost should be distributed among the two classes results in a fairness dilemma. Respectively, there is not a consensus on how rich and poor should contribute to climate negotiations: Should the rich and the poor invest the same amount? Or should the rich contribute more?

In the study [38], it was found that a shared fairness notion among countries is a precondition to reach global coordination. In this section, we analyze some fairness assumptions, concerning wealth inequality, to understand what can maximize cooperation.

#### I. At the Individual Level

In the former section, we considered that the contributions of individuals were proportional to their wealth, being a relative value. Here, we investigate what happens when the two classes contribute an absolute amount, equal for both of them. In particular, in the former setting, players contribute a fraction $c$ of their endowment, as rich individuals have a contribution of $c_r = cb_r$ and poor individuals of $c_p = cb_p$. In the latter setting, both have the same contribution, that is, $c_r = c_p = 0.1$. With this value, we assure that the average contribution of the network per individual remains equal in both settings, as $\frac{Z_r c_r + Z_p c_p}{Z} = 0.1$.

Observe that having rich and poor contributing the same amount differs from a homogeneous distribution of wealth, as the payoff of a rich individual will be distinct from a poor since their endowments are different (see Equation (4.5)).

In Figure 5.13, we show the average group achievement as a function of the endowment of the rich, considering the two contribution scenarios previously explained, and the reference scenario with no wealth inequality. In the simulations, the perception of risk of all individuals is considered to be the same ($r = 0.5$) and we assume a positive correlation between wealth and connectivity, as we have discussed that this is the correlation that portrays a more realistic scenario.

We can observe that cooperation is more viable when the rich contribute larger amounts than the poor (the contribution is proportional to their wealth). Correspondingly, the configuration of similar contributions does not appear to have a notable impact in comparison with the reference scenario.

To explain this result, let us consider the star-graph example illustrated in Figure 5.11. Since we are testing the effects of considering different types of contributions, it is useful to think in terms of the average contribution available per game. When contributions are proportional to the endowments, the average contribution available per game in 5.11a is higher than in 5.11b, given that the average endowment available is larger in this setting (as concluded previously from Figure 5.12). Conversely, when we consider an absolute value for the contributions, even if rich and poor have different endowments, the contributions of the two wealth classes are the same. As a result, the average contribution available per game in 5.11a is going to be equal to 5.11b. Besides, as discussed above, in 5.11a the average endowment per game is strongly dependent on the endowment of the rich. Hence, the average con-

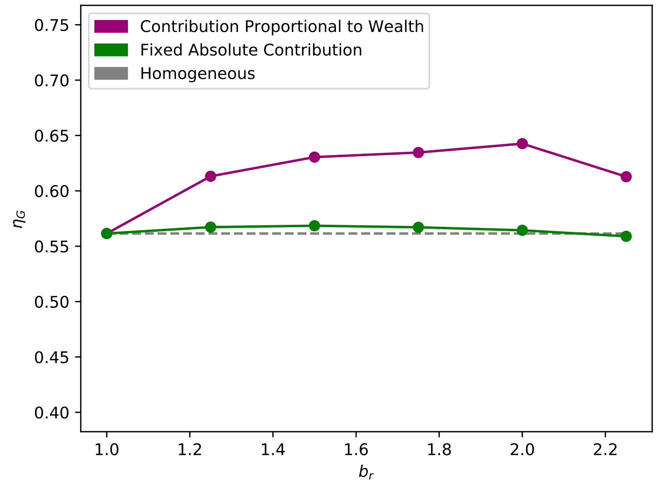



Figure 5.13: Group achievement as a function of the endowment of the rich $b_r$, considering different types of contributions. As the average endowment of the population $\bar{b} = 1$, the endowment of the poor is $b_p = \frac{Z - Z_r b_r}{Z_p}$. We consider two distinct ways of contributions: in the purple curve contribution is proportional to wealth, which means that rich contribute more than poor; in the green curve, the contribution is fixed for the two wealth classes, meaning that rich and poor contribute the same absolute terms. Other parameters: population size $Z = 1000$, average group size $\bar{N} = 7$, threshold factor $M = 4N/7$, average risk $\bar{r} = 0.5$, strength of selection $\beta = 6.0$.

