Evolutionary Multi-Sector Analysis of Open-Access Adoption in Scientific Communication

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Declaração

Declaro que o presente documento é um trabalho original da minha autoria e que cumpre todos os requisitos do Código de Conduta e Boas Práticas da Universidade de Lisboa.

Declaration

I declare that this document is an original work of my own authorship and that it fulfills all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa.

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I have always looked forward to the future, but it has never been a future built solely by my own hands. I owe much to various people, who even with the slightest of gestures changed me into the person I am today.

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Abstract

Open-Access (OA) publishing has seen a considerable rise in adoption and public support as an alternative to traditional Closed-Access (CA). Despite its benefits for researchers, OA faces challenges regarding publisher adoption, as there is no clear revenue compensation. Additionally, various proposed government laws seek to enforce OA for publicly financed research. We present a model to investigate the adoption of OA, and its limiting factors, by taking into consideration the three main actors in the scientific communication system: funders, publishers and researchers. With it, we extract the impact of key factors, such as funding, revenue, publishing fees, taxes, and other relevant parameters on the resulting adoption dynamics. We also assess the impact of the most common alternative publishing methods: hybrid and Green OA publishing. Furthermore, we discuss policies to incentivize the adoption of OA. Our framework resorts to evolutionary game theory (EGT) applied to multiple populations to capture the multi-sector interactions between the different main actors, where the success of an individual is directly influenced by the other sectors.

Keywords

Evolutionary Game Theory — Multi-Population — Open-Access — Complex Systems — Cooperation

Resumo

Publicações em acesso aberto (OA) têm visto um aumento considerável na sua adoção e no apoio público como uma alternativa ao acesso fechado (CA) tradicional. Embora apresente benefícios para os investigadores, o OA enfrenta desafios na adoção pelos publicadores, já que não há uma compensação clara nas receitas. Adicionalmente, várias leis governamentais propostas visam obrigar a utilização de OA para investigadores financiados por instituições publicas. Apresentamos um modelo para investigar a adoção de OA, e os seus fatores limitantes, tendo em consideração os três atores principais no sistema de comunicação científica: financiadores, publicadores e investigadores. Com este modelo, descrevemos o impacto dos fatores-chave, como o financiamento, as receitas, os custos de publicação, as taxas, entre outros, nas dinâmicas de adoção resultantes. Avaliamos também o impacto dos métodos de publicação alternativos mais comuns: publicações híbridas e publicações em 'Green' OA. Discutimos ainda políticas para incentivar a adoção de OA. A nossa framework recorre à teoria dos jogos evolutiva (EGT) aplicada a múltiplas populações para capturar as interações multissetoriais entre os diferentes atores principais, onde o sucesso de um indivíduo é diretamente influenciado pelos outros setores.

Palavras Chave

Teoria de Jogos Evolutiva — Multi-População — Acesso Aberto — Sistemas Complexos — Cooperação

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Acronyms

APC Article Processing Charge

CA Closed-Access

EGT Evolutionary Game Theory

ESS Evolutionarily Stable Strategy

MC Markov chain

NE Nash Equilibrium

OA Open-Access

PCR Pairwise Comparison Rule

PRFS Performance-based Research Funding Systems

REF Research Excellence Framework

1

Introduction

”An individual has not started living until he can rise above the narrow confines of his individualistic concerns to the broader concerns of all humanity.”

Martin Luther King Jr.

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Humans are aware of the limitations of their individual physical and intellectual capabilities. The short story is that, to address this, we evolved and learned to work together. And yet, however obvious it may seem at first glance, it is not clear why collaborating and creating dependencies between us is not only a tremendously advantageous strategy, but a central piece in the history of mankind. Drawing a parallel with computational systems, this kind of horizontal scaling (more connected nodes), as opposed to the vertical scaling (more resources in a node) that stems from individual development, is ubiquitous throughout times: From single cells to multicellular organisms, from a single ant to a colony [1], and for us, not just from individuals to tribes, but to a worldwide network of cities and towns. It is such a powerful concept, that we even applied it in our technology: single core processors gave birth to multicore processors, and single machines to colossal servers [2]. This very behavior, which between living beings is known as **cooperation**, is present in a large amount of species [3], but it is distinctly developed in humans.

Throughout modern societies, there are several examples of the large scale of human cooperation: labor is commonly divided to increase efficiency [4], not only on a local or national scale, but on a global scope as well, surpassing cultural barriers [5]; and numerous international treaties are regularly struck, with the aim of aligning strategies and creating cooperative efforts regarding many topics, such as climate change mitigation, economic development, or international security. And yet, having noticed this behavior, Charles Darwin remarked its counter-intuitiveness: if one has the objective of reproductive success, one must thrive in the presence of others — a supposedly competitive task where only those most adapted to the environment get to prosper; However, cooperation is based in assisting others at the cost of oneself, therefore presumably reducing the chances of reproduction [6]. Let us consider the following example: While it is true that I am capable of assisting someone in constructing a house, there are many repercussions to such an endeavor. Firstly, the resulting house does not belong to me, it is instead improving the life of someone else. Secondly, it took a toll on my energy supplies. And all this required a shared language for us to coordinate our actions. So how did cooperation become so widespread? And, in particular, how does it spread in communities of unrelated individuals?

This question is also crucial to economic theory, whose central tenet states that agents, i.e. people, will always act in an effort to maximize their individual well-being. Simply put, a person will pick the action that leads to the greatest benefit, after subtracting the cost of such action. This is known as the **rational** choice [7]. Although this is an oversimplification of human behavior, due to how it seemingly disregards **altruism** — the concern for the welfare of others — this assumption does not render cooperation impossible. Individual benefits can still originate in the long run via cooperation, and therefore make it a potentially winning strategy, as long as their cost-benefit ratio outweighs that of an individualistic approach. As stated by Robert Axelrod in his major work *The Evolution of Cooperation*: "*For cooperation to prove stable, the future must have a sufficiently large shadow... the importance of the* *next encounter between the same two individuals must be great enough to make [noncooperation] an unprofitable strategy.*" [8]. This long-term perception cannot, however, originate solely from analyzing the costs and benefits of each action at each instance, as we will discuss further ahead. This necessarily means there must be additional mechanisms underlying the decision-making process of an individual. Nowak noted five primary mechanisms that promote cooperation over individualistic thinking: kin selection, direct reciprocity, indirect reciprocity, network reciprocity, and group selection [9]. The presence of cooperation is also influenced by other aspects, such as signaling [10] or risk-perception [11, 12]. But, even if we know what factors influence individual cooperation, how does that translate to an understanding of the large scope dynamics of cooperation adoption?

There have also been efforts in understanding not just the process behind individual decision-making, but the behavioral dynamics of **populations**. This macro-perspective allows us to consider factors beyond the immediate decisions, and start considering major movements across societies [13]. Although individuals are the ones making decisions, a successful action of an individual is often **imitated** by others. New strategies can also emerge from factors such as the creation and propagation of new ideas, akin to genetic **mutations**. Understanding the rich dynamics of how strategies spread in a population can teach us a lot — from how to best spread a strategy throughout the population [14], to understanding what is stopping such a strategy from spreading in the first place, or to predict where each strategy is most likely to spread [15]. Creating models of such social systems can also help us measure the impact new strategies can have, and the required measures we must take for them to become widespread — a pivotal step in problems where coordinated action is key, such as climate change mitigation. The concern is not only on achieving maximum cooperation, but doing so while simultaneously achieving the best outcome for everyone. This analysis can be applied to any social system. In this dissertation, we turn our focus into **scientific communication**, the current standard for propagating new scientific ideas.

Although the writing and sharing of articles as means of propagating scientific knowledge has been practiced for centuries, and has been growing in usage [16], its methodology has undergone many changes. The appearance of commercial publishers, the popularization of the internet, and now the rise of open science have all caused major shifts in the scientific communication landscape [17, 18]. By understanding its underlying mechanisms, one can model them and subsequently test whether the current practices are the most beneficial. If they are not, one can identify what is hindering the shift towards the optimal paradigm. Currently, the two primary strategies for scientific communication are: **Open-Access (OA)**, where published articles can be freely accessed by everyone, and **Closed-Access (CA)**, where published articles can only be accessed by those with a paid subscription, with the latter being the traditional and most widespread approach [19, 20].

The Closed-Access vs Open-Access debate is of major importance not only to the scientific community, but also to society as a whole, which benefits from the research produced and is directly impacted by the way it is propagated. Open-Access guarantees that scientific knowledge is available to everyone, which is particularly significant for researchers in less funded environments, leading to reduced inequality in knowledge accessibility [21]. However, under such a model, publishers lose on a primary source of revenue: the subscriptions. Additionally, there is ongoing debate about how Open-Access should be conducted. Several proposals exist, each with different costs for publishers and different approaches to making the articles accessible. Furthermore, discussions also encompass aspects related to the distribution of funds in science and the costs of publishing, originated from a mistrust in publishers due to their secrecy about operating costs [22]. Although the focus of this dissertation lies in the dynamics of Closed-Access and Open-Access adoption, it is crucial to consider all these aspects to achieve the most beneficial solution, considering every party involved.

Modelling such a system has particular difficulties, as it cannot be approached from a single perspective. Many different sectors exist, whose interests must be considered to attain an accurate model. Particularly, **publishers** will only continue to operate in the market if it is beneficial for them to do so. Therefore, they will choose the strategy that results in the best outcome for them, considering the actions of other parties (as we will see, this rationale is applied by all sectors). Additionally, it is relevant to consider **funding agencies and universities**, as they provide scientists with the necessary funds to proceed with their research, as well as financing certain aspects of scientific publication [23]. Evidently, the **researchers** themselves will not only have beliefs regarding the ideal approach that should be taken, but also act taking their own well-being into account. Each one of these parties must be considered distinct, as they have different benefits and costs for each publishing method. All these aspects and more will be later expanded upon, as we define the essential features to represent in our model.

1.1 Goals

Our primary aim lies on the creation of a model that can accurately predict the dynamics of Open-Access and Closed-Access adoption in the scientific communication system. More precisely, our goal is to study the influence of each factor of the system, such as funding distributions, revenues, publications costs and more in the adoption patterns of each of its three primary parties: funders, publishers, and researchers. We also seek to assess the impact of the most common alternative publishing methods: hybrid and Green OA publishing. We achieve this by creating flexible models that incorporate parameters related to these real-world factors.

With many proposed laws mandating OA in publicly-funded research, such as those emerging in the United States of America and the European Union [24, 25], we also aim to gain insight on how to effectively promote OA. We seek to identify the limiting factors in OA adoption, providing guidelines to policy-makers on the most efficient actions to take to promote it, while also minimizing the impact on each sector.

1.2 Outline

The first chapter of this thesis introduced the problem and its relevance, and defined the objectives of the proposed solution. Next, in Chapter 2, we introduce the background theory required to understand the general modelling of social systems, and provide details about the scientific communication system. This chapter sets the stage for the development of the model by highlighting the relevant aspects to consider. Chapter 3 presents previous work on the modelling of the scientific communication system, and their predictions on Open-Access adoption. We also explore prior efforts in modelling other social systems, whose methods can be applied in our model. Afterward, in Chapter 4, we formalize the scientific communication system and its underlying social interaction, followed by a theoretical explanation and a presentation of the main proposed model and its variations. In Chapter 5, we evaluate and compare the results of our models to those of computer simulations and of a supplementary model, to assess their validity and accuracy. We then delve into the primary objective of investigating the impact of each system factor on the resulting adoption patterns. Additionally, we analyze the logical coherence and consistency of these results to verify their meaningfulness and applicability. Next, we make use of our prior results to extract policies that promote OA adoption. We also appraise the alignment of our results with those from past work. Finally, Chapter 6 summarizes our contributions, suggests directions for future work and offers concluding remarks.

2

Background Theory

”It takes something more than
intelligence to act intelligently.”

Fyodor Dostoevsky

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In this chapter, we provide the necessary theoretical knowledge to understand our contributions. This is divided into two major sections. In Section 2.1, we define some key concepts behind game theory, a framework that is commonly employed to formally describe social interactions and which we ourselves will employ in our model, along with other tools which we will also rely on. In Section 2.2, we delve into the scientific communication system to understand what are the crucial aspects that our model must include.

2.1 Formalizing social interactions

To begin modeling our problem, it is first necessary to translate human interactions into a formalized language, which we can build upon to create our model. We begin, in Section 2.1.1, by defining the key concepts in game theory, along with formalizing the term 'cooperation', which has been loosely used until now. We also employ game theory to examine a classic example where behaving rationally and cooperating are seemingly incompatible. In addition, we introduce the concept of Nash Equilibrium, which is used to predict the outcome of interactions. In Section 2.1.2, we expand our analysis of interactions from individuals to a population, followed by the study of multi-population dynamics, where we will gain insight on how each population influences the others. In Section 2.1.3, we delve into evolutionary game theory to capture the dynamics of how the strategies of individuals can change over time. This section also introduces some key concepts, such as evolutionarily stable strategies and the replicator equation. Finally, in Section 2.1.4, we introduce Markov chains, and explore their use in modelling a social system, a concept which will also be of use in our model.

2.1.1 Modelling cooperation

To model cooperation, we first need to formalize the human interactions in which cooperation can take place. The fundamental assumption we follow is that we can model any human interaction as a game. That is, we can assume that each agent in the interaction can pick a set of actions, and based on what actions the agents picked, each one will obtain either a reward or a punishment. The study of such games, played by rational agents, is at the core of **game theory** [26]. As previously mentioned, a rational agent selects actions based on a cost-benefit analysis — more precisely, by assessing the difference between the benefits and costs of each action. This means we can collapse these two values and focus only on their difference, which is called the **payoff**.

There are crucial aspects which need to be understood in order to translate real interactions into games. First, following economic theory, we assume it is possible to value every possible outcome as a payoff, where a greater payoff is always more desirable. Necessarily, different outcomes with the same payoff must be equally likable. Secondly, we assume all agents select actions simultaneously, and no agent knows what the others will do beforehand (although it is acceptable for agents to deduce). Finally, we assume that every agent is aware of the reward that each agent can get for each possible set of actions, as well as being aware that every agent is behaving rationally.

Let us start by modeling a classic example, the *Prisoner's Dilemma* [27], following the widely accepted notation: Let there be 2 prisoners accused of committing a crime together. Each prisoner is being questioned separately by the police, with no chance to communicate between them, and each is given two choices — To cooperate with the police by admitting they were responsible, or to defect, blaming the other. They know that if both cooperate, each will get 5 years in prison. If only one cooperates, while the other defects, the cooperator gets 20 years, while the defector gets none. If both defect, they each get 15 years. We can formalize the possible actions and their outcome in a **payoff matrix**, represented in Table 2.1, where each letter in a row corresponds to a possible action of a prisoner, and the letters in each column correspond to the actions of the other prisoner. In this case, each prisoner can either cooperate (C) or defect (D). Any given entry in the matrix contains the payoff that each agent receives for that specific combination of actions. Since years in prison are unwanted, we represent them as negative payoffs.

		Prisoner 2	
		C	D
Prisoner 1	C	$-5, -5$	$-20, 0$
	D	$0, -20$	$-15, -15$

Table 2.1: An example of a payoff matrix for a Prisoner's Dilemma game.

Looking at the problem through the lens of one of the prisoners, even if we do not know what the other agent will do, if it happens to choose action C, our reward is maximized by picking D. Similarly, if the other agent picks D, we also maximize our reward by picking D. This means that the rational choice is achieved by choosing action D, regardless of what the other agent will do. However, after observing the payoff matrix, it is evident that a greater payoff can be obtained if both agents choose action C instead. When no player has an incentive to unilaterally deviate from a specific strategy — that is, if when changing the strategy of only one of the players it only obtains a worst outcome than before, we reach what is known as a **Nash Equilibrium (NE)** [28]. This result is crucial for understanding the difficulties associated with making a coordinated effort to reach better outcomes among rational agents.

Formally, the Nash Equilibrium can be defined by considering $u_i(s_i, s_{-i})$ to be the outcome of any agent i, given it uses strategy $s_i \in S_i$ and s_{-i} contains all the other strategies used by the other agents. A NE is any strategy set that respects the following condition:

$$u_i(s_i, s_{-i}) \geq u_i(s_i^*, s_{-i}), s_i^* \in S_i \tag{2.1}$$

or the following condition, for a strict Nash Equilibrium:

$$u_i(s_i, s_{-i}) > u_i(s_i^*, s_{-i}), s_i^* \in S_i \tag{2.2}$$

While seemingly simple when applied to a fictional scenario like the one above, examining problems like these can provide us with great insight. As Axelrod writes: "*Today, the most important problems facing humanity are in the arena of international relations, where independent, egoistic nations face each other in a state of near anarchy. Many of these problems take the form of an iterated Prisoner's Dilemma. Examples can include arms races, nuclear proliferation, crisis bargaining, and military escalation.*" [8]. Keeping this quote from Axelrod in mind, we will later observe that, no matter how desirable a state is, coordinated efforts can still be paramount to reach it. Next, we expand on this powerful framework to increase the amount of scenarios it can express.

2.1.2 Representing multi-population interactions

By developing a payoff table, we can define interactions between specific individuals. However, how can use it to model interactions within an entire population of similar individuals? Moreover, what if there are several types of individuals to consider? As we will later see, these cases require more than a single population to represent. We now expand upon the prior framework to accommodate such possibilities.

Before representing multiple populations, we need to first understand how to represent a single population. As opposed to the *Prisoner's Dilemma* case, where only two agents exist, let us instead consider a population of size *N*, that is, with *N* agents. We first need to define whom each agent can interact with. For problems where this question is of particular relevance, this can be done by resorting to a network, where each node represents an agent in the system. If two nodes are connected with an edge, it means that the corresponding agents can interact. Multiple types of networks exist [29], which define the way such a network is interconnected. Scenarios modelled using these networks are impacted not just by the interaction between the agents, but by the way information propagates through the network, as a consequence of its topography. As such, one must be cautious to consider aspects such as how many edges each node has (the degree distribution), how far apart each node is from others (the average path length), and more [30]. In the extreme case where every node is connected to every other node, allowing any agent to interact with any other agent, we obtain a complete graph (thus giving us a **well-mixed population**), which, due to its simplicity, makes the use of an explicit network unnecessary. We adopt this type of network for our model, as it greatly reduces the number of aspects to consider, allowing us to better focus on the specific factors of the scientific communication system. Figure 2.1 illustrates the difference between a randomly connected and a complete network.

Given a well-mixed population, a common setting is to repeatedly pair together members of the

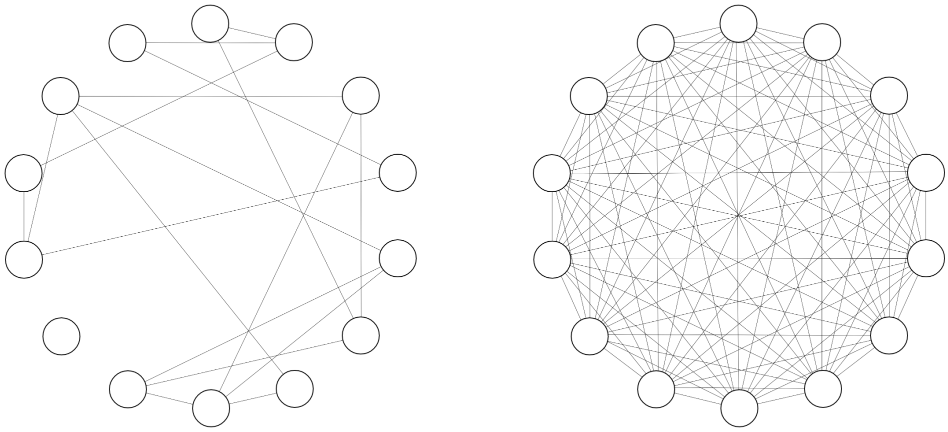

Figure 2.1: Left: Representation of a randomly connected network; Right: Representation of a complete network. Nodes represent agents of the system, and connected agents can interact.

population and have them play a simple game between them [31], allowing us to use games like the previously seen Prisoner's Dilemma in the context of an entire population.

