Evolutionary Dynamics of Technology Adoption Coordination and the Application of Commitment

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Abstract

In the context of social dilemmas, it has been demonstrated that establishing pre-commitments of future actions is an evolutionary viable mechanism, ensuring high levels of mutual cooperation among self-interested individuals. Coordination is one of the numerous group behaviours that can be accomplished through pre-commitments. There may be multiple desirable collective outcomes and players might have distinct, incompatible preferences in terms of which outcome should be agreed upon, thus leading to a larger behavioural space, making coordination difficult to attain.

In this thesis, we develop mathematical and computational formulations to explore the evolutionary dynamics of technology adoption decision making and competition amongst firms. Using methods from Evolutionary Game Theory (EGT), we first explored how pre-commitments can be adopted as a tool for enhancing coordination when its outcomes exhibit an asymmetric payoff structure, in pairwise interaction and thereafter expanded the interaction to accommodate a multiplayer interaction. We further explored how to resolve difficult coordination when there is a need for a group mixture or diversity of group choices.

We then extend our study from the well-mixed population to spatial networked population settings, to investigate the impact of different population structures including square lattice and scale-free (SF) networks on our technology adoption model.

We find, through an in-depth mathematical analysis and comprehensive numerical simulation, that pre-commitment would be a viable evolutionary mechanism for enhancing coordination and the overall population social welfare but this strongly depends on (i) the collective benefit of coordination, (ii) how asymmetric benefits are resolved in a commitment deal, (iii) severity of competition and (iv) the cost of arranging a pre-commitment in relation to the benefit derived from coordinating the interactions. Additionally, results from our multiplayer interactions show that pre-commitments prove to be crucial when a high level of group diversity is required for optimal coordination. The results are robust for different selection intensities.

Similarly to well-mixed analyses, our study of different network settings has shown that pre-commitments enhance coordination and the overall population payoff in structured populations, especially when the cost of commitment is justified against the benefit of

coordination, and when the technology market is highly competitive. When commitments are absent, slightly higher levels of coordination and population welfare are obtained in SF than lattice. In the presence of commitments and when the market is very competitive, the overall population welfare is similar in both lattice and heterogeneous networks; though it is slightly lower in SF when the market competition is low. Overall, we observe that commitments can improve coordination and population welfare in both well-mixed and structured populations. The outcome of evolutionary dynamics is, interestingly, not sensitive to changes in the network structure.

Overall, the analyses and findings from this thesis provide new insights into the complexity and beauty of behavioral evolution driven by humans' capacity for commitment, as well as for the design of self-organised and distributed multi-agent systems for ensuring coordination among autonomous agents.

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Chapter 1

Introduction

The study of collective behaviour among self-interested individuals in an evolving population has been of significant interest in different fields of study in recent time. The issue of collective actions, that is, the potential for group members to give up their immediate self-interest in favour of the long-term good of the group has been extensively investigated. In the first chapter of this thesis, we first describe issues related to social dilemmas research, dynamics and evolution of collective behaviour, and mechanisms underlying them. We look at games of particular interest, namely, coordination and anti-coordination games. We further explore how pre-commitments can be used as a viable strategy for promoting collective behaviours. Also, we introduce the use of methods from evolutionary game theory to model technology adoption decision making. We propose to study the dynamics of technology adoption using these methods to understand the strategic interactions and decision making amongst firms adopting technology. We also explore how pre-commitments can be utilised in promoting high levels of coordination in this technology adoption decision making problem. Our aims and objectives, main contributions and outline of the thesis are also covered in this chapter.