tribution per game in this setting will also highly depend on the contributions of the rich. Considering that when contributions are identical, the rich contribute less, the average contribution will be inferior to scenario 5.11a with proportional contributions. Given that the threshold depends on the contributions of the groups (see Equation (4.5)), the chances of having the demanded amount are not going to improve in 5.11a when considering equal contributions. Thus, the advantage in group success conferred by the nodes with high centrality being rich does not remain valid if they do not contribute proportionally to their wealth.

This leads us to conclude that, in order to reach climate agreements, the rich - which have typically more centrality in the network of environmental agreements - should contribute the most.

#### II. At the Group Level

In the preceding results, we have assumed that the threshold is based on the number of players that take part in the groups. Yet, this presumption disregards the complexity introduced when considering heterogeneity in the investments of a population organized in a scale-free network. Correspondingly, as we have seen before, the capacity available to contribute per group is different and can influence the population dynamics. In particular, until this point, we demanded the same amount of contributions irrespective of the wealth composition of the groups. However, requiring the same contribution from a group composed of, for example, ten rich countries and a group composed of ten poor countries might not be a fair assumption. Taking this into consideration, here we study the differences in collective success when we consider: *1)* a threshold that is agnostic to inequality (as considered previously) and *2)* a threshold that defines success in a more fair measure and discriminates the wealth of the individuals in groups.

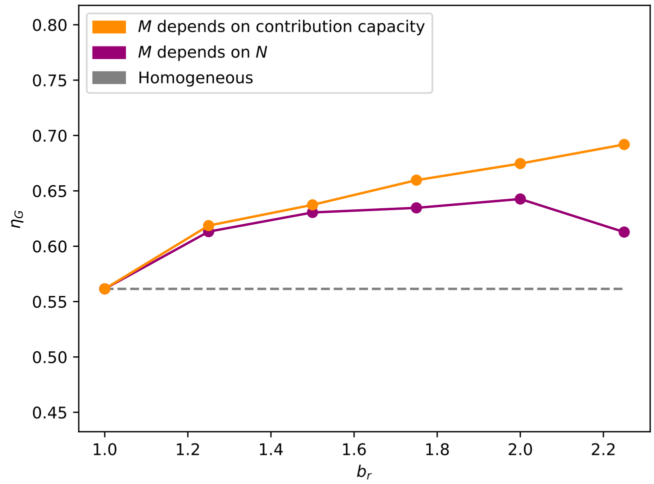



Figure 5.14: Group achievement as a function of the endowment of the rich $b_r$, considering different types of thresholds. As the average endowment of the population $\bar{b} = 1$, the endowment of the poor is $b_p = \frac{Z - Z_r b_r}{Z_p}$. We consider two distinct thresholds: the orange curve corresponds to a threshold that increases with the contribution capacity of the groups, whereas the purple curve represents a threshold that increases with the group size and is agnostic to group contribution capacity. Other parameters: population size $Z = 1000$, average group size $\bar{N} = 7$, fraction of contribution $c = 0.1$, average risk $\bar{r} = 0.5$, strength of selection $\beta = 6.0$.

For the latter setting *(2)*, instead of calculating the demanded threshold factor $M$ of a group regarding the number of individuals that take part in that group, we consider the amount of contribution that is available in the group. Specifically, to calculate the threshold of a group $i$, which corresponds to $M_i c\bar{b}$ (see Equation (4.5)), we assume $M_i = 4 \times \frac{Ci}{\bar{C}}$, where $C_i$ is the contribution capacity available in group $i$ and $\bar{C}$ the average contribution capacity per group in the network. This is opposed to what was being assumed until now, with $M_i = 4 \times \frac{N_i}{\bar{N}} = 4 \times \frac{N_i}{7}$.