Although this is a richer approach, there are still limitations associated with using a single population. In particular, when there is only one population, it is not possible to distinguish between individuals using the same strategy, and individuals cannot have different sets of strategies and payoffs. Therefore, in cases such as the scientific communication system, where it is clear that there are fundamental differences when modelling the payoffs of funders, publishers and researchers, it is necessary to distinguish between them. This is achieved by creating different sets — that is, populations — of individuals.

Extending the single-population approach to cases of multiple populations, we can play games involving groups composed of at least one member of each population. In our scenario, an interaction will always involve one funder, one publisher and one researcher. This approach requires, however, that the payoff table for the game states the payoff for the individuals of each population, for each combination of strategies.

2.1.3 Modelling strategy evolution over time

Up to this point, we have based the behavior of agents on the assumption that they always employ rational decision-making, therefore making it possible to predict what actions would be selected and the resulting outcome of each game. However, in scenarios with a high complexity or uncertainty (such as long-term decision-making, or coordination problems), not enough information could be available for the agents to make rational choices [32]. In such cases, humans regularly rely on simpler approaches to make decisions, such as imitating the actions of the successful [27, 31]. This results in a learning process, where individuals evolve through time as they adapt to the environment and the actions of the other agents. Next, we explain how to translate such a process into the game theory framework.

We study the evolution of strategies over time by employing **Evolutionary Game Theory (EGT)**, where the **fitness** of an individual playing a specific strategy is defined by the average payoff of that strategy in that population. Individuals with a smaller fitness will tend to imitate those with a larger fitness, a feature we model using the **Pairwise Comparison Rule (PCR)** [33], which we will later define. As previously stated, we employ the well-mixed approximation. This results in all individuals playing the same strategy to have the same fitness. Consequentially, instead of following the evolution of strategies across time, in EGT we follow the evolution of the fraction of individuals that play a given strategy across time.

EGT takes heavy inspiration from natural selection, correlating the fitness of an individual to his ability to reproduce [27]. In game theory, this translates to individuals with a greater payoff being more likely to be imitated by others, a process called **imitation**. This is one of the two reproduction mechanics we will use with EGT, with the second being **mutations**. Mutations aim to capture the appearance of new strategies, or previously extinct ones, in the population. Theoretically, they are defined as a chance that one of the individuals in a population changes strategy to one of the available ones, independently of the success of the strategy or its prevalence in the system. Without mutations, in a population where all individuals are using the same strategy, no new strategies could appear independently of the success of the prevailing strategy, as any imitation would lead to the same strategy.

This approach gives us a more flexible model, where agents are not constrained to always act rationally, as they only have to be *good enough* to exist in the population. EGT might, therefore, provide a basis for an explanation for the existence of cooperation as a viable strategy: The cost of cooperating might make it irrational in a single interaction, but when considering a wider time frame, where imitation dynamics can be considered, it can be *good enough* to survive — potentially even becoming widespread.

It is noteworthy that, despite imitation suggesting a higher average fitness in every generation, a change in one population can have negative consequences on the other. This interconnectedness between the evolving populations is discussed by Nowak: "*Although the environment selects the adaptations, these adaptations can shape the environment. By moving across a fitness landscape, populations change that landscape. [...] Therefore, the fitness landscape is shaped by the phenotypic distributions of the involved populations. As the population moves through the fitness landscape, new peaks and valleys form, channeling its further motion.*" [34]. Thus, attention should be paid not only to the strategy adoption over time, but also to the resulting payoffs of such adoptions, as they depend on the strategies of all populations and give us insight on the well-being of each individual.

In the theoretical case of an infinite population, the fraction of agents using each strategy under

EGT can be modelled using the **replicator equation**. For the case where two strategies (A and B) are available, the replicator equation is described as such:

$$\dot{x} = x(1-x)(f_A(x) - f_B(x)) \tag{2.3}$$

where $f_A(x)$ and $f_B(x)$ are the fitness of the population using strategy A and B, respectively, and x is the fraction of the population using strategy A. The replicator equation provides the **gradient of selection**; therefore, it tells us if, for a given fraction x using strategy A, this fraction will increase or decrease over time. In Chapters 3 and 4, we discuss the replication equation in the context of multiple co-evolving populations.

Similarly to the Nash Equilibrium in traditional game theory, EGT features **Evolutionarily Stable Strategies (ESSs)** [31]. Given that we are now discussing not just the best strategy for a given interaction, but the time evolution of fractions of populations using given strategies, we define an ESS as any strategy that, when adopted by a population, can not be displaced by any other strategy via the replication mechanisms. A strategy s_i is an ESS if

$$u_i(s_i, s_i) > u_i(s_k, s_i), \forall i \neq k, \tag{2.4}$$

or,

$$u_i(s_i, s_i) = u_i(s_k, s_i) \wedge u_i(s_i, s_k) = u_i(s_k, s_k), \forall i \neq k, \tag{2.5}$$

where the first condition is equivalent to the strict Nash Equilibrium. The second condition states that, although the payoff of both strategies may be the same, s_i has the advantage when played against s_k.

Despite these promising results showing easily predictable dynamics, social systems such as the scientific communication system cannot rely on the assumption of an infinite population. The fact that populations are finite means that the fraction of agents using each strategy is clearly affected by stochasticity. The details of how such dynamics are implemented in cases of finite populations will later be discussed in Section 4.

2.1.4 Markov chains

A Markov chain (MC) presents an alternative way to model a system and its evolution through time. Fundamentally, a Markov chain is a system that can be in one of various states, and, for each state, there is a particular probability of moving to any other state [35]. This allows us to express a stochastic dynamical system knowing only the present state and the probability of moving to each state in the next time-step — therefore being *memoryless* — i.e. the past has no implications on the current probabilities. This is a sequential process that evolves in discrete time steps, where the state of the process at time-step t can be represented as x_t.

Formally, the sole dependence on the current state is called the **Markov property**, and is described by the following equation:

$$\mathbb{P}[\mathsf{x}_t = y|\mathsf{x}_{0:t-1} = x_{0:t-1}] = \mathbb{P}[\mathsf{x}_t = y|\mathsf{x}_{t-1} = x_{t-1}] \tag{2.6}$$

In cases where the transition probabilities are independent of the time-step (a time-homogeneous Markov chain), we can store them in a matrix $\mathcal{P}$, where $[\mathcal{P}]_{ij}$ represents the probability of moving from state i to state j:

$$[\mathcal{P}]_{ij} = \mathbb{P}[\mathsf{x}_t = j|\mathsf{x}_{t-1} = i] \tag{2.7}$$

Furthermore, we can use induction to obtain the probabilities of ending up in any state after k time-steps:

$$[\mathcal{P}^k]_{ij} = \mathbb{P}[\mathsf{x}_{t+k} = j|\mathsf{x}_t = i] \tag{2.8}$$

If any state can be reached from any other state in a finite number of steps, that is, $\mathcal{P}^t(y|\mathsf{x}) > 0$, then a chain is considered **irreducible**. If that is the case, we can find a unique distribution of probabilities π over the state space such that:

$$\pi = \pi\mathcal{P} \tag{2.9}$$

That is, if the probability of being in any state in a specific time-step is given by π, after a transition, the probabilities of being in any state will remain the same as before. This is called the **stationary distribution**, and can be found using equation 2.10:

$$\lim_{t \to +\infty} \pi_0 \mathcal{P}^t = \pi \tag{2.10}$$

where π_0 is any initial distribution. In other words, independently of the initial distribution, any irreducible chain will always tend towards the unique stationary distribution. Furthermore, equation 2.9 shows that π is a left eigenvector of $\mathcal{P}$ associated with an eigenvalue of 1, giving us a clear way to find the stationary distribution.

MCs, whenever applicable, present us an alternative way to model finite population dynamics, naturally taking finite size stochastic effects into consideration. If we are dealing with multiple populations under a well-mixed regime, the only differentiating factors of an individual are the population it belongs to and what strategy it opts for. As such, the populations can be fully described by the current fraction of each population using each strategy, which is enough to model how it will evolve in the following time-step, therefore possessing the Markov propriety. Such a process under EGT is further explained in Chapter 3.

2.2 Overview of scientific communication

When modelling a system, we aim to capture its essential characteristics — these are the ones that are *fundamental* to characterize the system, and that, when considered, are *enough* to create the dynamics we intend to describe. To be able to find these characteristics for a particular system, domain knowledge is paramount. As such, we will now present the primary aspects of the scientific communication system.

2.2.1 Main actors

Scientific publications are, currently, the main way scientific knowledge is transmitted throughout the community [36]. These publications are created by **researchers**, and are submitted to journals owned by **publishers**, who will select, verify, format, compile, and finally reject or publish these articles in various formats. These publications are then accessed, read, and used as references by scientists when doing further research, therefore creating a cycle [23, 37]. Researchers are financed via public and private institutions, which include universities, funding agencies, foundations, and other entities — for simplicity, we address all these as **funders**. These are themselves either publicly or privately financed, with the objective of generating quality research.

Publishers can be of various origins: scholar publishers – that are associated with a particular university; independent publishers – which originate from and are maintained by a small amount of individuals; and commercial publishers – these are private companies with monetary incentives. Commercial publishers constitute the vast majority of well-reputed publishers [37], and as such, will be the ones we will be addressing.

2.2.2 Publishing articles

Publishing an article requires a lengthy and primarily human-driven, and therefore costly, process [22]. Submitted articles need to go through various evaluation processes, such as checking for plagiarism and verifying scientific correctness, with the latter usually done by resorting to **peer-review** — that is, other researchers that voluntarily review the article and reject, accept, or demand revisions. The selected articles are then formatted to a journal-specific style, a process that is sometimes done by the authors of the article. Recently, web versions of the articles are also being made available, requiring an extra step of preparation. Finally, these articles are published in journals, which can be exclusively digital, or also printed. Since there are costs associated with processing, storing, and maintaining a platform on which to access the various articles, publishers often obtain revenue by charging for their services [22]. A common approach is to charge individuals for each article they want to access, or offer a subscription-based model, where a paid subscription is required to access all the published articles from a journal. These are called **Closed-Access** publishers. Additionally, an Article Processing Charge (APC), the called **publishing fee**, is often charged to the author of each submitted paper, as to cover for the processing costs. Due to the often high costs of publishing and accessing articles, funders such as universities often make deals with particular publishers in order to let their researchers freely access their articles, and potentially finance a fraction, or the totality, of the APCs [22, 38].

Alternatively to CA, there have been publishers who freely let anyone access their articles. These are known as **Open-Access** publishers. Their popularity has been on the rise [18, 39, 40], and many previously exclusive CA publishers have been creating options to publish under OA, an approach which have seen a strong support from the European Union and the United States of America. This must necessarily mean, however, that these publishers are funded via other sources. Most commonly, these are directly financed by funders and publishing fees, although the practice of not charging any processing fees for publications is also on the rise [41], instead relying on other sources of revenue, such as advertising. There are also CA publishers that offer journals with the option to publish articles as OA, at an additional fee to the author — these are called **hybrid journals** [21].

Various laws have been proposed regarding the use of OA. In 2018, 'Plan S', an European-backed program, mandated all signed countries to require scientists who benefited from public funding to publish in OA publishers or repositories [24]. Horizon Europe, a research funding framework created by the European Union in 2021, also originated under similar publishing rules to that of 'Plan S' [42]. In 2022, the United States of America also announced that, by the end of 2025, all federally funded research should be made free to access as soon as it is published. All these laws show a clear interest in part of states to make Open-Access the standard publishing method.

2.2.3 Types of Open-Access

It is crucial to understand that OA is not a formalized procedure, but a general term with varying implementations. Numerous types of Open-Access exist, but the most common are [43, 44]:

- **Gold** OA – where the article is free to access via the platform of the publisher from the moment it is published. However, APCs are still present;
- **Green** OA – in which the article is published in a subscription journal, but it is also accessible in an Open-Access repository. Publishers may enforce a period where such self-archiving is prohibited,

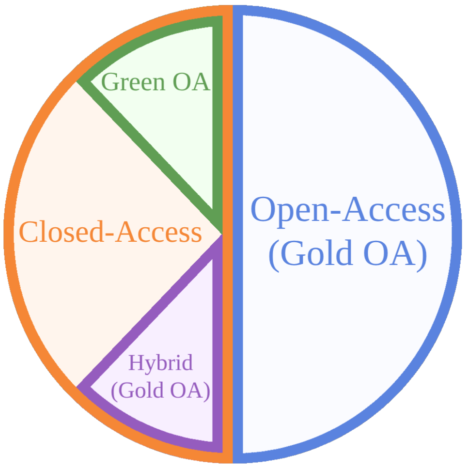

Figure 2.2: Types of publisher models: Open-Access publishers utilize solely Gold OA; Closed-Access publishers can be purely CA, offer hybrid options under Gold OA, or offer the option to publish under Green OA. The fractions used for each publishing type are not illustrative of their true presence. Other alternative publishing methods are omitted.

as to make the article only accessible to subscribers during that period. However, there are no costs to archive or to access the archived article;

- **Diamond OA** – where no publishing fees are applied, and the article is freely available at the time of publishing.

In this work, we focus on both Gold OA and Green OA, as they are the most common implementations of Open-Access [43]. Figure 2.2 illustrates the types of publishing methods we will consider in our model.

2.2.4 Other aspects of the scientific communication system

Just like there are more prolific and well-known researchers, there are also large variations on the dimension and acclaim between journals and publishers. These can be measured using diverse methods, with the most popular being the impact factor [45]. The existence of more well-regarded journals leads to more researchers wanting to publish there, and therefore the respective publishers having a greater influence on the publishing landscape [17]. Beyond the publisher itself, the accessibility of an article has also been shown to have a central impact on the attention that article gets, with OA articles often having a significantly greater number of downloads and citations [46–49].

There are, however, difficulties associated with reasoning about the costs and benefits of both approaches. No correlation has been found between the quality of an article and the associated cost to access it [22]. Moreover, publishing fees vary greatly between publishers, and have generally been on the rise — a trend that is difficult to justify due to the secrecy behind the costs associated with publishing [50]. This trend is especially noticeable in hybrid journals, which, although offer researchers with the option to publish in Open-Access, frequently requires paying significantly higher publishing fees [38].

A final aspect to consider is research reviewing. This process aims to guarantee that the monetary investments done by a funder are providing the expected results by evaluating the research produced. For that end, the various research results are graded and sorted to help steer funders towards a more efficient distribution of funds [51]. These are called **Performance-based Research Funding Systems (PRFS)**. While the evaluation criteria used worldwide are not universal, a primary example is that of the Research Excellence Framework (REF), from the United Kingdom [52]. The REF considers aspects such as the number of research outputs, the impact of the research produced, as well as the environment of the researcher, with the latter encompassing aspects such as the number of postgraduate research completed, the generated income and the quality of the infrastructure and facilities.

3

Related Work

”You have to know the past to understand the present.”

Carl Sagan

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As we saw in the previous chapter, EGT and Markov chains are powerful tools that can even model multi-population interactions. However, direct use of such tools would require extensive use of simulations, since these are stochastic processes. As we will see later in this chapter, more recent models rely on more sophisticated frameworks. These attempt instead to predict the direction of evolution. Yet, before that, we first review previous efforts to model the scientific communication system. This will provide us with a reference for the factors that are typically considered into account when modeling the system, as well as a baseline against which to compare our results.

In Section 3.1, we look at these prior models of the scientific communication system, also remarking any relevant conclusions. In addition, we present the current predictions regarding Open-Access adoption. In Section 3.2, we analyze work related to the modelling of other social systems under the evolutionary game theory framework. Our objective is to identify analogous problems and models, which we can use to construct our theoretical framework for analyzing the scientific communication system.

3.1 Models of the scientific communication system

While many models of the scientific communication system have been developed, they have heavily relied on data collection, followed by manual cost and benefit analysis. Such approaches are, however, limited by the data that can be collected, as many publishers have remained secretive about their internal workings [22]. This analysis has also been a historically incomplete view of the system, as research is often done with a particular party in mind, commonly researchers or publishers, or conducted in specific countries. Nevertheless, previous work can give us insight into what are considered the critical aspects of this system, as well as provide estimates for parameters and references to compare our results.

A formalized and full-scale model of the scientific communication process was developed by Björk [23]. This provides a detailed view of the entirety of the publication process for a single article, both for Closed-Access and Open-Access publishing. This also includes the workflow for activities related to peer-review, article accessing and reading, and usage of repositories, aspects that can be considered if a more complex model is deemed necessary. While highly descriptive, and therefore unpractical to adapt to a game theoretical framework, it provides fundamental insight to the publishing system.

This model was later extended by Houghton [53–55] and used to study the economic impacts of various types of Open-Access publishing in the UK, Denmark, and the Netherlands. There, focus was given to the implications that such publication models have on funders, publishers and researchers, as well as libraries, governments and universities. These studies were conducted using data that was publicly available, which was primarily the data originated from the governmental sections of the publishing system, such as public funding organizations, universities and research institutes. Data regarding publishing costs was, however, estimated, since it was not publicly available. Such research postulated a variety of consequences of the application of OA for each sector, when compared to CA. The major findings include: funders are likely to have similar costs with both approaches; researchers often have fewer costs and greater research visibility, although less funded fields might suffer from high author-side payments; and finally, publishers will need to compensate the potentially lower revenue with other sources of income, such as advertising. All this provides us with crucial insight regarding the necessary aspects to take into consideration when designing our model.

Predictive models and statistical studies have also been made regarding the future adoption of Open-Access [39,56]. Based on past adoption trends, these predict Open-Access to reach a dominant position in the publishing landscape, becoming the new norm. These predictions do not, however, consider aspects beyond the current adoption patterns, such as aspects pertaining to the social factors limiting or promoting OA adoption, and, as such, are potentially missing key transition phases. Other works try to achieve a greater reasoning behind the growth of Open-Access by analyzing all these different components at play, offering a variety of conclusions and predictions. David W. Lewis [57] suggests that Open-Access appears as a disruptive innovation, hinting that it only became a possibility when it started being practiced by publishers, and that its adoption will continually accelerate over time until it dominates the publishing landscape. This highlights the compatibility of EGT for modelling innovation diffusion, as the embracing of innovations has two primary contributions [58]: spontaneous exploration (captured through mutations), and success imitation (captured through imitations). The work also suggests that the transition to Open-Access offers a large benefit to researchers, for the added visibility and ease of usability, and to publishers, as Open-Access becomes more trustworthy, cheaper and more economically viable. Even more interestingly, it predicts a lack of effectiveness of hybrid publishers in supporting the transition to Open-Access, while highlighting the role of Green OA as a potential secondary factor in promoting it (although with limited effectiveness when Gold OA becomes widespread). Björk [59], and later Forrester [60], also examined the current barriers to Open-Access adoption and defined some limitations that need to be addressed to successfully promote it: first, the evaluation and recognition of researchers must not be negatively affected by publishing under OA, a consequence of the historically low reputation OA publishers; and second, OA revenues must be sufficient to keep publishers afloat. These predictions will later serve as a point of comparison for the results of our model.