1.1 Social Dilemmas

Social dilemmas can be described as situations in which collective interest conflicts with individual interest. In these situations, the selfish and rational behaviour would return an outcome worse than the one the individual would obtain if they acted collectively (Capraro, 2013; Nowak, 2006b; Sigmund, 2010). However, humans are often faced with a dilemma between group interest and their personal interest, which results to failure in achieving the collectively preferred behaviour (e.g. cooperation or coordination). With a social dilemma, there is tension between collective interest, selfishness and cooperation. A result that the outcome completely relies on the choice of others, with many individuals having diverse and conflicting interests possibly resulting in a cacophony of conflicts. In his Leviathan from 1651, Hobbes claimed that selfish urgings lead to “such a war as is every man against every man” (Hobbes, 2009; Sigmund, 2010). In the absence of a central authority suppressing these conflicts, human life is “solitary, nasty, brutish, and short.” His French contemporary Pascal held an equally pessimistic view: “We are born unfair; for everyone inclines towards himself. The tendency towards oneself is the origin of every disorder in war, polity, economy etc.” Selfishness was depicted as the root of all evil (Sigmund, 2010).

Our study is in the context of strategic interactions within a population of agents that have conflicting interests. This collective action is a problem commonly referred to as a social dilemma and it has been an interesting subject of study for decades. Many of the world’s most pressing problems represent social dilemmas. These include problems such as overpopulation, over-harvesting of fishes, build-up of greenhouse gasses due to over-reliance on cars and many others (Dawes, 1980). These are presented as problems because acting on one’s selfish interest is tempting to all parties involved, even though everyone benefits from acting in the longer-term collective interest. As such, a broad knowledge of social dilemmas will help us understand not only the theoretical puzzles of why people cooperate, but also to investigate the ways in which cooperation in groups and organisations can be maintained or promoted (Dawes and Messick, 2000; Pletzer et al., 2018; Van Lange et al., 2013).

1.1.1 Cooperation and Punishment

Cooperation has had a major role in the success of almost all species in nature (Szathmáry and Smith, 1995). Despite individual’s having their own self-interest, cooperation has provided a long-term success to the social success of the species. Cooperation is abundant across all scales of biological life (Maynard Smith et al., 1998), from the emergence of genomes, cells, multi-cellular organisms, social insects and human society, they are all based on cooperation (West et al., 2007). In his theory of natural selection, Darwin portrayed the eusocial insects as a “special difficulty, which at first appeared to [him] insuperable and actually fatal to [his] theory”. Indeed, eusociality presents an apparent paradox: if adaptive evolution is mediated by differential reproduction of individuals on which natural selection acts, how can individuals who are incapable of passing on their genes evolve and persist? (Legendre and Condamine, 2018).

Evolution is based on a fierce competition between individuals which should only reward selfish behaviour. Which means every gene, cell and organism should be designed to promote its own evolutionary success at the expense of its competitors (Nowak, 2006b). Yet, there has been cooperation on different levels of biological organizations, with humans as the champions of cooperation; from hunter gatherer societies to nation states, cooperation is the decisive organizing principle of human society (Perc, 2016; Szathmáry and Smith, 1995). Building a high or more complex organism requires cooperation for the evolutionary success of one species against a severe existential competition from its competitor from the same or another species. Cooperation will mean that the selfish individuals will forgo some of their reproductive potential to assist one another, however, natural selection involves competition and so resists cooperation unless a defined mechanism is put in place (Nowak, 2006b).

Cooperation is a converging topic in evolution and explains why individual act in a way that benefits others especially if such an action has a cost to the individual. Hence the question of how natural selection can lead to cooperative behaviour has fascinated evolutionary biologists for several decades. Biologists have shown great interest in cooperation as it seems to be the opposition to the competition that is fundamental to natural selection. Exploring the emergence of cooperative behaviour amongst a group of selfish individuals is one of the crucial problems of evolutionary game theory (Hofbauer and Sigmund, 1998). In the New Year 2000 edition of Science, the editors listed "The Evolution of Cooperation" as one of the ten most challenging problems of the century (Sigmund, 2010). Hence, it is essential for understanding the origins of successive levels of evolutionary biological organization. This understanding has been substantiated with the development of the Prisoner's Dilemma and other cooperation dilemmas, using methods from (evolutionary) game theory. Game theory in turn has justified how numerous other examples of cooperation can be explained and better understood (Laird, 2018).