In Figure 5.14, we plot the average group achievement as a function of the endowment of the rich (with the wealth inequality increasing along the x-axis), considering the two aforementioned thresholds. Analogously to the previous experiment, the perception of risk of all individuals is considered to be $r = 0.5$ and we assume a positive correlation between wealth and connectivity.

It is possible to observe that the wealth-dependent threshold promotes cooperation in comparison with the threshold that was being analyzed (that depends on the group sizes). This improvement is particularly notorious when $b_r$ takes larger values and the poor become poorer. Namely, we can observe that when $b_r = 2.25$, there is a decrease in the group achievement in the threshold that is grounded in the size of the groups, whereas it increases in the threshold that considers the composition of wealth.

Notice that, in the particular distribution of rich and poor we are considering, 80% of individuals are poor, whereas only 20% are rich. To investigate how the capacity available per group is distributed in the network, in Figure 5.15 we plot the histogram of the available contribution capacity for all groups, where the dashed black line represents the average contribution per group. We can observe that the majority of the groups are poorer than the average, whereas there is a richer minority - which is a consequence of the properties of scale-free networks.

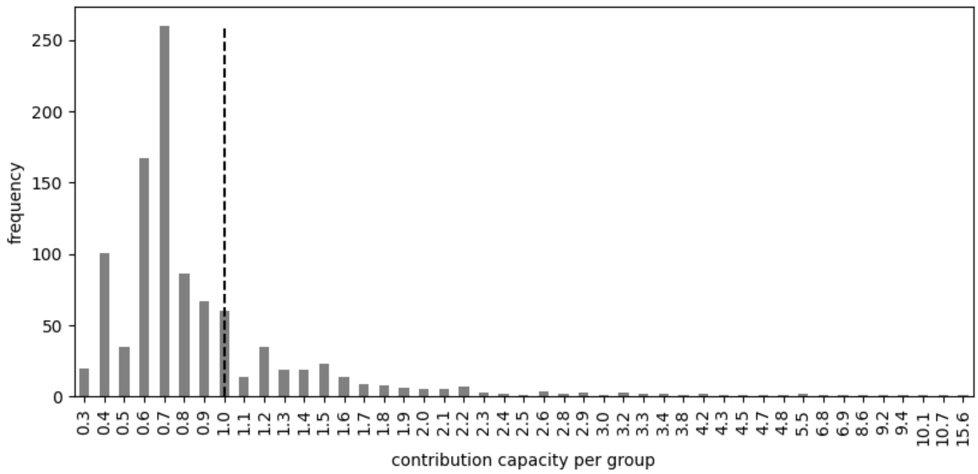



Figure 5.15: Frequency of the contribution capacity per group, considering the maximum disparities in wealth of our experiments ($b_r = 2.25$ and $b_p = 0.6875$). For visual clarity, we present the contribution per group in a rounded format for a illustrative scale-free network. The dashed black line represents the average contribution per group. Portraying wealth inequality in scale-free networks results in a distribution of wealth where the majority of the groups are poorer, whereas a minority is richer. Specifically, we verify that in the $1000$ groups of the network, $777$ had a capacity available smaller than the average capacity of the groups. Other parameters: population size $Z = 1000$, average group size $\bar{N} = 7$, fraction of contribution $c = 0.1$, average endowment $\bar{b} = 1$.

In the threshold that discriminates the wealth, the effort rate of the groups is being considered, as we are requiring that groups contribute an amount based on what they can contribute. By contrast, in the threshold that ignores the composition of the groups, this effort is disregarded. As a result, when the poor get significantly poor in the latter case (as in $b_r = 2.25$), there will be many groups with mostly poor individuals that face severe requirements, given that they have a small available budget to contribute. In these groups, even if poor individuals cooperate it is extremely difficult to achieve the threshold, which naturally affects the global success in the network. This negative effect can be alleviated if we recognize the capacity available in the groups. Specifically, when the threshold considers the wealth composition of the groups, we are lowering the threshold in poorer groups (as the capacity available to contribute in these groups is inferior). Considering that the majority of the groups are poorer (as shown in Figure 5.15), there will be considerably more groups that will find it easier to surpass the requirements.