3.2 Models of other social systems

Although general work in game theory is abundant, any particular social system will have inherent mechanics whose translation into the game theory framework is not trivial. In the case of scientific communication, we first need to analyze its inner workings in order to find what are the fundamental aspects that are best suited to describe it. Only then can we translate these aspects and implement them in our model. Looking at how this process has been done for other systems can give us clues about how to model certain dynamics that apply to our scenario.

As previously mentioned, our particular problem cannot be captured by relying on a single class of individuals, as differentiation is critical to model the distinct motivations of each sector. Furthermore, this type of social problem is also a **co-evolutionary problem**, meaning that the success of each strategy for a given population depends on the success of the strategies currently being employed by other populations. If we aim to reach a certain state, this originates the added complexity of having to consider not only the motivations of each sector, but also the order in which transitions occur, as the adoption of a strategy by one sector affects the adoption patterns of the other sectors.

To this end, Santos et al. [61] formulated a base framework which can be used to conduct multi-population modelling utilizing EGT, without resorting to simulations. This can be used as a theoretical baseline, requiring the development of a payoff matrix which describes the desired multi-sector interaction. From there, a system of non-linear differential equations can be derived from the replicator equation. These describe how the system evolves over time, given the fraction of individuals in each population playing each of the possible strategies. By determining the **fixed points** of this system of equations — the points where the magnitude of the gradient of selection is zero — we can find the population configurations that are stable, this is, the configurations the system will converge to.

Although this approach can only determine the dynamics for a given instance of the parameters from the payoff table, it allows us to study how the system will evolve over time, for any starting configuration. Additionally, it allows us to determine the nature of fixed points (including trivial solutions, like the state of full OA adoption), providing us with information on whether these states are stable or not. Moreover, we can study the effects that each parameter has on the nature of the fixed points and their basins of attraction, as well as finding the existence of any evolutionary cycles or other phenomena. This approach does have its caveats, particularly, the difficulty associated with solving the system of differential equations. Furthermore, the dependency on the replicator equation implies the assumption of infinite populations, an unrealistic approach for our scenario.

Another approach with the same goal of anticipating multi-population dynamics under EGT was developed by Encarnação et al. [62]. In this approach, the behavioral dynamics happen in a three-dimensional space, where each point of rational coordinates (x, y, z) corresponds to a state in which a fraction x, y, and z of each of the three populations cooperates (in each population, two strategies — **C**ooperate or **D**efect — are available). As such, $0 \leq x, y, z \leq 1$. Consequentially, such a space is shaped like a cube, where each vertex gives us one of the possible **monomorphic configurations**, that is, configurations where each population is either fully defecting or fully cooperating. In turn, each point in an edge corresponds to scenarios where only one of the populations contains individuals using both strategies. Configurations where populations contain individuals using different strategies are called **polymorphic configurations**. The model is characterized by a Markov chain (formally, a so-called embedded MC) with eight states, one for each monomorphic configuration, each connected to the three states where the strategy of only one population differs. Using the payoff table, it calculates where each state will evolve towards after a mutation, followed by an indeterminate number of imitations (the gradient of selection), from which the transition probabilities for the MC are derived. It is then possible to extract a set of conditions which dictate how the transitions will most likely occur, based on the values of the parameters. Consequently, one can extract what conditions have to be met to make a path from full defection to full cooperation. Thus, by analyzing the changes in parameters to fulfil such conditions, it is possible to conclude what needs to change in the system to achieve full cooperation.

Assuming that the system starts in the monomorphic state of full defection, as with any monomorphic state, a different strategy will only appear in a particular population following a mutation. By considering mutations to happen so rarely that no other mutations occurs while the system is unbalanced — that is, in a polymorphic state — the system can only end in one of two scenarios: either the new strategy becomes extinct, therefore the previous state is again reached; or the new strategy dominates the previous one, leading to a new monomorphic state. This assumption about the mutations is known as the **small mutation limit** [63, 64]. Cases of co-existence between the two strategies are discarded, as no assumptions are made about the time necessary for a monomorphic state to be reached. That is, it assumes that any polymorphic configuration is unstable, and therefore it is guaranteed it will fall into a monomorphic configuration after an unspecified amount of time. As such, this model loses the ability to tell how long it takes for a transition to happen. Although this approach lacks the possibility of studying co-existing strategies inside a population, it is drastically easier to calculate than the first approach by Santos et al.

This second approach has successfully been used to study various scenarios, such as sustainable tourism [65]. Particularly, it was also adopted by Encarnação et al. [66] to describe the adoption of electric vehicles. There, we also see the emergence of a coordination problem in order to move from the initial state of full defection towards the state of full cooperation (cooperation meaning the adoption of electric vehicles). Due to the instability of the states when only one of the sectors is cooperating, multiple sectors must coordinate to simultaneously adopt a cooperative strategy for the new state to be stable. Additionally, the factors that are limiting the transition to electric vehicles were also highlighted. Since the model relies on real-world parameters, this type of analysis offers realistic options that each sector can take in order to promote the adoption of electric vehicles, as well as the required coordination efforts.

4

Model

”Art is a lie that makes us realize truth, at least the truth that is given us to understand.”

Pablo Picasso

Contents

We now possess a solid background to start building the way up to our models. Our solution will be based on the aforementioned framework by Encarnação et al. [62], allowing us to predict the outcome of multi-population interactions without resorting to simulations, and requiring only a payoff table to be developed. This framework will be used to develop two models: one pertaining to the core problem of studying the adoption patterns for traditional Closed-Access and Gold OA; and a variation of this model capable of studying the system also under the presence of hybrid and Green OA publishers. Afterward, a model based on the work by Santos et al. [61] will also be developed, as it allows us to discover any possible stable polymorphic configurations and have a more precise representation of the evolutionary dynamics of the system, for any given parameterization.

As previously stated, we consider three populations: **Researchers** (R), **Publishers** (P), and **Funders** (F). Each will have two strategies available, representing the publication method supported by the individual: **Open-Access** (O), or **Closed-Access** (C). For every three-way interaction, the payoff of each individual will be given in accordance to a payoff matrix, as explained in Section 2.1.2. The size of each population is finite and, for simplicity, given by $\mathbb{Z}_{researchers} = \mathbb{Z}_{publishers} = \mathbb{Z}_{funders} = \mathbb{Z}$. Throughout our examples, we fixate $\mathbb{Z} = 50$.

In Section 4.1, we start by developing the payoff matrices that describe the tripartite interaction between our agents. We first reach the payoff matrix for the core problem, and afterward we derive the payoff matrix supporting the existence of the alternative publication methods mentioned above. Following that, in Section 4.2, we elaborate on the theory behind our models and present them.

4.1 Payoff table

We will now derive the payoff tables that aim to capture the essential characteristics of the scientific communication system, as exposed in Section 2.2. This will be done incrementally, by considering each aspect of the system, as seen in Chapters 2 and 3, and describing how to integrate it in the payoff table. Initially, we will build a payoff table, Table 4.2, pertaining only to the scenario where no hybrid or Green OA publishers are present, which we call the **core model**. Therefore, a researcher can only publish under Closed-Access or Gold Open-Access. Afterward, Table 4.3 will be constructed for the scenario where all CA publishers are hybrid, as an intermediate step to implement hybrid publishers. Then, Table 4.4 will be made by interpolating between Table 4.2 and Table 4.3, thus allowing us to decide how abundant hybrid publishers are. We then build Table 4.5, where we consider the scenario where all CA publishers allow Green OA, however, hybrid publishers are not present. Finally, we combine Tables 4.4 and 4.5 to create a payoff table where we are able to decide how predominant hybrid and Green OA publishers are. We refer to this as the **enhanced model**, which is presented in Table 4.6. The list of parameters used to construct the payoff tables is available in Table 4.1.

Game Parameters	Notation
Investment available by the funder	I
Share of I received by CA publishers	γ
Share of I received by OA publishers	δ
Open-Access revenue	A
Closed-Access subscription cost	S
Fixed cost page charges	F
Punishment imposed by the researchers on the funders	P_{RF}
Punishment imposed by the researchers on the publishers	P_{RP}
Funder-researcher synergistic effects	d_{FR}
Publisher-researcher synergistic effects	d_{PR}
Benefit from researchers publishing under OA	B
Taxes levied on publisher revenue	t
Fraction of hybrid CA publishers	h
Fraction of CA publishers offering Green OA	u
Fraction of revenue obtained from subscriptions when using Green OA	g
Fraction of O's in population F, P and R	Z_F, Z_P, Z_R

Table 4.1: Parameters for the game.

4.1.1 Payoff table for the core model: Without hybrid publishers or Green OA

In every interaction event, we witness a 3-party encounter featuring one member of each population. This comprises all the activities related to scientific communication, from investments by the funders, to publishing, and the accessing of published articles. Furthermore, we consider that, in each tripartite interaction, publishers dictate the publishing model which will be used. For example, if a publisher uses strategy O, the researcher has no option but to publish under Open-Access.

We start by modelling how funders distribute their **investments**. Let us first consider a quantity I each funder is willing to invest per interaction. I has to be divided between researchers and publishers, and thus represents a cost for the funder, and a benefit to who receives it. Although researchers and funders might be of different strategies, it is safe to assume researchers will always maintain basic income, and, as such, I should only represent additional investment to be used in their activities. Therefore, a simple yet reasonable approach is to give a fraction of I to the researchers, and another fraction to the publishers, whenever any matches the strategy of the funder. If only one party is aligned with the funder, only that party receives their respective fraction. Additionally, since monetary requirements can change between CA and OA, we define the parameters γ and δ, which indicate the fraction of I the publisher receives when using the same strategy as the funder, for strategy C and O respectively. Consequentially, the researcher will receive $(1-\gamma)I$ when both it and the funder support CA, and $(1-\delta)I$ in the case of OA being mutually used. Finally, in the case where none match the strategy of the funder, no one receives any investment, and hence there is also no cost for the funder. Moreover, although I represents an expenditure to the funder, investing funds is its primary objective, and thus any investment is represented as a benefit (representing the accomplishment of its purpose), instead of a negative payoff.

Defining the **page charges** as F, we can represent them as a cost for the researcher to be paid to the publishers. These costs can, however, be covered by the funder whenever it is aligned with the researcher. As such, F does not appear in these cases, and is considered to be part of the fraction of I offered to the researcher. In addition, although the publisher receives the fee, no benefit can be conferred because the fees are intended to cover only the costs associated with the specific publication, and are, therefore, considered to be fully spent.

When publishers opt for Closed-Access, it is necessary to consider **subscription costs**, represented as S. These are charged to the researcher, as it is assumed they access CA articles in the interaction. Analogous to the publishing fees, whenever funders are aligned with the publishers, we presume their fraction of I includes S as to cover these subscription costs for researchers. When this is not the case, that is, funders and publishers are not aligned, and publishers use CA, S becomes a cost to the researchers. With this, we can establish a relationship between I, F and S, since they all represent costs that are potentially covered by the funders. At most, the funders will pay for both the subscription fees and the publishing costs, and potentially more than that. As such, $I(1-\delta) \geq F$, $I(1-\gamma) \geq F$ and $I\gamma \geq S$.

Unlike CA publishers, OA publishers do not have a standardized method of obtaining revenue — they can rely on advertising, revenue from other journals they publish, or multiple other sources. This means that, contrary to the revenue obtained from subscription costs, their revenue can potentially originate outside the three-sector system. Thus, a generalized approach is taken by denoting the revenue received by OA publishers as A, that is obtained whenever publishers are using strategy O.

Another important aspect to consider is that of **boycotts**, where individuals resort to paying a cost as a method of social punishment in an effort to incentivize change. This encompasses possible collective social actions such as activism, therefore having a greater impact the more people participate [67]. Since group boycotts are carried out by individuals, we consider them feasible only for the research sector, as the other sectors are comprised of organizations. We implement such punishments whenever publishers or funders disagree with the strategy of the researcher, and represent them via a cost P_{RF} for the punishment imposed by researchers on the funders, and as P_{RP} for one imposed on the publishers. This cost is paid both by the punished and the punisher. Since the effectiveness of the punishment is greater the more people participate, we simulate this effect by scaling the cost paid by each researcher by the fraction of the researchers following the same strategy. For this, we denote by Z_R, with $0 \leq Z_R \leq 1$, the fraction of researchers using strategy O. This dependency on the fraction of individuals using a given strategy is known as a **frequency-dependent payoff**. As such, for researchers using strategy O, the individual cost for a punishment against the funders is $(1 - Z_R)P_{RF}$, while, if the researchers are using strategy C, the cost for a punishment towards the funders will be $Z_R P_{RF}$. For the cases with punishments against publishers, it is constructed similarly, only using P_{RP} instead.

Yet another type of social punishment is that of **taxes**, used as a way to internalize negative externalities that a market generates [68]. These can be placed by states in order to incentivize the other sectors to change. An example of these are carbon taxes, which aim to pressure companies to move towards less carbon intensive technologies. In our case, these can be levied by the funders, which also assume the role of state, on the revenue of the publishers. Since funders directly finance researchers, and are their only revenue source, there is no motivation for taxing them. Thus, taxes are only applicable whenever funders and publishers have opposing strategies. We model taxes as a cost of a fraction t of the profits generated by the publisher, that are then given to the funder. In the scenarios where they apply, the profit is either the subscription fees, S, in CA, or the Open-Access revenue, A, in OA. Therefore, the publisher is taxed St or At, or, similarly, it only obtains a benefit of $S(1-t)$ or $A(1-t)$, with St or At being given to the funder.

There are also benefits which originate from coordination between sectors. Examples of those in the publication landscape are: added compensatory funding and promoted usage of scholarly-publishers when funders and researchers are aligned and publishers are not; or better deals from publishers to assist scientists, when only the funders are not aligned. These can be represented as an added benefit to the two coordinated parties, only happening when the third party is not — a so-called **synergistic effect**. We represent these benefits using the variables d_{FR} and d_{PR}, for the aligned pairs funder-researcher and publisher-researcher, respectively. Since CA is, historically, the default publication method, we only consider these synergistic benefits when the agreeing pairs are using OA.

As the objective of the researcher is to publish research with maximum visibility, a benefit B is given to it whenever a publication happens under OA, as it boasts a higher count of accesses [46–49]. Although, in the current scenario, B appears only when the publisher is OA, we will later see that this stops being the case when hybrid and Green OA publishers are possible.

Considering all these aspects, the payoff table describing the **core model** is presented below. It represents the payoff for all the possible interactions, for all possible strategies of each agent.

Strategies			**Payoffs**		
F.	P.	R.	Funders	Publishers	Researchers
O	O	O	I	$I\delta + A$	$I(1-\delta) + B$
O	O	C	$I\delta - P_{RF}$	$I\delta + A - P_{RP}$	$B - F - (P_{RF} + P_{RP})Z_R$
O	C	O	$I(1-\delta) + St + d_{FR}$	$S(1-t) - P_{RP}$	$I(1-\delta) + d_{FR} - S - P_{RP}(1-Z_R)$
O	C	C	$St - P_{RF}$	$S(1-t)$	$-F - S - P_{RF}Z_R$
C	O	O	$At - P_{RF}$	$A(1-t) + d_{PR}$	$d_{PR} + B - F - P_{RF}(1-Z_R)$
C	O	C	$I(1-\gamma) + At$	$A(1-t) - P_{RP}$	$I(1-\gamma) + B - P_{RP}Z_R$
C	C	O	$I\gamma - P_{RF}$	$I\gamma - P_{RP}$	$-F - (P_{RP} + P_{RF})(1-Z_R)$
C	C	C	I	$I\gamma$	$I(1-\gamma)$

Table 4.2: Payoff table for the core model game, without hybrid or Green OA publishers.

4.1.2 Payoff table in which CA publishers are hybrid

Hybrid publishers provide researchers with an opportunity to publish their articles in OA, even when the journal is subscription-based. To implement this, we first consider the case where every CA publisher is hybrid. Their presence only manifests in the scenarios where the researcher is using strategy O and the publisher strategy C, where, due to the usage of the hybrid model, a publication will now happen using Open-Access. In all other scenarios, either the publisher is already Open-Access, or the researcher rather publish under CA. When it applies, punishments by the researchers to the publishers will cease to occur. Instead, researchers will pay increased publishing fees — for simplicity, twice as much, $2F$, a usual value for hybrid journals [38] — and the publisher, due to only having an operating cost of F, will benefit F. Since, in this scenario, despite using strategy C, the publisher is effectively only OA, it will receive a revenue of A instead of S. This revenue is, however, still prone to taxes whenever publishers and funders are misaligned. The researcher will also receive B since a publication was made effectively under OA. The investments from the funder and all remaining aspects will occur as usual.

The payoff table below describes this new scenario, with the altered entries highlighted — in all the remaining cases, the table is identical to Table 4.2.

Strategies			**Payoffs**		
F.	P.	R.	Funders	Publishers	Researchers
O	O	O	I	$I\delta + A$	$I(1-\delta) + B$
O	O	C	$I\delta - P_{RF}$	$I\delta + A - P_{RP}$	$B - F - (P_{RF} + P_{RP})Z_R$
O	C	O	$I(1-\delta) + d_{FR}$	$A + F$	$I(1-\delta) + d_{FR} + B - F$
O	C	C	$St - P_{RF}$	$S(1-t)$	$-F - S - P_{RF}Z_R$
C	O	O	$At - P_{RF}$	$A(1-t) + d_{PR}$	$d_{PR} + B - F - P_{RF}(1 - Z_R)$
C	O	C	$I(1-\gamma) + At$	$A(1-t) - P_{RP}$	$I(1-\gamma) + B - P_{RP}Z_R$
C	C	O	$I\gamma + At - P_{RF}$	$I\gamma + A(1-t) + F$	$B - 2F - P_{RF}(1 - Z_R)$
C	C	C	I	$I\gamma$	$I(1-\gamma)$

Table 4.3: Payoff table for the game in which all CA publishers are hybrid.

4.1.3 Payoff table with a fraction of hybrid publishers and no Green OA

Having both the payoff table for the scenario where no hybrid publishers exist and the scenario in which every CA publisher is hybrid, we can interpolate between the two payoff tables to define a scenario where only a fraction of such publishers are using a hybrid model. To that end, we define h, with $0 \leq h \leq 1$, to be the fraction of CA publishers that offer an hybrid option. As such, every entry in this payoff table will be equal to $(1-h)$ times the corresponding entry in Table 4.2 plus h times the corresponding entry in Table 4.3. It is important to note that, by applying this procedure, the payoffs stop representing the outcome of an individual following an interaction, but that of the average individual in that scenario.

The payoff table below describes this new scenario, with the relevant entries highlighted — in all the remaining cases, the table is identical to Tables 4.2 and 4.3.