Recognising how cooperation has worked over the decades and having an insight of the evolution of cooperation would enable the designing of complex models that can be used to study human interactions and understand the world (Paiva et al., 2018). The complex evolutionary dynamics behind cooperation can bring major solutions on how to tackle issues in various facets of life such as climate change (Góis et al., 2019; Van Lange et al., 2018) and even corruption (Huang et al., 2018). Again, although an individual is selfish, cooperation benefits the individual in many ways, albeit there is trade-off that motivates the individual to be cooperative. There are many mechanisms that motivate this trade-off. The trade-off is often called a cost, but it is essentially any utility function, e.g. a fitness measure that is generally defined as a larger-the-better metric. In cooperation, a cooperator is an agent who pays a cost (c) for another individual to benefit (b). A defector incurs no loss nor expends no benefit. During reproduction, a mutation might cause defection.

For cooperation there are at least two players, each of which has a set of at least 2 choices. When each player makes their choice, there is an outcome, a utility measure that is jointly determined by the players' choices. The outcome is represented as a payoff matrix. In the case of the one-shot pairwise Prisoner's Dilemma, the choice of the players is to remain silent or betray. Silent in this payoff matrix corresponds to cooperation, whilst betray to defect. Thus, there are four outcomes as shown in Table 1.1.

Table 1.1 Possible Outcomes in a 2×2 Game Model

No.	Alice	Brian
1	Silent	Silent
2	Silent	Betray
3	Betray	Silent
4	Betray	Betray

The choices are silent or betray, resulting in four possible outcomes. The possible payoffs are the reward for mutual cooperation, R, which is greater than the punishment for mutual defection, P. The dilemma is caused by the fact that the temptation payoff for unilateral defection T, is greater than the defector's payoff for unilateral cooperation, S. The Prisoner's Dilemma is characterised by the ordering $T > R > P > S$. A second condition is usually added so that mutual cooperation is better than coordinated alternation of cooperation: $R > (S+T)/2$ (Axelrod, 2000).

Table 1.2 Payoff for 2 Prisoners

		Brian	
		Cooperate	Defect
Alice	Cooperate	$(3,3)$	$(0,4)$
	Defect	$(4,0)$	$(2,2)$

For a one-shot Prisoner's Dilemma, their payoffs can just be like 4 greater than 2 greater than 1 greater than 0. The best strategy in a Prisoner's Dilemma would be to always defect. In a one-off game, defecting has no consequence and always gives a higher payoff as shown in the payoff matrix. In an iterated game the same is not true because the players can change their strategy at the next move. When a player can change a move depending on the other player, defecting always is not the best strategy.

Trivers (1971) further explains how cooperation can evolve when individuals can target their beneficence preferentially towards cooperators and away from free riders who take the benefits of others cooperating without paying the cost of reciprocating. The tit for tat conditional cooperation (Axelrod, 1984) can also thwart free riders in very small groups but not in larger groups of non relatives, such as in the provision of public goods, because one cannot selectively punish free riders by refusing further cooperation when such withholding hurts cooperators and free riders alike (Boyd and Richerson, 1988).

Cooperation among individuals can also be stable when the individuals have a reputation for helping and if others are more likely to help those who have performed helping (Nowak and Sigmund, 1998; Panchanathan and Boyd, 2004), but this also relies on people being able to help specific individuals and refuse help to non-cooperators (i.e. defectors).

1.1.2 Evolution of Coordination

A considerable amount of research on social interactions has centred around social dilemmas where there is a conflict between personal and collective interests. In our everyday life, there is often the need to engage in interactions which requires us to coordinate our behaviour with others. This implies that we may have to consider the actions of others in an interactive situation before deciding on our own actions in order to reach a successful outcome. Achieving a joint venture among individuals with their own self-interest is a significant social and economic challenge in various societies (Barrett, 2016; Hardin, 1968; Ostrom, 1990a; Pitt et al., 2012; Sigmund, 2010). From the coordination of a set of employees working together to sustaining cooperative and trust-based relationship among organisations and nations, its success is often jeopardised by individuals' self-interest (Andras et al., 2018; Barrett et al., 2007; Han et al., 2021; Perc et al., 2017). Generally, the issue of coordination emerges when two or more individuals can achieve some mutually desired outcome or avoid some mutually undesired outcome, only by joining their actions in a particular way, where there is more than one possible combination.