Summarizing, the results of Figure 5.14 essentially suggest that if we try to reach an agreement based on what each group can contribute, cooperation is enhanced. In other words, it is easier to reach group success if the collective goals are adjusted to the effort and capacity of each group. This is complementary to the previous outcome of Figure 5.13, as it indicates that, in order to maximize cooperation, those who have more wealth should contribute more, which can be applied to individuals or groups.

Notwithstanding, it is important to stress that in the presence of severe wealth inequality, poor individuals start to have so few that the difference between achieving success or not is diluted. For instance, let us assume an extreme case of our model, where the endowment of the rich increases to the level of the poor having $0$. As a result, it is equal for the poor to cooperate or not: if they suffer a catastrophe they will lose a fraction of $0$ (see Equation (4.5)). This means that when we increase $b_r$ disproportionally, we are introducing many individuals who are indifferent to reaching the threshold or not, which negatively impacts cooperation. Correspondingly, as the philosopher Peter Singer in [3] refers: *"too great a disparity in power or wealth will remove the incentive for mutual cooperation. This strongly suggests a need to do something about the economic trends in developed nations which for the past decade or more have increased economic inequality. To leave a group of people so far outside the social commonwealth that they have nothing to contribute to it, is to alienate them from social practices and institutions..."*. As we mentioned at the beginning of this thesis, poorer countries are the ones who will suffer the most drastic consequences of climate change. If we do not reduce the emissions severely, poorer countries will be devasted to a point where they will be unable to cooperate. It is imperative that climate policies are compatible with poverty reduction, which is in line with the Sustainable Development Goals [57].

# Chapter 6

# Conclusions

In this work, we proposed to contribute to a deeper understanding of the factors under which cooperation in climate settings can prosper. We resorted to the tools of evolutionary game theory and complex networks, which enable us to predict the behavior of individuals in social dilemmas and illustrate important characteristics that are observed empirically.

In Chapter 3, we discussed several related methods that aim at understanding the paths of cooperation in evolution. Through an extensive analysis of literature, we observed that recognizing the ubiquitous diversity that is present worldwide is acquiring extreme importance in this field. We further clarified that this reasoning can be employed in the climate change dilemma, as the heterogeneity that characterizes countries can impact the dilemma in question.

In our contributions, we tackled the challenge of unraveling symmetries in the climate change dilemma, focusing on incorporating heterogeneity in social ties, risk diversity, and wealth inequality. As pointed out in Chapter 3, the effect of combining such heterogeneous layers in the CRD remains astray in the literature.

We started by performing preliminary experiments considering a typical CRD without any sort of heterogeneity, where all individuals were treated as equivalent in all respects (as in the work [45]). We reached the same two conclusions that are well-established in the literature: that perception of risk is a key factor in climate settings and cooperation is enhanced when agreements are established among smaller groups.

Subsequently, we transitioned to a more realistic representation of environmental agreements. We depicted the diversity that is intrinsic to social interactions through the means of scale-free networks, following the work in [21]. We demonstrated that organizing the population in heterogeneous networks can open an opportunity for cooperation. However, there is a lot of uncertainty associated with the results we obtained. We inferred that this uncertainty is rooted in the behavior of the hubs, with the overall success of the population passive of being strongly influenced by the initial strategy of these individuals.