Strategies			Payoffs		
F.	P.	R.	Funders	Publishers	Researchers
O	O	O	I	$I\delta + A$	$I(1-\delta) + B$
O	O	C	$I\delta - P_{RF}$	$I\delta + A - P_{RP}$	$B - F - (P_{RF} + P_{RP})Z_R$
O	C	O	$I(1-\delta) + St(1-h) + d_{FR}$	$S(1-t)(1-h) + (A+F)h - P_{RP}(1-h)$	$I(1-\delta) + d_{FR} + Bh - Fh - (S + P_{RP}(1-Z_R))(1-h)$
O	C	C	$St - P_{RF}$	$S(1-t)$	$-F - S - P_{RF}Z_R$
C	O	O	$At - P_{RF}$	$A(1-t) + d_{PR}$	$d_{PR} + B - F - P_{RF}(1-Z_R)$
C	O	C	$I(1-\gamma) + At$	$A(1-t) - P_{RP}$	$I(1-\gamma) + B - P_{RP}Z_R$
C	C	O	$I\gamma + Ath - P_{RF}$	$I\gamma + (A(1-t)+F)h - P_{RP}(1-h)$	$Bh - F(1+h) - (P_{RP}(1-h) + P_{RF})(1-Z_R)$
C	C	C	I	$I\gamma$	$I(1-\gamma)$

Table 4.4: Payoff table for the game with a fraction of hybrid publishers and no Green OA.

4.1.4 Payoff table in which all CA publishers are Green OA

Similarly to what was done in subsection 4.1.2, we introduce Green OA by first detailing the scenario where all CA publishers opt to allow it.

Green OA, similarly to the hybrid model, will be present in the scenarios where the publisher uses strategy C, and researchers use strategy O (and likewise, also replacing punishments). Since publications stay Closed-Access until a specific time has passed, publishers will only obtain a fraction of the subscriptions, with the remaining profit being Open-Access revenue. Researchers will only pay that same fraction of subscription costs to access these articles. We define this fraction of time under CA as g, where the publisher now obtains a revenue of $Sg + A(1-g)$. This revenue will be prone to taxes, with S being taxed when the funder is OA, and A being taxed when the funder is CA. Additionally, since $(1-g)$ of the time the publication will be under OA, a researcher will benefit $B(1-g)$ from increased visibility, and pay Sg in subscription costs, if not covered by the funder. The remaining elements present in these entries, such as investments and synergistic effects, are left untouched.

The payoff table below describes this new scenario, with the relevant entries highlighted and the remaining entries being the same as Table 4.2.

Strategies			Payoffs		
F.	P.	R.	Funders	Publishers	Researchers
O	O	O	I	$I\delta + A$	$I(1-\delta) + B$
O	O	C	$I\delta - P_{RF}$	$I\delta + A - P_{RP}$	$B - F - (P_{RF} + P_{RP})Z_R$
O	C	O	$I(1-\delta) + Stg + d_{FR}$	$S(1-t)g + A(1-g)$	$I(1-\delta) + d_{FR} + B(1-g) - Sg$
O	C	C	$St - P_{RF}$	$S(1-t)$	$-F - S - P_{RF}Z_R$
C	O	O	$At - P_{RF}$	$A(1-t) + d_{PR}$	$d_{PR} + B - F - P_{RF}(1-Z_R)$
C	O	C	$I(1-\gamma) + At$	$A(1-t) - P_{RP}$	$I(1-\gamma) + B - P_{RP}Z_R$
C	C	O	$I\gamma + At(1-g) - P_{RF}$	$I\gamma + A(1-t)(1-g)$	$B(1-g) - F - P_{RF}(1-Z_R)$
C	C	C	I	$I\gamma$	$I(1-\gamma)$

Table 4.5: Payoff table for the game in which all CA publishers are Green OA.

4.1.5 Payoff table for the enhanced model: with a fraction of hybrid publishers and of Green OA

To combine the possibility of having both hybrid and Green OA publishers, we are only missing a parameter for the fraction of CA publishers using Green OA. We define this fraction as u, where $0 \leq u + h \leq 1$, since the two options cannot happen simultaneously.

We can introduce both alternative publishing methods simultaneously, in a fashion similar to what was done to introduce hybrid publishers before: by multiplying the scenario in Table 4.5 by u, the scenario in Table 4.3 by h, and the scenario in Table 4.2 by $(1 - h - u)$, and adding them together. This achieves a payoff table capable of expressing the average payoff of any individual of any population, for each interaction scenario, for any fraction of hybrid or Green OA publishers simultaneously. In turn, by considering $h = 0$ and $u = 1$, we recover Table 4.5. Likewise, with $u = 0$ we retrieve Table 4.4. Finally, $h = u = 0$ allows us to return to the core model, in Table 4.2.

This final payoff table, describing the **enhanced model**, is presented below. The transformed entries, in reference to Table 4.2, are highlighted. The remaining entries are not altered.

Strategies			**Payoffs**		
F.	P.	R.	Funders	Publishers	Researchers
O	O	O	I	$I\delta+A$	$I(1-\delta)+B$
O	O	C	$I\delta-P_{RF}$	$I\delta+A-P_{RP}$	$B-F-(P_{RF}+P_{RP})Z_R$
O	C	O	$I(1-\delta)+St(1-h-(1-g)u)+d_{FR}$	$S(1-t)(1-h-(1-g)u)+Fh-P_{RP}(1-h-u)$	$I(1-\delta)+B(h+(1-g)u)+d_{FR}-Fh-S(1-h-(1-g)u)-P_{RP}(1-Z_R)(1-h-u)$
O	C	C	$St-P_{RF}$	$S(1-t)$	$-F-S-P_{RF}Z_R$
C	O	O	$At-P_{RF}$	$A(1-t)+d_{PR}$	$d_{PR}+B-F-P_{RF}(1-Z_R)$
C	O	C	$I(1-\gamma)+At$	$A(1-t)-P_{RP}$	$I(1-\gamma)+B-P_{RP}Z_R$
C	C	O	$I\gamma+At(h+(1-g)u)-P_{RF}$	$I\gamma+A(1-t)(h+(1-g)u)+Fh-P_{RP}(1-h-u)$	$B(h+(1-g)u)-F(1+h)-(P_{RP}(1-h-u)+P_{RF})(1-Z_R)$
C	C	C	I	$I\gamma$	$I(1-\gamma)$

Table 4.6: Payoff table for the enhanced model game, with a fraction of hybrid publishers and a fraction of Green OA publishers.

4.2 Population dynamics

With the payoff tables finalized, we will now go over the theory behind our models and introduce them. Let us first detail how individuals revise their strategy over time, and how we can model the strategy adoption dynamics within each sector. Similarly to Encarnação et al. [62], we analyze such interactions through an EGT framework, where the adoption of strategies follows a birth-death process (that is, the number of individuals using a strategy can increase or decrease by one at a time). As previously seen, we use two replication mechanisms, that result in updates to the strategy used by each individual: **imitation** (or social learning) — where individuals copy strategies that are already present in the population, based on their success; and **mutation** — an instantaneous adoption of one of the available strategies, that is independent of its success or adoption rate in the population.

We model imitation using the PCR, where individuals are more likely to imitate the strategies of individuals with greater fitness. By having access to the payoff table and the fraction of each population using each strategy, we define the **fitness** of an individual of a given population using a given strategy to be the average payoff obtained by individuals in that population that are also using the same strategy. For each population, and a given strategy $X \in \{O, C\}$, the fitness is given as:

$$
\begin{aligned}
f^F_{X\in\{O,C\}} &= Z_P Z_R T^F_{XOO} + (1-Z_P)Z_R T^F_{XCO} + Z_P(1-Z_R)T^F_{XOC} + (1-Z_P)(1-Z_R)T^F_{XCC} \\
f^P_{X\in\{O,C\}} &= Z_F Z_R T^P_{OXO} + (1-Z_F)Z_R T^P_{CXO} + Z_F(1-Z_R)T^P_{OXC} + (1-Z_F)(1-Z_R)T^P_{CXC} \\
f^R_{X\in\{O,C\}} &= Z_F Z_P T^R_{OOX} + (1-Z_F)Z_P T^R_{COX} + Z_F(1-Z_P)T^R_{OCX} + (1-Z_F)(1-Z_P)T^R_{CCX}
\end{aligned}
\quad (4.1)
$$

where $T^Y_{X_1 X_2 X_3}$ corresponds to the payoff obtained by an individual of population $Y \in \{F, P, R\}$, when the funder, publisher and researcher use strategies $X_1, X_2, X_3 \in \{O, C\}$, respectively.

At each time step, and for each sector, we select two random individuals i and j of that sector. The PCR [33, 69] gives us the probability of i imitating the strategy of j, where f_i and f_j correspond to the fitness of individuals i and j, respectively. The **imitation probability** is obtained by the equation below:

$$p = [1 + e^{-\beta(f_j - f_i)}]^{-1} \quad (4.2)$$

This probability increases with a greater difference between the fitness of j and i, such that there is always a higher chance to imitate an individual who has a better fitness. We also use a scaling factor, β, often called the **intensity of selection**, to represent the significance of individual fitness in the imitation process. When $\beta = 0$, we have that $p = 0.5$, and therefore the fitness of the individuals is irrelevant for imitation to happen, and imitation is instead ruled by a random process. By increasing β, we are increasing how deterministic the process is. In the case where $\beta = 1$, we approach a strong selection process, which is common when modelling human social dynamics [70, 71], and, as such, is the one we will resort to.

Regarding mutations, since there are only two strategies available, these can be defined by a probability p_m, such that, at each time step, a randomly chosen individual in each population has a probability p_m of changing to the other strategy.

4.2.1 Simplex Model

In order to predict the evolution of the system over time, we base our approach on that of Encarnação et al. [62], as explained in Section 3.2. This allows us to obtain the expected transitions between monomorphic states for any parameter set, enabling us to make judgements on the impact of each parameter and to determine the best path towards a given goal state. We refer to such a construction as the **simplex model** (adopting 'simplex' from its usage to visualize the direction of evolution for each system state).

To this end, it is necessary to calculate the probability that, given a mutation when the populations are in a monomorphic state, the new strategy dominates the current one and a new monomorphic state is reached. As stated in [33, 72, 73], the probability that a single individual with a strategy *b* successfully invades a population of $\mathbb{Z} - 1$ individuals using a strategy *a*, called the **fixation probability** (ρ_{ab}), can be calculated by:

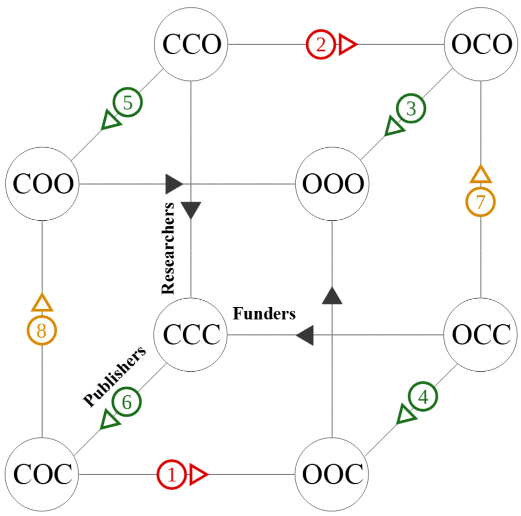
$$\rho_{ab} = (1 + \sum_{i-1}^{\mathbb{Z}-1} \prod_{j=1}^{i} \frac{\mathbb{T}_j^-}{\mathbb{T}_j^+})^{-1} \tag{4.3}$$

Where $\mathbb{T}_j^+$ ($\mathbb{T}_j^-$) represents the probability that one more (less) individual imitates the *j* individuals already using strategy *b* in the population. For the PCR process described above, $\mathbb{T}_j^{\pm}$ is given by:

$$\mathbb{T}_j^{\pm} = \frac{j}{\mathbb{Z}} \frac{\mathbb{Z} - j}{\mathbb{Z}} [1 + e^{\mp\beta(f_a - f_b)}]^{-1} \tag{4.4}$$

where f_a and f_b represent the fitness of individuals using strategy a and b, respectively. Since that, under the small mutation limit, mutations only happen at most in one population before stabilizing to a monomorphic state, transitions will only happen along the edges of the cubic space. As such, if $\rho_{CO} > \rho_{OC}$ for a specific population, while keeping the strategies of the other populations fixed, we can say that selection favors the invasion of an O individual in a population of Cs over the opposite case. The parallel is true if, instead, $\rho_{OC} > \rho_{CO}$, where a C individual will successfully invade a population of Os. In the case where $\rho_{CO} = \rho_{OC}$, we are in the presence of a **neutral drift**, where no dominance occurs. By calculating this for all monomorphic states following a mutation in each population, we are then capable of predicting the transition direction for any pair of adjacent monomorphic states in the cubic space. Since the value of these conditions is dependent on the payoffs obtained under each strategy, is it possible for **conditional transitions** to appear. That is, transitions whose directions depend on the value of the parameters of the payoff table. Since these parameters describe the system, the factors of each conditional transition can be analyzed to study the effect that each parameter has in the resulting dynamics.

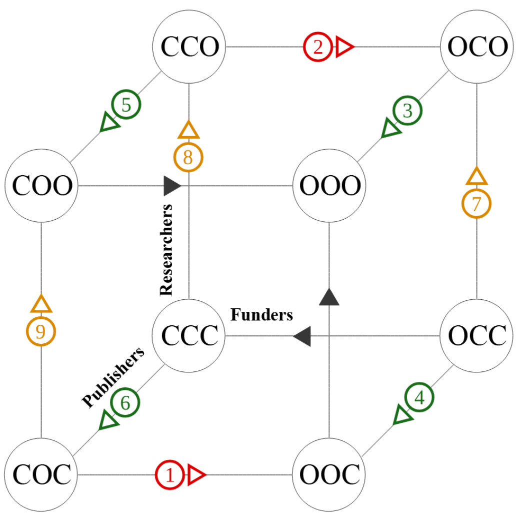
For the payoff table of the core model, Table 4.2, a representation of the monomorphic state spaces, as well as the predicted transitions along each edge and the conditions for each transition, is shown in Figure 4.1. A similar representation for the enhanced model, in Table 4.6, is presented in Figure 4.2.



Conditions for Cooperation

1. $I(\delta + \gamma - 1) > At + P_{RF}$
2. $d_{FR} + P_{RF} + St > I(\delta + \gamma - 1)$
3. $A + I\delta + P_{RP} > S(1-t)$
4. $A + I\delta > P_{RP} + S(1-t)$
5. $A(1-t) + d_{PR} + P_{RP} > I\gamma$
6. $A(1-t) > I\gamma + P_{RP}$
7. $I(1-\delta) + F + d_{FR} + P_{RF}/2 > P_{RP}/2$
8. $d_{PR} + P_{RP}/2 > I(1-\gamma) + F + P_{RF}/2$

Figure 4.1: Representation of the monomorphic state-space and the predicted evolutionary dynamics for the core model. Transitions are constrained to happen along the edges. Dark-gray arrows point towards the direction of evolution of unconditional dominance dynamics, when under the condition that all parameters are greater than 0. When parameters can be equal to 0, neutral drift becomes possible. Numbered arrows indicate conditional dominance, where such dominance dynamics only take place when under the respective conditions, detailed in the right. Otherwise, dominance happens in the opposite direction.



Conditions for Cooperation

1. $I(\delta + \gamma - 1) > At + P_{RF}$
2. $St(1-h-(1-g)u) + d_{FR} + P_{RF} > I(\delta + \gamma - 1) + At(h+(1-g)u)$
3. $A(1-h-(1-g)u) + I\delta + P_{RP}(1-h-u) > Fh + S(1-t)(1-h-(1-g)u)$
4. $A + I\delta > P_{RP} + S(1-t)$
5. $A(1-t)(1-h-(1-g)u) + d_{PR} + P_{RP}(1-h-u) > I\gamma + Fh$
6. $A(1-t) > I\gamma + P_{RP}$
7. $I(1-\delta) + F(1-h) + d_{FR} + P_{RF}/2 + S(h+(1-g)u) > P_{RP}(1-h-u)/2$
8. $P_{RF}/2 + B\,(h+(1-g)u) > I(1-\gamma) + F(1+h) + P_{RP}(1-h-u)/2$
9. $d_{PR} + P_{RP}/2 > I(1-\gamma) + F + P_{RF}/2$

Figure 4.2: Representation of the monomorphic state-space and the predicted evolutionary dynamics for the enhanced model.

By examining the parameters associated with each condition, one can define real-world proposals that would impact those respective parameters, and therefore guide the system to a desirable state. This analysis, which is at the center of our research question, will be conducted further ahead, in Section 5.

The **stationary distribution** for the Markov chain can also be computed, therefore giving us access to the fraction of time spent in each of the monomorphic states. This can be done by first calculating the transition matrix $\mathcal{T}$ from the fixation probabilities, where $\mathcal{T}_{ij} = 0$ if the two monomorphic states i and j are not connected; $\mathcal{T}_{ij} = \rho_{ij}/3$ if the states are connected and $i \neq j$; and $\mathcal{T}_{ii} = 1 - \sum_{a \neq b} \mathcal{T}_{ab}$. Due to the irreducibility of the Markov chain, the stationary distribution is unique, and given by the eigenvector of $\mathcal{T}$ paired with the eigenvalue equal to 1 [63, 74]. From the stationary distribution, by defining the values for the parameters of the system, we obtain the fraction of time in each state. An example of the stationary distribution for a given parameter set in the core model is represented in Figure 4.3.

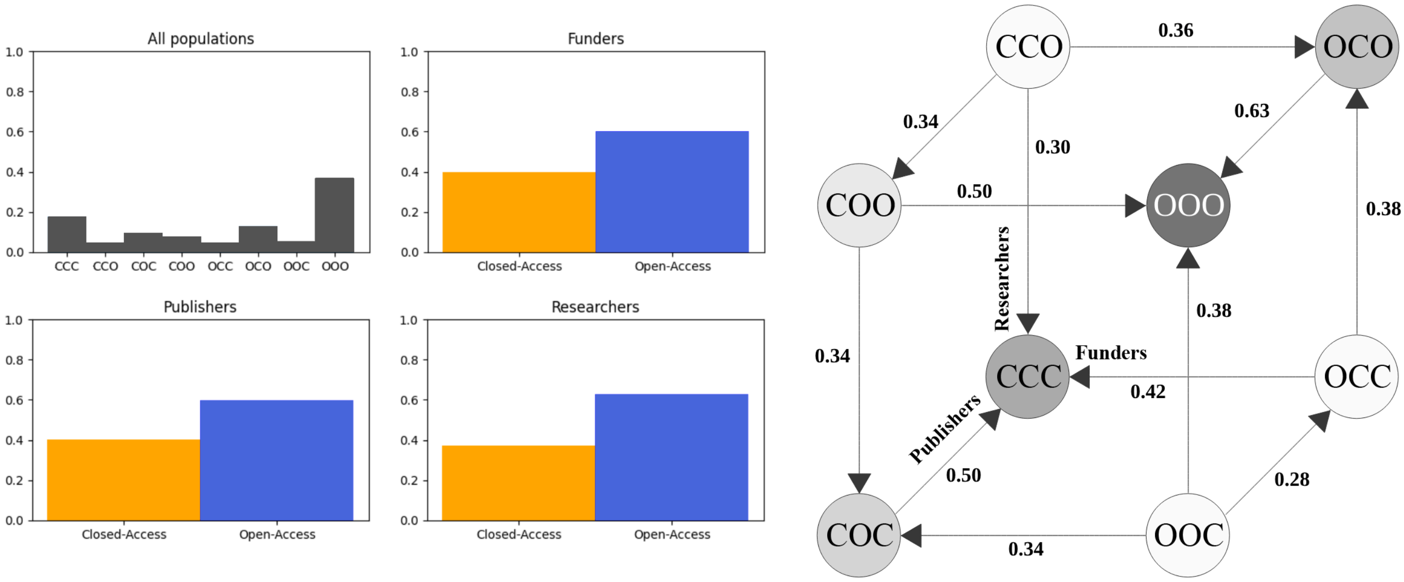


Figure 4.3: The stationary distribution for a given parameter set under the core model. Left panel: Histograms displaying the fraction of time spent in each configuration and, for each sector, the time spent in OA and CA. Right panel: Figure 4.1 is redrawn to show the transitions based on the model parameters, and the hue of each monomorphic state translates to the fraction of time spent there (whiter means less time). The labels in each arrow correspond to the transition probability of the dominant transition, normalized excluding self-loops. Model parameters: $I = 1$, $\gamma = 0.5$, $\delta = 0.5$, $A = 0.5$, $S = 0.8$, $F = 0.2$, $P_{RF} = 0.8$, $P_{RP} = 0.8$, $d_{FR} = 0.4$, $d_{PR} = 0.4$, $B = 0.3$, $t = 0.25$, $h = 0$, $u = 0$, $g = 0$.