Coordination games also describe incentive structures that reward conformity, any deviation from a player would lead to a lower payoff for the entire population (Bayer et al., 2022). With its characteristics of having multiple pure strategy Nash equilibria, a problem of equilibrium selection arises in a coordination game. A pure-strategy Nash equilibrium is an action profile with the property that no single player i can obtain a higher payoff by choosing an action different from a_i, given every other player j adheres to a_j (Jin et al., 2012).

Pure coordination, a subclass of coordination, portrays a game where positive payoffs are only achieved if all the individuals involved in a game choose the same strategy and gets zero payoffs for any other strategy combination.

Where the rewards of coordination are identical, the game is ascribed to as choosing sides. A typical example of this game is driving on either side of the road. If participants all adhere to driving on the same side, the traffic flows and payoffs are positive, otherwise chaos ensues and payoffs are zero. A less stringent class in terms of punishing discoordination is the stag hunt game.

The stag hunt game was first proposed by Rousseau as a representation of the possibility of two participants coordinating their actions when trying to hunt for their survival. The game has received more attention after being reviewed by Skyrms (2003). In the stag hunt, one strategy offers low rewards but does not require coordination, the other offers high rewards that can only be attained by coordination. Thus, putting players in a position where they rely on the cooperation of others to successfully hunt a stag.

While our research work is closely related to a coordination problem, let's look at an anti-coordination game. Anti-coordination games can be illustrated by an example from street traffic. Where two cars meet, crossing at a street intersection. Each of them has two strategies: to wait or to go. If both stop, they simply reproduce the problem, for payoffs of zero; but if both go, they will crash, for payoffs of -100. If one goes and the other waits, the one who goes "wins" getting through the intersection first, for 5, while the other goes through the intersection second (but safely) for a payoff of 1.

In this game, there are two Nash equilibria, each of the strategy pairs at which one car waits and the other goes. It is also necessary in the game for the players to choose different strategies in a coordinated way, in order to realise a Nash equilibrium, and while they are not equally well off at the equilibrium, both are better off than they will be at a non-equilibrium strategy pair. The decision-makers involved in the game will need some level of information from outside the game in order to appropriately coordinate their strategies, it is necessary that in an anti-coordination game, that each player gets a different bit of information, that can signal one to go and the other to stop (McCain and Hamilton, 2014).

In the real world, coordination and anti-coordination games are more complex than a two-player cooperate or defect game (Prisoner's Dilemma game). People, companies and even countries engage in this type of multi-party games simultaneously with one another. Another way to model this game is with a graph, whose vertices correspond to agents and whose edges capture their pairwise interactions. A vertex then chooses one of K strategies, trying to anti-coordinate with all its neighbours simultaneously. The payoff of a vertex is the sum of the payoffs of its games with its neighbours, namely the number of neighbours with which it has successfully anti-coordinated. Coordination issues can be resolved in both games if players are allowed to communicate prior to engaging in the game (Jones et al., 2021).

1.1.3 Pre-Commitment

Different mechanisms responsible for the emergence and stability of collective behaviours among individuals have been proposed, which include kin and group selection, direct and indirect reciprocity, spatial networks, reward and punishment (Nowak, 2006a; Okada, 2020; Perc et al., 2017; Skyrms, 1996; West et al., 2007). These mechanisms may be relevant in tackling collective behaviours, but are they sufficient? There may be other alternatives to promoting pro-social behaviours that have been neglected.