In order to answer our main research questions and to portray a more accurate description of climate agreements, we developed a model that allows for multiple dimensions of heterogeneity by modifying and adapting models of relevant related works (described in Chapter 4). Namely, we considered diversity in terms of risk perception, wealth and connectivity. In Chapter 5, a set of computational simulations were performed following our model. With our experiments, we were able to analyze emergent properties that result from the collective dynamics of the population, when individuals interact and learn. Now, we concisely answer our main research questions through the interpretation of the results of Chapter 5.

**What is the impact of correlations between risk perception and network connectivity?**

As referred in Chapter 3, our work differs from the previous approaches as it considers that individuals can engage in the dilemma with different risk perceptions.

Our results indicate that risk diversity exhibits distinct effects depending on how we correlate risk with connectivity. In particular, we found that assuming a positive correlation between individual risk and centrality can unleash a wave of cooperation in the network. This is particularly true the higher the heterogeneity we consider, i.e, the more accentuated is the difference between high and low risks in the population. We further observed that assuring that some few highly central players are assigned with a high perception of risk is enough to nudge an entire population into cooperation. Conversely, assuming a negative correlation, where hubs face a low perception of risk, reverts to the scenario where defection prevails.

**What is the effect of correlations between wealth and network centrality?**

To study wealth inequality on top of scale-free networks in the CRD, we introduced a new variation in the work [39], which was employed in unstructured populations, to consider populations organized in scale-free networks. This enabled us to explore more intricate components that are unique to complex networks, such as the effects of correlations between wealth and connectivity in the network.

Similar to the conclusions we obtained in the previous question, we found that heterogeneity in wealth has opposite effects depending on the correlation between wealth and degree that is considered. Specifically, our results indicate that assuming a positive correlation increases the chances of achieving global cooperation, whereas considering a negative correlation reduces them. Notwithstanding, through our simulations, we observed that risk diversity appears to be more impactful than wealth inequality.

**How can information about network heterogeneity, risk diversity and wealth inequality be combined to leverage cooperation in climate settings?**

To answer this question, we merged the three heterogeneous layers described above in the CRD. We essentially concluded that group success is fostered when the three sources of heterogeneity are aligned. In particular, our results indicate that the increase in cooperation conferred by assuming a positive correlation between centrality and risk is enhanced whenever risk and centrality are positively correlated with individuals' wealth. In other words, assuming that hubs have a high perception of risk and have more to contribute is the arrangement that provides better results.

**Regarding the distinct classes of wealth, how should the cost of cooperating be distributed?** Lastly, we explored the impact of considering distinct fairness notions in our model, regarding wealth inequality. In particular, we investigated how the cost of cooperating should be allocated to improve the chances of achieving environmental agreements. Our findings demonstrate that richer individuals should contribute more to improve cooperation. To analyze fairness at a group level, we proposed a new threshold for the dilemma, capable of embracing the complexity introduced when considering wealth inequality in scale-free networks. In this threshold, we adapt the requirements of a group based on the capacity available of the groups. We concluded that cooperation is fostered if the collective goals are adjusted to the effort and capacity of each group, where richer groups should contribute more. It is noteworthy that our results may have implications for policy-making concerned with equity and fairness.

On a final remark, our experiments indicate that the course of the climate change dilemma strongly depends on the hubs - the climate leaders. This is particularly evident in their perception of risk, which, as we have discussed, remains minimal given that they are not being directly affected by climate damage. As a result, their contributions to the dilemma remain insufficient, shadowing the feasibility of climate agreements. It is imperative that leaders recognize the urgency that this challenge entails. Consistently, the climate change dilemma requires a profound interrogation of how everything is interconnected and how climate chaos will eventually be suffered worldwide. As pointed out in Section 5.3, environmental damage will cause the collapse of severe complex systems, in which humans from all over the world are essentially dependent. Accordingly, as Martin Luther reminds us: *"We are caught in an inescapable network of mutuality, tied in a single garment of destiny. Whatever affects one directly, affects all indirectly."* [58].