While the simplex model allows us to determine the transitions between the monomorphic state for any parameter set, the stationary distribution completes that information for a given parameter set, allowing us to know if a given state is not just reachable, but also actively maintained.

Besides the evolutionary trajectory of the system, another fundamental aspect of policymaking is evaluating the effectiveness of different decisions. In our case, this amounts to studying the impact that each parameter can have in the final result of our system. This can be achieved by fixating all variables except our target variable, and calculating the resulting stationary distribution across the range of values the target variable can take (in our case, between zero and one). This study will be conducted further ahead, in the Discussion chapter.

4.2.2 Gradient Model

We also derive a more granular model, which we call the **gradient model**. With it, we can, for a specific set of parameters, analyze the **gradient of selection** for each point inside the cubic space, similarly to what was done by Santos et al. [61]. Since that, for each set of parameters, the gradient field needs to be calculated, it will solely be used to provide a baseline to evaluate the prior model, as well as to provide a better understanding of the dynamics that happen in polymorphic states and, in particular, in the fixed points of the system.

As mentioned in Section 2.1.3, the replicator equation can be used to determine the evolution of a system over time, under the assumption of an infinite population. Since we are dealing with three populations, at any point (Z_F, Z_P, Z_R), the evolution will be governed by the following system:

$$\Delta(\vec{g}) = \Delta(Z_F, Z_P, Z_R) = \begin{cases} Z_F(1 - Z_F)(f_O^F - f_C^F) \\ Z_P(1 - Z_P)(f_O^P - f_C^P) \\ Z_R(1 - Z_R)(f_O^R - f_C^R) \end{cases} \tag{4.5}$$

where Z_Y indicates the fraction of a population $Y \in \{F, P, R\}$ using the strategy O, and f_X^Y is the fitness of an individual in population Y using strategy $X \in \{C, O\}$, as expressed in Equation 4.1.

Having obtained the gradient of selection, the fixed points will be those where this gradient is equal to zero. This includes the trivial corner solutions where Z_F, Z_P and Z_R are equal to zero or one (the monomorphic states), but also points where the average payoff of both strategies is the same, for all populations.

These fixed points can be classified as either **attractors**, where, in a neighborhood, all gradients point towards the point, or **repellers**, where there are points in a neighborhood whose gradients point away from the fixed point. From an evolutionary perspective, this tells us if a fixed point is stable or not, being able to withstand in the presence of replication mechanisms. We can classify the nature of these points by first calculating the Jacobian matrix of $\Delta(Z_F, Z_P, Z_R)$ at the fixed point. These points will be classified as stable if the Jacobian matrix evaluated at that point has all three eigenvalues negative. Otherwise, it is considered unstable. Figure 4.4 presents an example of the gradient of selection field in the cubic space, including the various fixed points.

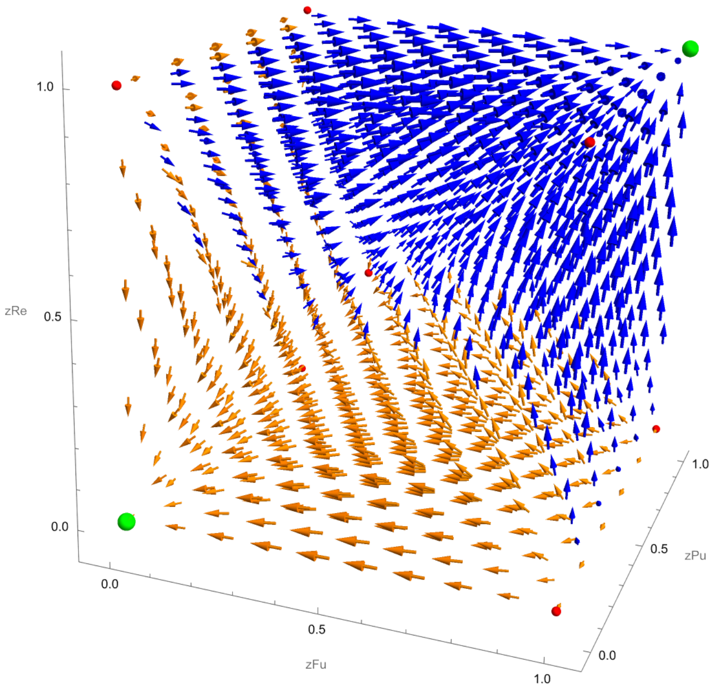


Figure 4.4: Visualization of the gradient model, using the gradient of selection. Each vector represents the most probable evolutionary direction for the fractions of each population at that point, when considering an infinite population. Gradient vectors that point towards the monomorphic states of CA majority are colored blue, while those that point to states of OA majority are colored orange. Stable fixed points are colored green, while unstable fixed points are colored red. The model parameters are identical to Figure 4.3. Stability is found in the points (0,0,0) and (1,1,1). In addition, an unstable internal fixed point is also presented in (0.292,0.726,0.410).

5

Evaluation and Discussion

"The power of a theory is exactly proportional to the diversity of situations it can explain."

Elinor Ostrom

Contents

We now have our two main models in hand: the simplex for the core model, and the simplex for the enhanced model. In the next section, we will address the evaluation of these models, which is of particular importance to our work, since we need to ensure that the approximations made by the models do not compromise their predictive accuracy. Following that, we move to the Discussion section, where we will extract results from the models and obtain information on the influence that each parameter has on the system. We also explore the practical implications of these findings. Based on these implications, we will derive policies that decision-makers can apply to promote Open-Access usage. Finally, a comparison is made between the obtained results and the predictions from past research.

5.1 Evaluation

5.1.1 Methodology

Our models rely on predicting the most likely evolutionary trajectory of a stochastic process without resorting to simulations. This was made possible by relying on assumptions, such as the small mutation limit and the focus on the stability of monomorphic states. However, the correctness of such assumptions must be tested. To that end, in Section 5.1.2, multiple computer simulations will also be conducted as to confirm the results of our model. These will employ the exact same payoff table and population dynamics as those described in Chapter 4, and will be run for multiple parameter sets. These results will then be compared to those of our simplex model using the same parameters. Due to the nature of the simulations, these will not rely on the small mutation limit and can, therefore, give us insight about the accuracy of such an approximation. Having the model in-line with what is expected from the simulation, in Section 5.1.3, we evaluate the descriptive capabilities of our simplex model against those from the gradient model. Although the gradient model also contains its own assumptions, in particular, that of an infinite population, it provides us with an additional comparison point.

5.1.2 Computer simulations

Our approach relies on analytical models that approximate the behavior of a dynamical system, collapsing the time dimension and anticipating the direction of evolution in time, and thus, the expected outcomes of the system, for any starting point. Although the stochastic nature of the evolutionary process means that any system will always have variations in how it evolves, it is necessary that our models are aligned with the most frequent evolutionary paths.

To this end, in this section, we explain the methodology to develop computer simulations that execute the evolutionary process described in Chapter 4. We also present the results of such simulations. With these results, we aim to evaluate the predictive nature of our model by comparing the predicted and simulated evolutionary trajectories on equal sets of parameters.

5.1.2.A Methods

We developed a program in **Python** to simulate the evolution of the system across time. In this program, we define an agent as having a population it belongs to (Funder, Publisher or Researcher), a strategy (C or O), as well as storing its fitness.

The program contains various parameters. These are: the parameters of the payoff table, as seen in Table 4.1; the size of each population; the initial fraction of agents using strategy O in each population; the chance of mutation per time step; the total number of time steps for a run; and the total number of runs. For our simulations, we fixate the population sizes at 200 agents each (to mitigate stochastic effects), a mutation chance of 1%, with runs between 75000 and 125000 time steps (depending on the required time to stabilize), and 20 runs per simulation.

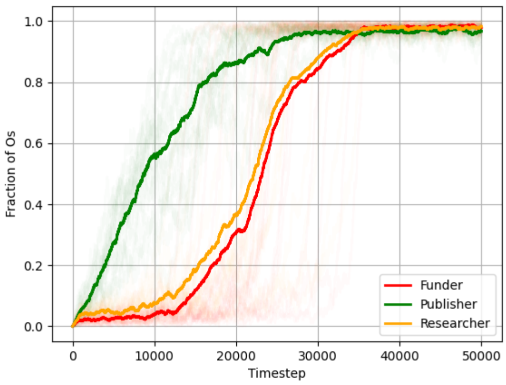
For each step, the program executes the following processes: it stochastically picks one agent of each population; the agents interact following the payoff table; the fitness of each agent is updated; the strategies are then updated following an imitation process; and finally, mutations are introduced.

The fitness update follows the rules described in Equation 4.1. That is, the fitness of an individual using a given strategy will be equal to the average fitness of the individuals of that population using the same strategy.

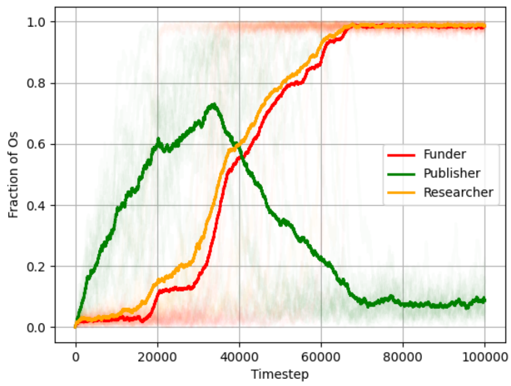
The imitation phase is also identical to that described in the prior chapter, with the intensity of selection fixated at 1. Having the fitness of every individual updated following the last interaction, we randomly select two individuals in each population. The first individual will then have a probability of copying the strategy used by the second individual according to PCR, as described in Equation 4.2. Regarding mutations, a random individual will be selected from each population, and its strategy will be switched to the other available strategy, using the mutation probability from the simulation parameters.

5.1.2.B Results

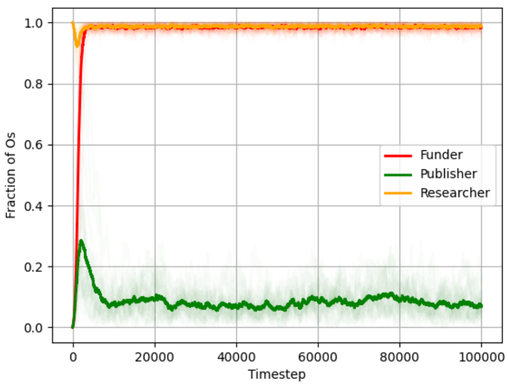
We now present the obtained results from our computer simulations. These focus on scenarios that correspond to different expected trajectories from the Simplex model. As such, the values for the parameters were selected so that the various transition conditions are tested in each direction, whenever possible. We focus our evaluation in the core model, as it holds fewer parameters to consider. Since the procedure to generate both the core and the enhanced model is identical, the accuracy of the approximation obtained by the methodology used should remain consistent irrespective of the complexity of the payoff table.



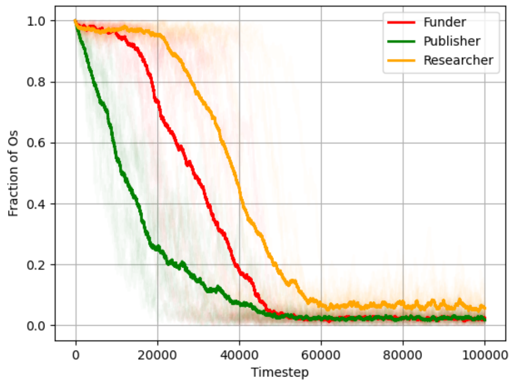
((a)) Parameters: $(Z_F, Z_P, Z_R) = (0, 0, 0)$, $I = 1$, $\gamma = 0.4$, $\delta = 0.5$, $A = 0.7$, $S = 0.9$, $F = 0.1$, $P_{RF} = 0.2$, $P_{RP} = 0.2$, $d_{FR} = 0.75$, $d_{PR} = 0.75$, $B = 0.5$, $t = 0.1$.



((b)) Parameters: $(Z_F, Z_P, Z_R) = (0, 0, 0)$, $I = 1$, $\gamma = 0.35$, $\delta = 0.03$, $A = 0.5$, $S = 0.95$, $F = 0.03$, $P_{RF} = 0.1$, $P_{RP} = 0.12$, $d_{FR} = 0.95$, $d_{PR} = 0.75$, $B = 0.5$, $t = 0.05$.



((c)) Parameters: $(Z_F, Z_P, Z_R) = (0, 0, 1)$, $I = 1$, $\gamma = 0.35$, $\delta = 0.03$, $A = 0.5$, $S = 0.95$, $F = 0.03$, $P_{RF} = 0.1$, $P_{RP} = 0.12$, $d_{FR} = 0.95$, $d_{PR} = 0.75$, $B = 0.5$, $t = 0.05$.



((d)) Parameters: $(Z_F, Z_P, Z_R) = (1, 1, 1)$, $I = 1$, $\gamma = 0.95$, $\delta = 0.6$, $A = 0.1$, $S = 0.95$, $F = 0.1$, $P_{RF} = 0.1$, $P_{RP} = 0.1$, $d_{FR} = 0.1$, $d_{PR} = 0.5$, $B = 0.5$, $t = 0.1$.

Figure 5.1: Average fraction of individuals using strategy O for each population over multiple runs, using computer simulations. Results from individual runs are shown using low opacity lines. The average result across runs is shown using high opacity lines. Figures b) and c) feature the same payoff table parameterization, but different starting points. The remaining figures contain different parameterizations.

Figure 5.1 a) showcases the results of the computer simulations for a parameterization in which our simplex model predicts the trajectory CCC-COC-COO-OOO. Having the initial point at CCC, the results display the transition from the publishers towards OA, followed by the same transition from the researchers, and afterward the funders. The OOO configuration then remains stable. This shows the simulation behaved very much in-line with what was predicted by the simplex model.

Figures 5.1 b) and c) feature the same parameters, having only different starting points: CCC and CCO, respectively. In our simplex model, this parameterization causes conditions 2, 5, 6, 7 and 8 to be true, with the remaining conditions false. For the initial point CCC, the model predicts the path CCC-COC-COO-OOO-OCO. As for the initial configuration CCO, it starts by evolving either to OCO, CCC, or COO, all of which belong to the prior path towards OCO. Figure b) reveals an initial transition towards OOO via an initial change from the publishers, leading to OCO, then again the researchers followed by the funders. However, before it is fully realized, publishers return to strategy C, leading to an ending state of OCO, as predicted by the model. Figure c) shows an almost direct transition towards OCO, one of three possible paths predicted from the simplex model. Similarly to what was done in Figure 4.3, calculating the resulting transition probabilities at the point CCO gives us CCO-to-CCC = 0.302, CCO-to-COO = 0.323 and CCO-to-OCO = 0.375. Thus, the average results follow the most probable path of our model.

Finally, Figure 5.1 d) presents a scenario where Open-Access publications are clearly less beneficial to the publishers. In the simplex model, this scenario only allows for conditions 1, 7 and 8 hold. As such, the predicted path when starting in OOO is OOO-OCO-CCO-CCC. This is reflected in the simulations, where the transitions towards supporting CA happen in the same order as predicted.

While multiple other simulations were conducted, here we present only some interesting scenarios. Appendix A contains results pertaining to a different scenario, with other evolutionary dynamics, under various starting points. This provides further study of the accuracy of the model. For ease of analysis, we also provide the predicted simplex trajectories and stationary distribution, as well as the gradient model. These additional results also show how the transition probabilities in each state can predict the resulting fractions in the simulations, since states with multiple outgoing transitions have different likelihoods of executing each transition.

5.1.3 Comparisons against the gradient model

Comparing our results with those from the gradient model poses some difficulties. In particular, the gradient model relies on the assumption of an infinite population, which our model does not follow. In addition, its greatest strength, the capacity to describe the evolution of the system under a polymorphic configuration, has no counterpart in comparison to our model. Despite these limitations, the gradient model still provides us with a valuable tool to evaluate the accuracy of the simplex model. For any monomorphic state, we can study the stability of the fixed points in the gradient model, as well as the predicted trajectories of evolution, comparing them with those from the simplex model.

Figures 4.3 and 4.4 show an example of the two models under the same scenario. The results show a strong alignment between the predicted trajectories in the simplex and the gradient models. In addition, whenever there is a monomorphic state with more than one outgoing transition, we find the gradient model pointing more towards the direction of the greater transition probability under the simplex model. In addition, the stable fixed points of the gradient model line up with the monomorphic states with no outgoing transitions. Appendix A contain further results of the gradient model, along with those from computer simulations and the predicted simplex model. These examples further exemplify the high concordance among all models. On the other end, Appendix B contain results that highlight the limitation that an infinite population poses. In such scenarios, fixed points are labeled stable even though it would be beneficial for a population to change strategy. This happens because the population cannot gather a high enough fraction of individuals to change strategy, as the population is infinite. However, this constitutes an error not of the simplex model, but of the gradient model. Based on our results, we conclude that, despite the approximations, the simplex model follows the results of the gradient model, as well as those from the computer simulations, serving as a valid predictor of the evolutionary dynamics of the system.

5.2 Discussion

Having the model validated, we now study the influence of the constituting components of our model on the resulting dynamics of the system. Namely, in Section 5.2.1, we start by investigating the effects of the multiple types of parameters in the core model (such as punishments, synergistic effects, and revenues), as to clarify their role in the system. Section 5.2.2 follows with an exploration of the effect of hybrid publishers in the transitions towards full OA support. A similar study is then conducted in Section 5.2.3 for the existence of Green OA publishers. In Section 5.2.4, we combine all prior information to achieve a set of possible actions that aim to effectively promote Open-Access across all sectors. Finally, in Section 5.2.5, we compare our results and policies with those from past work.

5.2.1 Effects of the core model parameters

In this subsection, we will go over the effects that changes of parameters have in the resulting evolutionary dynamics of the system. We go over each of the parameters in groups, dividing them by what they represent in the real-world. This analysis focuses on the core model, as it presents simpler dynamics, and thus allows for an easier understanding of the impacts of each parameter. Since the enhanced model contains alterations to the role of each parameter, it is expected that some conclusions about the parameters in the core model do not hold true in the presence of hybrid and Green OA publishers. These differences will be discussed further ahead. Since the total investment of the funders, I, represents the majority of the monetary resources present in the system, we fixate it at $I = 1$ and constrain all remaining parameters to be between 0 and 1.

This analysis will be conducted taking into account a single set of parameters. Although this results in a specific evolutionary dynamic, since the parameters operate independently (unless specified, like is the case with taxes), the effect of each parameter remains visible and consistent when fixating the remaining parameters. As such, for each of the parameters studied, we vary that parameter while keeping the others fixated. We then study the effect that the variation of the parameter of interest has in aspects such as the resulting payoffs and the stationary distribution. An evaluation of these results will also be conducted, as they must make empirical sense, and the conditions associated with the monomorphic state transitions must be reasonable. As an example, if the revenue in Closed-Access decreases to the point where it vastly exceeded by that of Open-Access, and no other compensation exists, it must be the case that it results in more incentives towards OA, as CA becomes unsustainable. The effects of each parameter, including those related to hybrid and Green OA publishers, are summed up in Table 5.1.

5.2.1.A Consequences of funding distributions

The funding distribution parameters, γ and δ, represent the fraction of investment under CA and OA, respectively, that the publisher receives when aligned with the funder. Consequentially, a raise in each of these values constitutes a higher payoff for publishers, and a lower payoff for researchers, in the cases where they apply. As the payoff of the funders increases the more they invest, a raise in the amount invested in publishers leads to a negative impact whenever they only invest in researchers, but an increased payoff when they invest solely in publishers. The changes in the payoff of an individual of each sector, as a function of γ, are presented in Figure 5.3. Since δ occurs in the symmetrical cases of γ, changes to it have the same effect as γ, only in the symmetrical cases.

These changes in payoff incite changes in the resulting stationary distribution. Figure 5.2 illustrates the stationary distribution obtained as a function of γ and δ. In both cases, we observe a higher sensitivity in the scenarios where only the publishers or the researchers are exclusively aligned with the funders. Our results show that increasing γ leads to CCO occurring more often, at the cost of the prevalence of COC. An increase in δ translates to the same effects for the inverse scenarios, with an increase of OOC over OCO. These results make sense, considering that a higher funding for one sector means a lower funding for the other, and those who are more financed have a bigger incentive to be aligned with the funder.

We now cross these conclusions with the transitions of the simplex model, presented in Figure 4.1, as

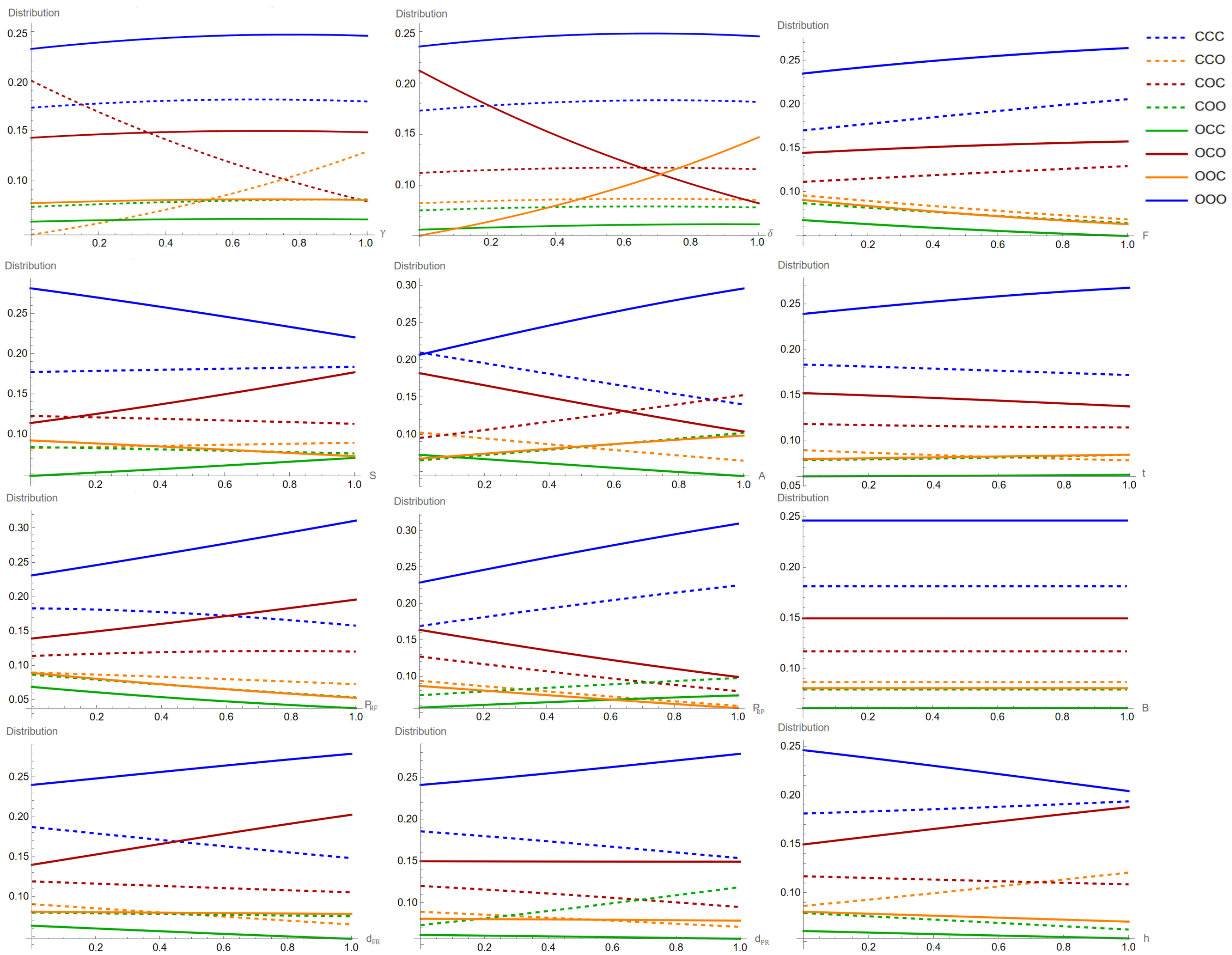
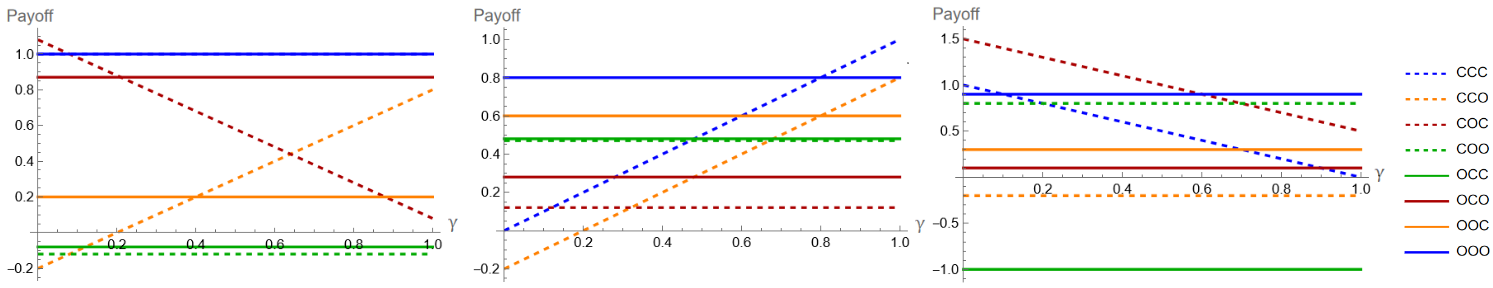


Figure 5.2: Stationary distribution as a function of each system parameter, obtained by fixating all remaining parameters. From left to right, and top to bottom: γ, δ, F, S, A, t, P_{RF}, P_{RP}, B, d_{FR}, d_{PR}, h. Parameters: $I = 1$, $\gamma = 0.6$, $\delta = 0.4$, $A = 0.4$, $S = 0.6$, $F = 0.3$, $P_{RF} = 0.2$, $P_{RP} = 0.2$, $d_{FR} = 0.15$, $d_{PR} = 0.15$, $B = 0.2$, $t = 0.2$.



((a)) Funders ((b)) Publishers ((c)) Researchers

Figure 5.3: Payoff of an individual of each sector as a function of γ. Parameters: $I = 1$, $\delta = 0.4$, $A = 0.4$, $S = 0.6$, $F = 0.3$, $P_{RF} = 0.2$, $P_{RP} = 0.2$, $d_{FR} = 0.15$, $d_{PR} = 0.15$, $B = 0.2$, $t = 0.2$.

these two parameters are abundant in its conditional transitions. For the funders, since the conditional transitions are between states where there is always one sector misaligned, any transition changes whose sector the funders will support. As such, the parameters appear in the format $I(\delta + \gamma - 1)$, corresponding to losing an investment and gaining the other, for instance $I\delta - I(1 - \gamma)$. In essence, with publishers and researchers misaligned, the investment distribution dictates if the funder can invest more by being aligned with one sector or the other. In both publishers and researchers, the parameters present a significant role in determining whether each sector opts for strategy C or O. These transitions are particularly relevant in these two sectors, as they mean either losing or obtaining alignment with the funder. As discussed before, a higher investment by the funder in a sector prompts that sector to align itself with the funder. Another important aspect is the lack of effect that γ and δ have on the stationary distribution of the monomorphic states of full alignment, although they are present in conditions 3 and 6. This could mean that changes in these parameters can make a transition towards full alignment possible, at the cost of some states of misalignment also becoming more likely. As such, these parameters are not particularly relevant in assuring the stability of the fully aligned states. These conclusions highlight the role of the funder, being the authority behind the investment distributions, as a strong influencer who can incentivize a sector to align by increasing their funding towards it.

5.2.1.B Influence of revenue sources and publishing costs

Similarly to the study conducted for the funding distributions, we now address the revenue sources for both CA and OA, as well as the fixed cost page charges. Figure 5.2 contains the stationary distribution as a function of each of the three parameters.

Starting with the subscription costs, S, they provide benefits to publishers and, whenever taxation applies, to the funders. This at a cost to the researchers whenever they are not subsidized. The stationary distributions outline that higher subscription costs foster CA publishers in scenarios where funders use strategy O, as these are the scenarios where the subscription costs are not subsidized by funders.

Under these conditions, we can correlate higher subscription costs with higher incentives for publishers to remain in Closed-Access. Additionally, the core model transitions emphasize the indifference of the researchers to the subscription costs, as the costs will manifest independently of the strategy they use.

As for the revenue gained by the publishers under Open-Access, A, it is modeled as a benefit to the publishers (and funders, when taxation applies) without a cost to researchers. Consequentially, increasing the revenue quickly increases the prevalence of Open-Access publishers. This is reflected by the presence of A on the left side of every conditional transition of the publishers, in the core model.

Finally, the fixed costs page charges, F, present an interesting case, as they are only directly relevant to researchers, since they present no impact in the payoff of the publisher. Nevertheless, the stationary distribution study shows a clear sensitivity towards F. In the conditional transitions, the fees are relevant in assuring alignment with the funders, since, if the funders and researchers are aligned, this cost is instead covered by the funders. As such, higher fees lead to researchers prioritizing alignment with funders. As a consequence, the stationary distribution changes to more frequently feature states where these two sectors are aligned. Since publishers exercise control over the subscription costs and page charges, and have influence on the obtained revenue under OA, they stand in an actionable position to steer the evolution of the system.

5.2.1.C Effectiveness of punishments and taxes

We now move over to analyzing the effectiveness of punishments and taxes. Punishments serve to allow a population to incentivize other populations to change strategy. In our payoff tables, punishments happen whenever researchers and another sector use differing strategies. When applicable, researchers will pay a cost (P_{RF} for funders, and P_{RP} for publishers), divided among all supporters, for the purpose of causing the same cost for the misaligned individual. This mechanism makes punishments a fundamentally different parameter than the remaining, as it is always a cost to both the punished and the punisher. On the other hand, the purpose of taxes is also to punish, but these come at no cost to the punisher. In our model, funders can earn part of the profits of disagreeing publishers. Following what was done prior, Figure 5.2 presents the resulting stationary distribution for the full range of each of these parameters.

Starting with punishments against funders, a higher value presents clear effects in synchronizing researchers and funders to adopt Open-Access. More significantly, it consequentially boosts the predominance of OOO. This is confirmed by looking at the transitions in the core model, where P_{RF} has a role in bringing the two sectors to use the same strategy, by pushing the system towards COC and OCO. Although they also apply when researchers opt for strategy C, it presents little effect in changing the predominance of Closed-Access scenarios. This can be attributed to the parameterization chosen, combined with the reduced effect of the punishment in the researchers, as a consequence of the division of the costs among supporters. As the states CCO and COO become less prevalent in favor of OCO and COC, these can then transition towards OOO.

Punishment towards publishers result in different dynamics of those against funders. With an increase in the punishment cost, we observe a raise in the prevalence of the states of fully adopted OA and CA. This dynamic is reflected in the conditional transitions of the core model: a higher P_{RP} means conditions 3, 5 and 8 are enabled, leading to states of researcher-publisher agreement, where the dominant transition COO-to-OOO then occurs. Conversely, a lower value causes conditions 4, 6 and 7 (an already weak condition) to fail, causing also funders to adopt strategy C, leading finally to CCC.

Since these punishments are ultimately set by researchers, it showcases their effectiveness in bringing any desired sector to alignment. Additionally, the cost of punishment is ultimately divided among the supporters, and, as such, the impact it has on their well-being is negligible if enough support is guaranteed.

Taxes, compared to the previous punishments, present more subtle dynamics. With their rise, the stationary distribution shows a slight decrease in states CCC, OCO and CCO, with a compensation of the OOO state. However, the transitions in the core model do not follow these conclusions, given that, for example, condition 6 fails with a high enough value of t, supposedly leading to a higher occurrence of CCC. Since taxes are applied as scalars to the revenue A or S, this suggests their effect depends on the values of the revenues. This is visible in Figure 5.4, which exhibits the stationary distribution for parametrizations where $A = S$ and $A > S$, complementing the parametrization used before. Taxes appear to promote the publication method with the lowest revenue; so, if $S > A$, then OA, particularly state OOO, becomes more common. If $S < A$, then the state CCC is benefited instead. However, even when $S < A$, taxes still play a relevant role in allowing certain transitions to happen, with the most important being CCC-to-COC, the only way to escape CCC. As such, to ensure maximum efficacy, funders should employ and change taxes depending not just on the state of the system, but also on the revenue of the publishers.

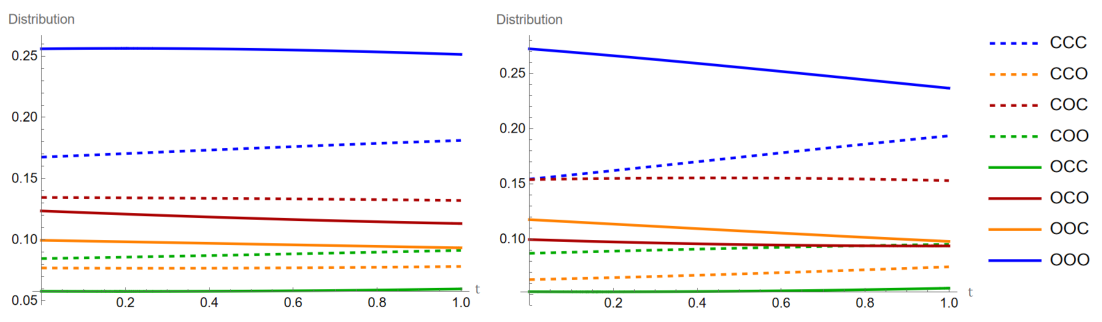


Figure 5.4: Stationary distribution as a function of t. Parameters used in the left: $A = 0.5$, $S = 0.5$. Parameters used in the right: $A = 0.6$, $S = 0.4$. The remaining parameters are identical to Figure 5.2.

5.2.1.D Advantages of synergistic effects and OA benefits

We now direct our focus towards synergistic effects and OA benefits. Once more, Figure 5.2 displays the stationary distribution as a function of each of these parameters.

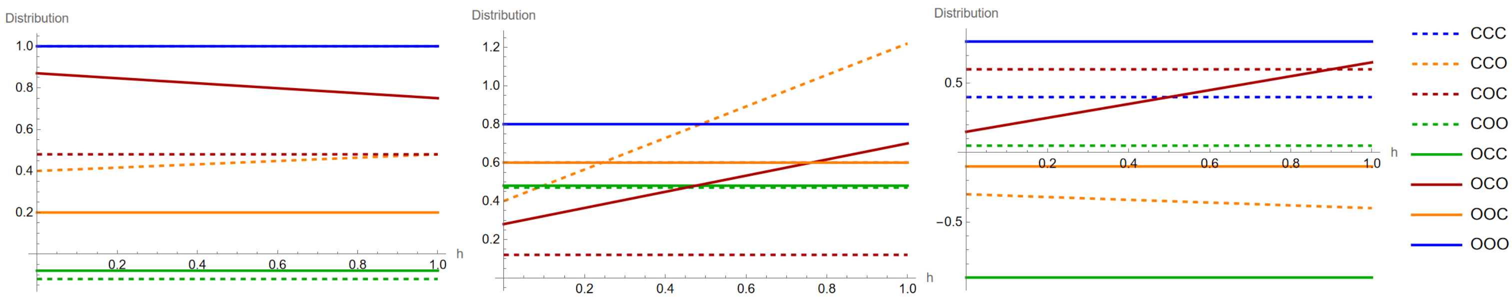
The purpose of synergistic effects is to reward pairs of coordinated sectors when the third sector is not. They can represent various types of benefits that the two sectors bring forth as to better manage against the uncooperative third sector. In our model, these are represented by the parameters d_{FR}, for the pair Funder-Researcher, and d_{PR}, for the pair Publisher-Researcher, and occur only when the two individuals opt for OA. Since these come at no cost, they are essentially a boost to OA. As expected, the stationary distribution shows an increase in OOO and the respective states where the pair is aligned in strategy O and the third sector opts for strategy C. This is also reflected in the conditional transitions, where the parameters appear whenever transitioning to states of exclusive coordination between the possible pairs. This highlights the positive role that synergistic effects can have: while punishments incentivize alignment through costs to both parties, synergies can incentivize it through benefits.

The benefit obtained by researchers publishing under OA, B, presents a curious case. It is not found in the transitions for the simplex model, and the stationary distribution remains identical throughout its full range of values (although both stop being the case in the enhanced model). Yet, being present in the payoff table, it definitely impacts the resulting payoff of the researchers, increasing it whenever the publisher opts for strategy O. This is a consequence of the conditions for its appearance: since the strategy of the publisher determines the publishing model, whenever it opts for O, B appears in the side of the researchers, independently of their strategy. This can be further understood by analyzing Equation 4.2, of the PCR, where the difference in the fitness of the researchers using strategy C and O is equal independently of B, since both strategies result in the researcher receiving B. As such, it presents no effects in the resulting evolutionary dynamics. Nevertheless, the resulting payoff is worth monitoring, as it is a measure of well-being, and so the parameter is also included in the core model.

5.2.2 Impact of Hybrid publishers

We now focus in investigating the impact that hybrid publishers have on the evolutionary dynamics. Since both hybrid and Green OA occur in the same cases, but in an exclusive fashion, these can be analyzed separately using the enhanced model, as they have no influence on each other. Additionally, since alternative publication methods have historically appeared as add-ons to existing publishers, we focus our analysis on the resulting dynamics rather than the impact of every parameter. For ease of viewing, Appendix C contains both the simplexes for the enhanced models with no Green OA ($h = 0$) and with no hybrid publishers ($u = 0$).