## 6.1 Future Work

Considering the plethora of possibilities in the CRD formulation, numerous research directions may follow from our contributions. Regarding network heterogeneity, risk diversity and wealth inequality, we address some potential topics that could be further explored, based on the work that has been completed thus far:

- **Other Complex Networks**: We performed our experiments with populations organized in scale-free networks, following the Barabási-Albert Model. This constitutes one of the most typical forms of modeling heterogeneous networks. Nonetheless, the Barabási-Albert model has some limitations. Consider the clustering coefficient, which corresponds to the measure of the degree to which the neighbors of a given node are linked. In social networks, the dependency of clustering in terms of degree is observable. Intuitively, the few neighbors of a lower degree node are likely to know themselves. However, hubs are connecting nodes from possibly different communities, so the chances that their neighbors know each other are significantly small. As the majority of the nodes have a low degree, social networks have a high clustering coefficient. In the Barabási-Albert

Model, this property is not reflected, as the clustering coefficient is modeled as independent of the degree. To translate the expected clustering behavior in social settings, performing simulations in highly clustered scale-free networks, as the Dorogovtsev-Goltsev-Mendes Minimal Model [59], could be of importance.

- **Hypergraphs**: In our model, we assumed that interactions only involve two individuals at a time. As we mentioned in Chapter 3, hypergraphs provide a mathematical framework that can represent interactions between larger groupings, instead of only considering pairs [36]. Our work could be extended to consider higher-order networks as a formalism to distinguish network heterogeneity in: *1)* the number of interaction groups and *2)* the size of the interaction groups where each individual takes part.

- **Other interpretations of risk heterogeneity in the network**: In Section 5.3, we mentioned that risk diversity can be reflected in the network from distinct perspectives. We considered the risk to be an individual property or at the level of the games. Nevertheless, other interpretations could be followed. For instance, between the two limits we considered, one could assume the risk of an individual to be the average risk of the games that this individual participates in.

- **Different risk levels**: Taking into consideration that the levels of risk perception, awareness and exposure to risk vary greatly across the world [49], instead of only considering binary risks on the population (high risk and low risk), some intermediate levels of risk could be explored to more realistically model environmental agreements.

- **Different wealth levels**: In our model, for simplicity, we only considered two wealth classes: rich and poor. Notwithstanding, examining the cooperation dynamics by introducing middle wealth levels should offer a more pragmatic representation of wealth inequality in climate settings.

- **Breaking symmetries in contributions**: Regarding the contributions in our model, we considered that individuals within the same wealth class contribute the same amount for all groups. However, this assumption disregards that some agreements may be more relevant than others to prevent costly climate risks. Individuals might decide to provide more contributions to some negotiations than others. Therefore, it could be suitable to examine the effect of assuming heterogeneity in the contributions among the different groups.

- **Financial Incentives:** In Chapter 3, we mentioned a recent study that illustrated the use of financial incentives from the wealthy to urge the poor to contribute to carbon reductions [41]. This analysis was employed in behavioral experiments and game-theoretical analysis. Studying the effect of financial incentives in the CRD on top of scale-free networks remains unexplored. One could extend our work to analyze how incentives can be applied based on transfers between classes to enhance cooperation in climate settings. For instance, redistribution mechanisms where individuals share a fraction of their wealth surplus with nearest neighbors [60] could be applicable to our model.

- **Institutions:** As discussed in Chapter 3, the study [14] suggested that applying rewards was fundamental to leverage cooperation, mostly when the perception of risk is low in the CRD. This work was performed in unstructured populations. However, when using populations organized in scale-free networks new paths can emerge. For instance, considering the crucial role of hubs and that it is most likely that have a low perception of risk, testing the effects of applying rewards to these individuals could provide important contributions. Similarly, sanctions could also be employed to maintain cooperation. One could consider graduated sanctions that increase with the global harm caused by a defector [61]. The principle has been highlighted by Elinor Ostrom as being present in many human communities facing collective dilemmas, even identifying it as one of the main design principles for managing common pool resources [62].

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