Keeping the parameterization from the prior sections, we present, in Figure 5.2, the stationary dis-



((a)) Funders

((b)) Publishers

((c)) Researchers

Figure 5.5: Payoff of an individual of each sector as a function of h, with $u = 0$. The remaining parameters used are identical to Figure 5.2.

tribution as a function of h, the fraction of hybrid publishers. Although the expected result would be the promotion of Open-Access, the presence of hybrid publishers leads to a decrease in the usage of pure OA, being instead replaced by states where the hybrid model is available. The causes behind such dynamics can be understood by observing the resulting payoff of an individual of each population as a function of h, presented in Figure 5.5. By increasing h, the payoff of funders in the OCO state decreases as a consequence of the lack of taxing. In the same state, the payoff of researchers increases as they gradually stop paying subscriptions, refrain from punishing publishers, and receive benefits from B. However, publishers see a remarkably sharp increase in payoff whenever hybrid publications occur, as a consequence of the increased fixed cost page charges and lack of punishment. As such, there are incentives to keep using the hybrid model, instead of making a full transition towards OA.

The transitions of the simplex for the enhanced model further corroborate these conclusions. Both the revenue under OA, weakened by a factor of $(1 - h)$, and the added fees, Fh, contribute towards failing conditions 3 and 5. In condition 2, the driving force of subscription costs is attenuated, and also features a new tax incentive, Ath, for funders to stay in CA. The side of the researchers proposes a more optimistic outcome: condition 7 is strengthened; and a new, albeit weak condition is added, which enables researchers to transition from strategy C to O, when in CCC. Under the presence of hybrid publishers, similarly to what we will later see with Green OA, a high B paired with a high h (and/or high u with low g, in Green OA) increases the prevalence of OA researchers, with a particular increase in CCO, due to this new transition. Nevertheless, this indicates that, despite appearing to offer researchers an alternative to facilitate publishing under OA, hybrid publishers actively discourage a full adoption of Open-Access — instead, these are more prone to keep offering the hybrid alternative contrary to using it as a temporary step.

5.2.3 Impact of Green OA

The final aspect of our model is the presence of Green Open-Access publishers. This is controlled by two parameters: u, which dictates the fraction of CA publishers that feature Green OA; and g, that defines the fraction of revenue that comes from subscriptions, when using Green OA. We start by studying the impact of g under a regime where $u = 1$, as it needs to be understood before investigating the consequences of Green OA. We then examine the impact of the presence of Green OA, similarly to what was conducted for hybrid publishers.

When $u = 1$ and $h = 0$, the payoffs of each interaction follow Table 4.5. By comparing it to the table in the core model, Table 4.2, it is clear that, when $g = 1$, both tables are equal besides the lack of punishment inflicted in the publishers. On the other hand, when $g = 0$, cases OCO and CCO occur like the publisher was fully OA, lacking only synergies and investments, when applicable. As such, the impact of g is tied to the resulting revenues in each publication method. Figure 5.6 demonstrates this relationship, showcasing the variation in stationary distribution as a function of g, for different sets of A and S. We observe that a higher g facilitates the full adoption of Open-Access whenever $A > S$, yet, has the inverse effect when $S > A$. In all circumstances, though to a varying degree, a higher g also results in less incidence of OCO and CCO, the states where Green OA is actively used.

We now address the impact of the presence of Green OA in the evolutionary dynamics. Since, in the payoff table, g always appears in the form of $(1 - g) * u$, an increase of u results in effects similar to a decrease of g, except for the scenarios where it is independent of g. Therefore, its effects will also depend on the values of A and S, as well as the value of g. Looking at the conditional transitions of the simplex for the enhanced model, the influence of Green OA on the evolutionary dynamics becomes clearer: a higher u compromises conditions 2, 5, and, particularly when S is higher than A, condition 3; it also boosts conditions 7 and 8, as Green OA causes less punishment and subscription costs for the researchers, as well as providing B, the Open-Access benefit. This leads to a higher concentration in states OCO and CCO, where Green OA takes place. The stationary distribution as a variation of u, presented in Figure 5.7, confirms these findings. Since the current real-world assumption is that the revenue under Closed-Access surpasses that of Open-Access, this suggests that, unlike the hybrid model, although Green OA incentivizes publishers to remain theoretically Closed-Access, it provides an intermediate step where CA support decreases in funders and researchers. However, if the revenue of OA increases, Green OA poses a limitation towards achieving fully-supported Open-Access.

5.2.4 Extracting Open-Access-promoting policies

With all parameters discussed, we can now answer our final major research question: What is the ideal way to promote a full adoption of Open-Access? Or, posing the question using the terminology of our

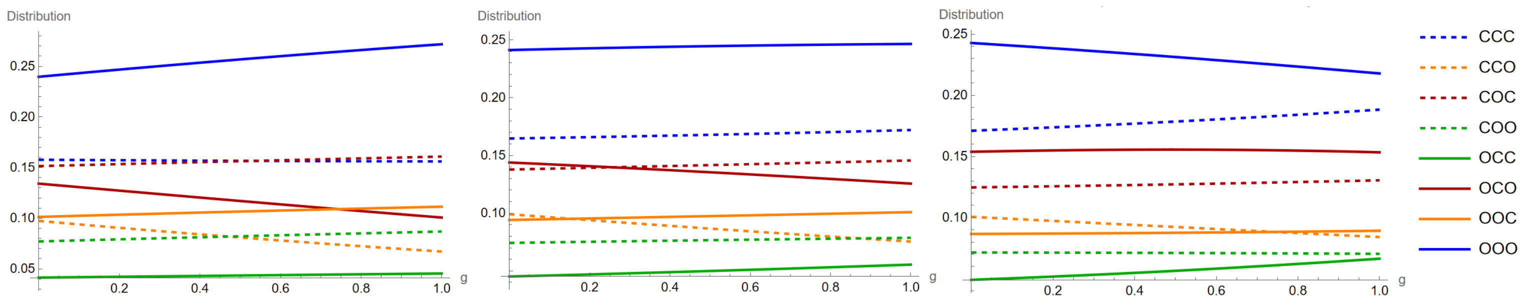


Figure 5.6: Stationary distribution as a function of g. Parameters used in the left: $A = 0.7, S = 0.3$. Parameters used in the center: $A = 0.5, S = 0.5$. Parameters used in the right: $A = 0.3, S = 0.7$. In all figures, $u = 1, h = 0$. The remaining parameters are identical to Figure 5.2.

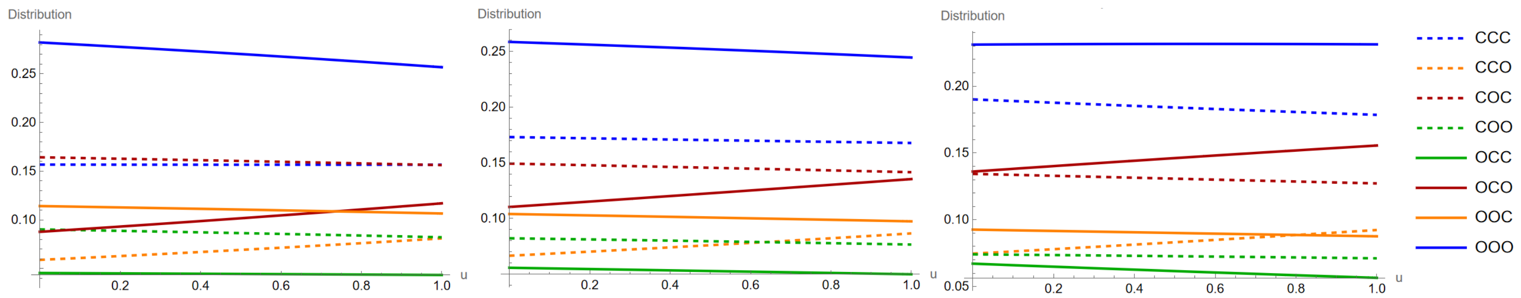


Figure 5.7: Stationary distribution as a function of u. Parameters used in the left: $A = 0.7, S = 0.3$. Parameters used in the center: $A = 0.5, S = 0.5$. Parameters used in the right: $A = 0.3, S = 0.7$. In all figures, $u = 1, h = 0$. We fixate g at 0.5, as this allows for a neutral weighting between A and S. The remaining parameters are identical to Figure 5.2.

Parameter	Primary effects of increasing parameter value	Responsible
γ	Increases exclusive F-P alignment and decreases exclusive F-R alignment in CA	Funder
δ	Increases exclusive F-P alignment and decreases exclusive F-R alignment in OA	Funder
A	Increase in OA publishers	Publisher
S	Increase in CA publishers when funders are OA	Publisher
F	Increases F-R alignment	Publisher
P_{RF}	Increases F-R alignment in OA	Researcher
P_{RP}	Increases P-R alignment and states of total alignment	Researcher
d_{FR}	Increases F-R alignment in OA	Fund., res.
d_{PR}	Increases F-P alignment in OA	Publ., res.
B	If $h > 0$ or $u > 0$: increase in OA researchers, particularly in full CA	All sectors
t	If $S > A$: increase in OA; else: increase in full CA	Funder
h	Increase in full CA publishers	Publisher
u	If $S > A$: increase in OA researchers and funders; else: increase in CA publishers	Publisher
g	If $S > A$ and $u > 0$: increase in full CA; else: increase in full OA	Publisher

Table 5.1: Effects of increasing each parameter in the system. Decreasing a parameter produces the opposite effect in each respective case. The I parameter is excluded as it is fixated at 1. The sectors with primary influence in each parameter are also highlighted.

model: What is the easiest change of parameters that can allow the system to transition from state CCC to state OOO?

A fundamental problem in achieving full OA support is that, although OOO can be more rewarding than CCC, the intermediate steps to reach it can be unsustainable in the long term. Figure 5.8 showcases an example of the coordination problem present in the system. For the given parameterization, despite CCC presenting a lower payoff for publishers and researchers when compared to OOO, any individual change of strategy is met with a lower payoff than before. This is similar to what was shown in the Prisoner's Dilemma. As such, coordination between sectors is ideal to maximize change, as change cannot be sustained by a single sector. Additionally, although we seemingly could increase any parameter that leads to the desired conditions being valid, or that boosts the stationary distribution at the state OOO, such options do not always guarantee a full path from CCC to OOO. Moreover, not only does OOO have to be reachable, but also stable, with no outgoing transitions.

We start by considering solely the core model simplex. Starting from CCC, the only option is for publishers to switch to Open-Access. The most efficient policy is to have a reduced investment in CA publishers, via a low γ. This is, however, unlikely, given that funders also support CA. An alternative is a high publisher revenue from Open-Access, paired with low taxation. As such, despite being a publisher transition, this step is highly influenced by funding institutions and state policies. From there, transitions 1 and 8 present themselves difficult to happen. Yet, a transition from either the funders or the researchers leads to the other sector following with the transition too. Given the possibility of a low γ, condition 8 is the easiest to fulfill. This can be achieved with synergies between publishers and researchers, combined with low publishing fees, leading to state COO. In essence, this is a transition primarily controlled by publishers and researchers. Finally, OOO is achieved naturally, as funders greatly benefit from being able to invest in a fully aligned Open-Access system. To ensure stability from the publishers, a high investment from the funders is necessary. Still, not so high that it results in opposition from the researchers, as shown by the increase of OOC following an increase of δ. Taking such measures, conditions 3, 4 and 5 can be kept true, ensuring high maintainability for OOO.

When alternative publishing methods are present, the policies above suffer some changes. The most feasible path leaving CCC is still condition 6, with no changes in the recommended actions. The same goes for the transition from COC to COO. However, in both condition 3 and 5, the presence of hybrid or Green OA provides publishers with an incentive to transition back to strategy C, leading to states where the alternative publishing methods occur. In this scenario, the optimal, yet unlikely policy is for publishers to cease such methods, as the added profits create incentives to remain CA. The alternative is an attractive funding for Open-Access publishers, paired with synergies between publishers and researchers. Under the assumption that $S > A$, short embargo periods under Green OA, defined by a low g, also facilitate an escape from CCC and a bigger stability of OOO. Hybrid publishers, on the other hand, only show benefits in helping research and funders transition to Open-Access, at the cost of substantially motivating publishers to remain Closed-Access. Therefore, the usage of hybrid publishers is not recommended to achieve a system-wide transition towards Open-Access.

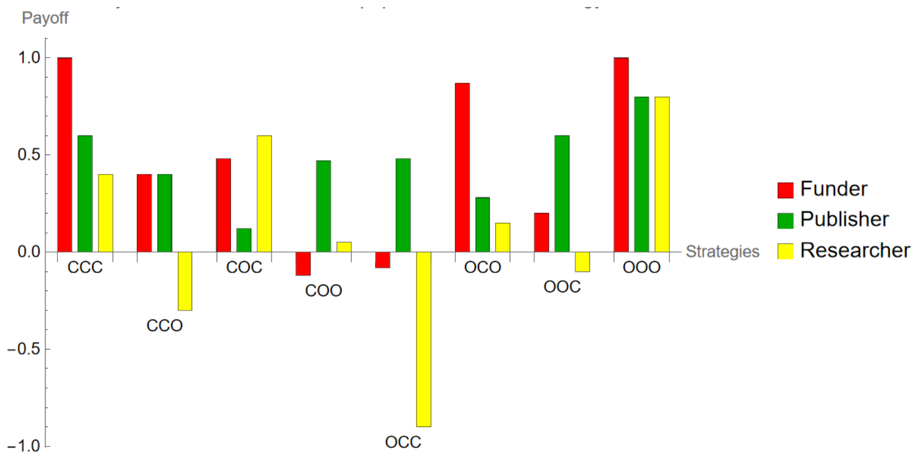


Figure 5.8: Payoff obtained by an individual of each population, for each strategy set, in the core model. The parameters used are identical to Figure 5.2.

5.2.5 Comparison against past work

Comparing our results with the predictions of past work, we observe that they stand in very large agreement. As stated in the Related Work, publishers appear to be the key factor in starting the transition towards Open-Access. This is reflected in our core simplex model, as the only transition from the state of full CA support is indeed from the publishers. Furthermore, as predicted by current studies, this is a transition that is largely dependent on the revenue obtained by the publishers. A higher revenue under Open-Access remarkably correlates to a higher incidence of Open-Access publishers. The synergistic effects, presented in our work as necessary to make researchers follow through with Open-Access, are also mentioned in the past work of Björk [59] and Forrester [60] as the major factors behind researcher adoption. As such, our suggested policies are also in line with the present limitations of Open-Access adoption. Finally, the results obtained for the impact of Hybrid and Green OA publishers are firmly aligned with the current predictions [46] — hybrid publishers seem to be an unlikely way to promote system-wide OA support, but Green OA can provide an intermediate step towards it.

6

Conclusion

”Now this is not the end. It is not even the beginning of the end. But it is, perhaps, the end of the beginning.”

Winston Churchill

Contents

In this work, we set to comprehend the adoption dynamics of the two main publication models in scientific communication. This took many steps, starting with an explanation of the tools we used to conduct our analysis of the underlying dynamics of the system. In our case, these tools were EGT applied to multiple populations, each representing one of our main sectors: funders, publishers and researchers. This was followed by studying the requirements to accurately model the social system. From there, a formalization of the social interaction was constructed, giving us a payoff table describing the interaction, together with a list of parameters that represent the different aspects of the system, and that ultimately control these payoffs. We then developed models, based on recent work, that allow us to predict the resulting dynamics for a given parameterization. These models were then evaluated, using computer simulations, the gradient model that was also developed, and empiric analysis. Having the models validated, we extracted information regarding the impact of each parameter on the evolutionary dynamics. This allowed us to sensibly propose policies that can promote Open-Access across all sectors. This chapter concludes our work by summarizing its contributions and proposing directions for future work, as well as offering some final remarks.

6.1 Contributions

We now present a summary of our contributions. For a complete detail of each contribution, refer to Chapters 4 and 5. We feature four major contribution fronts:

Corroborate and advance previous models — Our models are based in the framework developed by Encarnação et al. [62]. In this work, we confirm the viability and accuracy of this type of model in predicting the evolution of three-sector systems governed by complex tripartite social interactions. Additionally, we not only follow the analytical methods delineated in the previous work, but build upon them to further extract information on the impact of each parameter. As such, our work provides a solid framework to follow when dealing with intricate payoff tables.

Formalize scientific communication — We developed a novel formalization of the scientific communication system, based on game theory. Our flexible approach includes the three main actors of the system: funders, publishers and researchers. Additionally, we model not just Closed-Access and Open-Access, but also the most popular alternative publication methods: hybrid and Green OA publications. To achieve this, we identify the main aspects of the system and introduce them as parameters, grounding our model in the real world. By describing how such models were constructed, we also provide a reference on how to model similar aspects from any system.

Study the dynamics of the scientific communication system — In our work, we study the effects that each aspect of the science communication system has on the adoption patterns of Closed and Open-Access, in each sector. This provides valuable insight to all the sectors involved. Among the conclusions, we highlight: the influence that funders have, via adjusting the funding distribution and taxes; the importance of revenue and publishing costs in determining the most valuable approach for the publishers; the power of punishments and synergies in aligning pairs of sectors; and the negative impact of hybrid publishers, and the limitations of Green OA publishers, in establishing an intermediate step towards Open-Access. We also note how a transition from one sector impacts the remaining sectors, potentially leading to further transitions without changes in the parameters.

Present policies to promote Open-Access — By following the conclusions above, we define the most feasible and effective policies to promote system-wide Open-Access adoption, from a starting point of full support towards Closed-Access. These include: a greater funding towards OA publishers; the necessity of a high revenue for OA publishers, paired with low taxation rates; high synergies between publishers and researchers; and, under Green OA, low embargo periods. These actions are spread throughout all sectors, therefore highlighting the collaboration efforts required to achieve such a transition.

6.2 Future work

Whilst we offered concrete conclusions in our work, there are always more ways in which our developments can be enriched, expanded upon, or applied to other domains. We leave for future work:

Expanded sectors — Although we considered the three primary sectors of the scientific communication system, many other sectors exist. Björk [23] highlights, for example, the importance of libraries and research reviewers. Additionally, a separation between governments, universities and funding agencies can provide a more descriptive and accurate impact of each publication method.

Augmented interactions — We consider a large amount of parameters to describe the tripartite interaction. Yet, the payoff tables used are far from the only options. Arguments can be made in favor of, for example, other punishing directions and synergistic effects. The expressiveness of a parameter can also be enhanced via frequency dependency, representing the growth or decrease of each parameter as a specific strategy becomes more prevalent. Other types of parameters could also be added, pertaining to aspects such as research reviews, or more granular revenue for OA publishers.

Complex networks and population sizes — In our work, we consider only well-mixed and equally-sized populations. Although the reach of publishers and funders is global, not all of them share the same popularity. Some publishers and funders are notoriously sought-after. Additionally, researchers exhibit particular networks of collaboration [75]. As such, experiments can be made in scale-free networks and other topologies. Besides that, the assumption of equally sized populations can also be challenged, potentially leading to an increased importance of funders and publishers. By experimenting with these structures, other dynamics can emerge, or existing factors can lose or gain importance.

New models — Other types of models, departing from the EGT framework, such as multi-agent systems, can also be experimented with. Since different frameworks operate under different assumptions and rules, they can provide alternative insight about the dynamics of the system, or help corroborate current results.

Further applications — The models we developed can be used to describe any three-sector social system. Subsequently, other systems can benefit from this type of analysis. Albeit difficult to clearly identify systems with such a clear division of sectors and strategies, for those applicable, these models provide a straightforward tool to research the impact of each strategy and the evolutionary dynamics of the system.

6.3 Final remarks

Throughout this work, effort was put into guaranteeing an unbiased and balanced view of the scientific communication system. However, with ourselves being part of the system we modelled, this is an unsatisfiable task. Despite our efforts and the body of literature supporting our conclusions, we find importance in being transparent about areas where biases and preconceptions could play a role in the outcome and analysis of our results.

We identify the formation of the payoff tables describing the tripartite interactions as being of particular susceptibility towards biases. Although we selected parameters following prior work, the eligibility criteria for parameters is always debatable. It is for this reason that, as stated in the Future Work, we propose further research of the scientific communication system using different parameterizations. Furthermore, the sections regarding parameter impact analysis and Open-Access-promoting policy extraction are also prone to bias. Acknowledging the possibility of these biases, we believe the results we presented still hold considerable value for policy-makers and all the members of the scientific communication community. We present our results with intentions of reproducibility, and we invite the reader to do so, and explore the proposed models themselves.

Our work focused on studying the adoption of Open-Access and Closed-Access, giving both equal importance. However, as part of our objectives, we also aimed at finding policies that incentivize Open-Access usage. We want to address these seemingly conflicting interests. Current research presents Open-Access as the future leading method for scientific communication, with ever-increasing support from both researchers and state funders. Although publishers are also following through, a lack of proper incentives and coordination from each sector can lead to conflicts over what the laws regarding OA publishing demand from publishers and what is feasible for publishers to maintain their viability. This lack of coordination can also lead to unsatisfactory funding distributions, possibly damaging the stability of researchers and funding institutions. Our work serves as a guide to all these sectors to achieve this already ongoing transition in the most efficient and fair way possible. For this, our focus is on providing forecasts for the effects that different policies and actions can have across the three sectors, giving all of them equal relevance.

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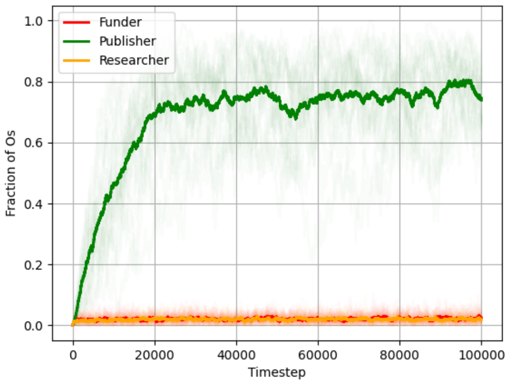
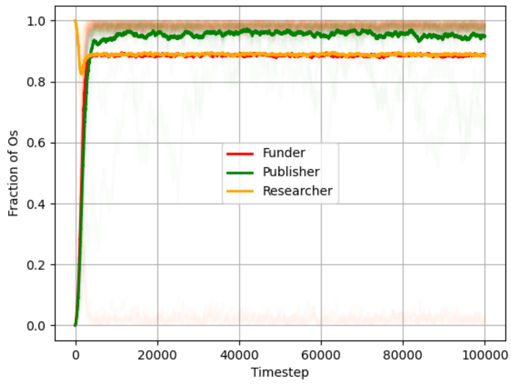
A

Appendix A: Additional results from computer simulations

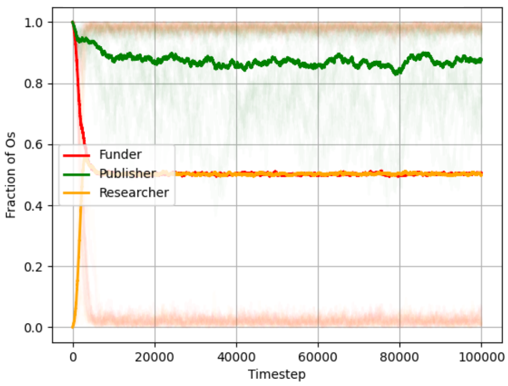
Since many computer simulations were conducted, only a selection of examples could be presented. Here, we display additional results from these computer simulations, using the same parameter set but evolving from different starting points. Additionally, we also present the predicted paths in the simplex model together with the stationary distribution, and the gradient model for the same parameter set. These results show not just the accuracy of the models, but also the relationship between the transition probabilities in each state and the resulting fractions in the simulations.



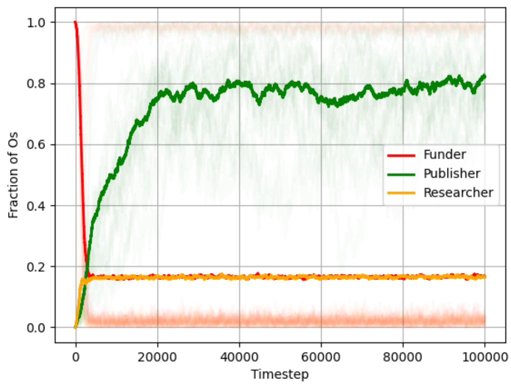
((a)) Starting point: $(Z_F, Z_P, Z_R) = (0, 0, 0)$.



((b)) Starting point: $(Z_F, Z_P, Z_R) = (0, 0, 1)$.



((c)) Starting point: $(Z_F, Z_P, Z_R) = (1, 1, 0)$.



((d)) Starting point: $(Z_F, Z_P, Z_R) = (1, 0, 0)$.

Figure A.1: Average fraction of individuals using strategy O for each population over multiple runs, using computer simulations. Each plot contains a different starting point, using the same payoff table parameters. Parameters used: $I = 1$, $\gamma = 0.2$, $\delta = 0.35$, $A = 0.75$, $S = 0.9$, $F = 0.2$, $P_{RF} = 0.4$, $P_{RP} = 0.4$, $d_{FR} = 0.25$, $d_{PR} = 0.25$, $B = 0.5$, $t = 0.15$, $h = 0$, $g = 0$, $u = 0$.

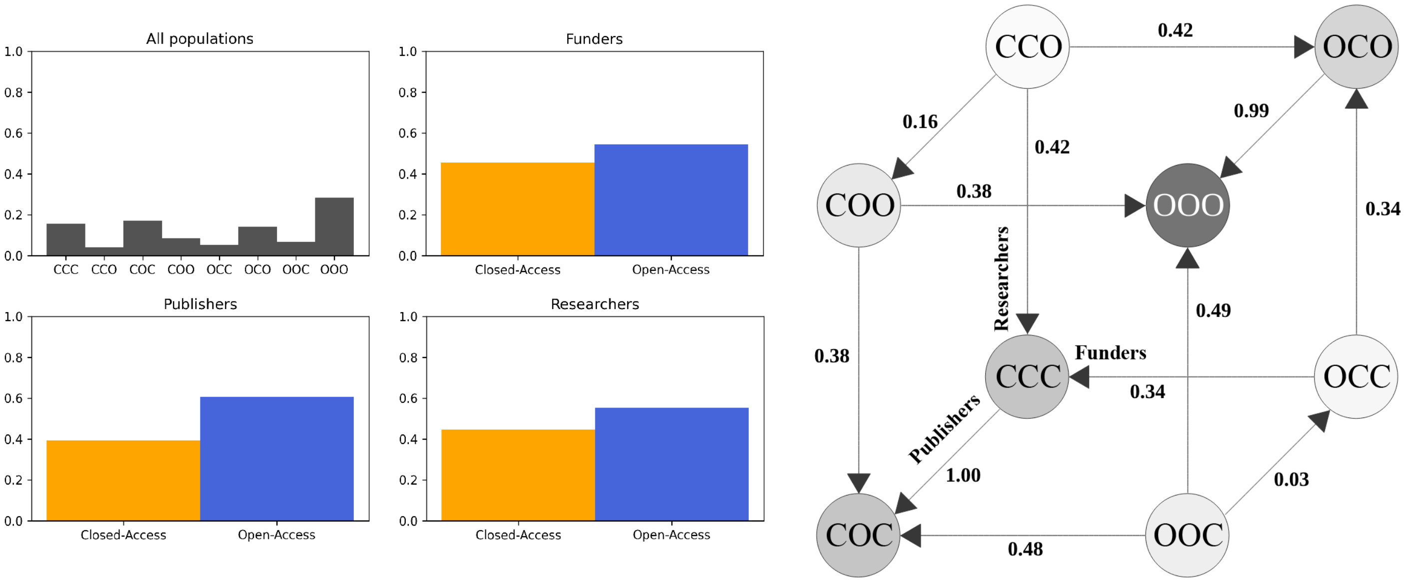


Figure A.2: The stationary distribution for the parameter set used in Figure A.1, under the core model. Left panel: Histograms displaying the fraction of time spent in each configuration and, for each sector, the time spent in OA and CA. Right panel: Figure 4.1 is redrawn to show the transitions based on the model parameters, and the hue of each monomorphic state translates to the fraction of time spent there (whiter means less time). The labels in each arrow correspond to the transition probability of the dominant transition, normalized excluding self-loops.

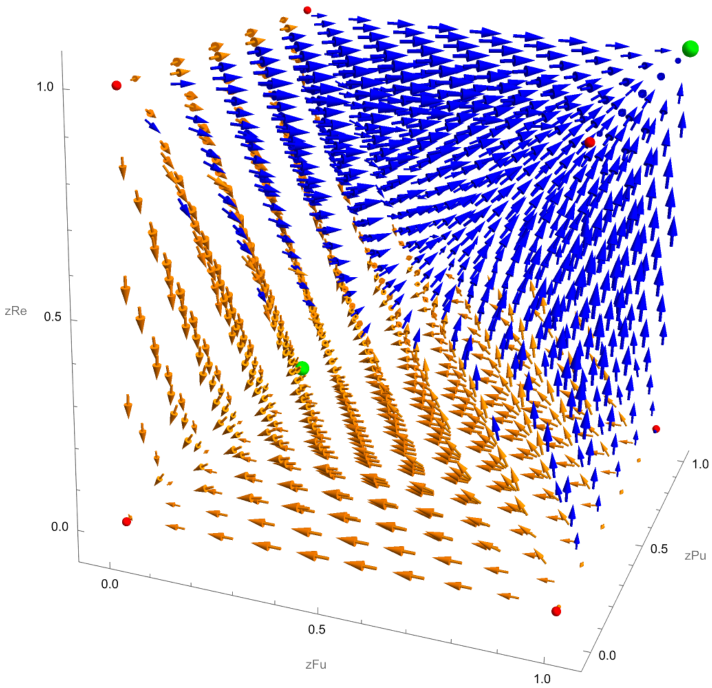


Figure A.3: Visualization of the gradient model. The fixed points are located at $(Z_F, Z_P, Z_R) = (0, 1, 0)$ and $(Z_F, Z_P, Z_R) = (1, 1, 1)$. The model parameters are identical to Figure A.1.

B

Appendix B: Complementary results from the Gradient Model

As to complement the results obtained in the computer simulations, this appendix contains the resulting gradient model for every scenario included in Figure 5.1. These results serve to further exemplify the general agreement between the results of the computer simulations, the simplex model, and the gradient model. However, they also demonstrate the limited viability of assuming an infinite population, leading to points being deemed stable even when switching strategies would be beneficial.

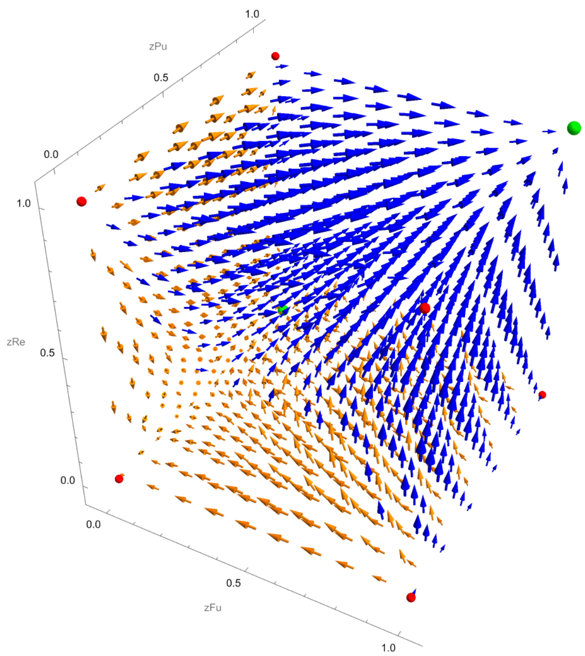


Figure B.1: Visualization of the gradient model. The fixed points are located at $(Z_F, Z_P, Z_R) = (0, 1, 0)$ and $(Z_F, Z_P, Z_R) = (1, 1, 1)$. The model parameters are identical to Figure 5.1 a).

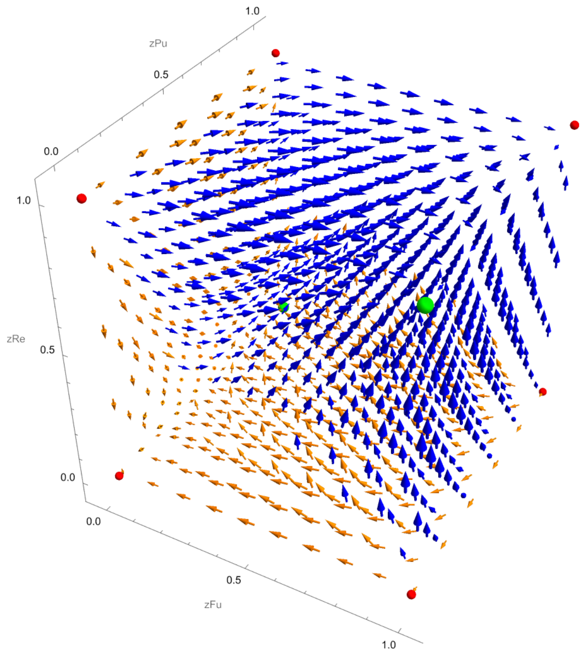


Figure B.2: Visualization of the gradient model. The fixed points are located at $(Z_F, Z_P, Z_R) = (0, 1, 0)$ and $(Z_F, Z_P, Z_R) = (1, 0, 1)$. The model parameters are identical to Figure 5.1 b) and c).

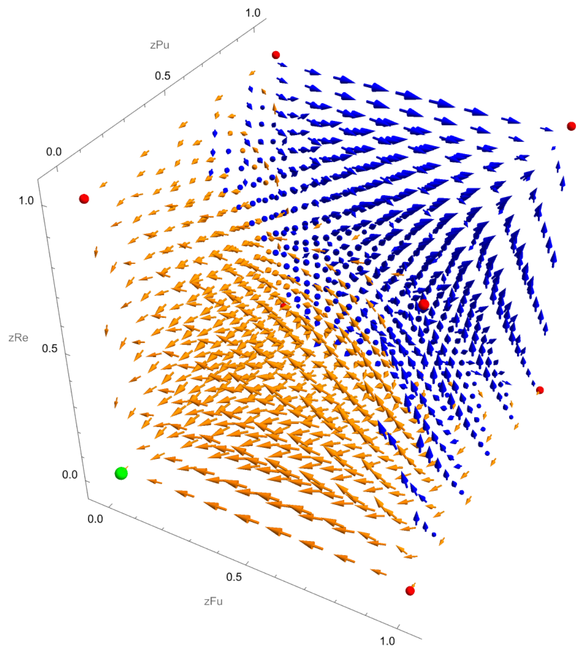
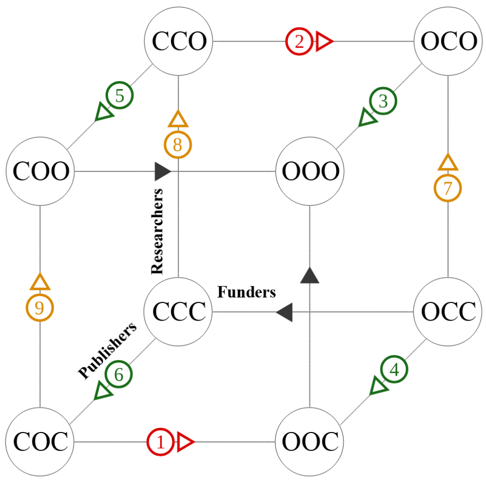


Figure B.3: Visualization of the gradient model. The only fixed point is located at $(Z_F, Z_P, Z_R) = (0, 0, 0)$. The model parameters are identical to Figure 5.1 d).

C

Appendix C: Supplementary simplexes

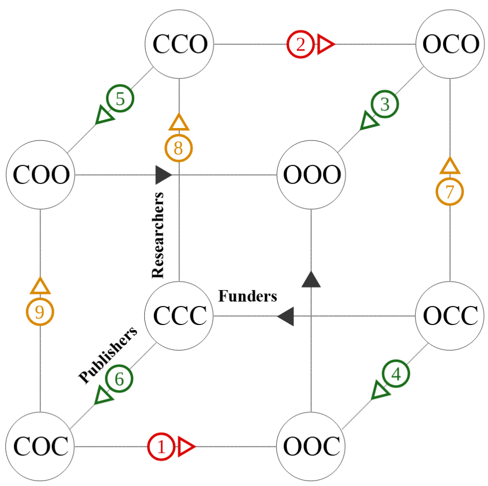
In order to facilitate the visualization of the conditions of the enhanced model, we present the simplexes for the enhanced model when no Green OA publishers exist ($u = 0$) and when no hybrid OA publishers exist ($h = 0$).



Conditions for Cooperation

1 ▷ $I(\delta + \gamma - 1) > At + P_{RF}$
2 ▷ $St(1-h) + d_{FR} + P_{RF} > I(\delta + \gamma - 1) + Ath$
3 ▷ $A(1-h) + I\delta + P_{RP}(1-h) > Fh + S(1-t)(1-h)$
4 ▷ $A + I\delta > P_{RP} + S(1-t)$
5 ▷ $A(1-t)(1-h) + d_{PR} + P_{RP}(1-h) > I\gamma + Fh$
6 ▷ $A(1-t) > I\gamma + P_{RP}$
7 ▷ $I(1-\delta) + F(1-h) + d_{FR} + P_{RF}/2 + Sh > P_{RP}(1-h)/2$
8 ▷ $P_{RF}/2 + Bh > I(1-\gamma) + F(1+h) + P_{RP}(1-h)/2$
9 ▷ $d_{PR} + P_{RP}/2 > I(1-\gamma) + F + P_{RF}/2$

Figure C.1: Representation of the monomorphic state-space and the predicted evolutionary dynamics for the enhanced model, where no Green OA publishers exist ($u = 0$).



Conditions for Cooperation

1 ▷ $I(\delta + \gamma - 1) > At + P_{RF}$
2 ▷ $St(1-(1-g)u) + d_{FR} + P_{RF} > I(\delta + \gamma - 1) + At(1-g)u$
3 ▷ $A(1-(1-g)u) + I\delta + P_{RP}(1-u) > S(1-t)(1-(1-g)u)$
4 ▷ $A + I\delta > P_{RP} + S(1-t)$
5 ▷ $A(1-t)(1-(1-g)u) + d_{PR} + P_{RP}(1-u) > I\gamma$
6 ▷ $A(1-t) > I\gamma + P_{RP}$
7 ▷ $I(1-\delta) + F + d_{FR} + P_{RF}/2 + S(1-g)u > P_{RP}(1-u)/2$
8 ▷ $P_{RF}/2 + B\,(1-g)u > I(1-\gamma) + F + P_{RP}(1-u)/2$
9 ▷ $d_{PR} + P_{RP}/2 > I(1-\gamma) + F + P_{RF}/2$

Figure C.2: Representation of the monomorphic state-space and the predicted evolutionary dynamics for the enhanced model, where no hybrid publishers exist ($h = 0$).