Recently, significant attention has been given to the introduction of pre-commitment as an evolutionary viable strategy that promotes cooperative behaviour in both pairwise and multi-player cooperation dilemma (Arvanitis et al., 2019; Cohen and Levesque, 1990; Frank, 1988; Han et al., 2015a; Han, 2016; Han et al., 2017a,b; Nesse, 2001a,b; Ohtsuki, 2018; Sasaki et al., 2015b) namely, the Prisoner's Dilemma (PD) (Han et al., 2013a; Hasan and Raja, 2013) and the Public Goods Game (PGG) (Han et al., 2015c, 2017a; Kurzban et al., 2001). Commitments, which allows the expression of an intention prior to an interaction rather than having it recognised stands as another alternative to resolve cooperation problems. Agents make commitments towards others when they give up options in order to influence others (Arvanitis et al., 2019; Han, 2013; Nesse, 2001a). Incentives are utilised in most commitments to ensure that the action is in the agent's interest and thus will be carried out, knowing that there is penalty for default (Nesse, 2001a). A commitment deal also involves paying a small cost of arranging the commitment to make it credible and entice those to accept to commit. More recently, Han (2022) studied explicitly how institutional incentives such as reward of commitment compliance and punishment of dishonest commitment behaviours, can be utilised to promote high levels of cooperation. Han (2022) showed that with a sufficient budget for providing incentives, rewarding of commitment compliant behaviours better promotes cooperation than punishment of non-compliant ones.

The introduction of pre-commitments has also provided an improvement to different types of punishment against inappropriate behaviours and of rewards to stimulate the appropriate ones (Chen et al., 2014; Martinez-Vaquero et al., 2015, 2017; Powers et al., 2012; Sasaki et al., 2015b; Szolnoki and Perc, 2012; Wang et al., 2019), allowing one to efficiently avoid free-riders (Han et al., 2015b; Han and Lenaerts, 2016b) and resolve the antisocial punishment problem (Han, 2016). These works have primarily focused on modelling pre-commitments for improving mutual cooperation among self-interested agents.

In the context of cooperation dilemma games (i.e. PD and PGG), mutual cooperation is the only desirable collective outcome to which all parties are required to commit if an agreement is to be formed. The same argument is applied to other pairwise and multi-player social dilemmas such as the stag hunt and chicken games, since although the nature of the games is different from the PD and PGG, mutual cooperation is the only desirable outcome to be achieved (Pacheco et al., 2009; Santos et al., 2006a; Skyrms, 2003). In our technology adoption game, there are multiple optimal or desirable collective outcomes such as in stag hunt and chicken games and players might have distinct, incompatible preferences regarding which outcome a mutual agreement should aim to achieve (e.g. due to asymmetric benefits).

Such (anti-)coordination problems are abundant in nature, ranging from collective hunting and foraging to international climate change actions and multi-sector coordination (Barrett, 2016; Bianca and Han, 2019; Ohtsuki, 2018; Ostrom, 1990a; Santos et al., 2016; Santos and Pacheco, 2011; Skyrms, 1996).

Studies have also shown that in order to improve cooperation, commitments will need to be adequately enforced among the players in a game and the cost of setting up the commitments is justified with respect to the benefit resulting from the interactions among players, which has been confirmed both in theoretical analysis and behavioural experiments (Arvanitis et al., 2019; Chen and Komorita, 1994; Cherry and McEvoy, 2013; Kurzban et al., 2001; Ostrom, 1990a). Although several studies have utilised the mechanism of pre-commitment in solving cooperation dilemmas, there is a research gap in the application of pre-commitment in resolving (anti-)coordination problems. Setting up the use of commitments for improving coordination is more complex, exhibiting a larger behavioural space and furthermore their outcomes are asymmetric (Bianca and Han, 2019).

It is worth reiterating that models that have been implemented in the past to demonstrate the evolution of cooperation or population structure in social dilemmas focused on using repeated interactions or long-term relationships (Back and Flache, 2008; de Vos et al., 2001; Trivers, 1971). For instance, conditions in direct reciprocity theory, which assumes that individuals who help a recipient get direct returns from a recipient, may play a role to foster cooperation. Axelrod (1984) further used two-person repeated prisoner's dilemma game to show that reciprocity based on the so-called 'Tit-for-Tat' strategy results in a stably cooperative society. His work assumes that each player repeatedly interacts many times with every other player. Likewise, the model of indirect reciprocity, see e.g, a study by Nowak and Sigmund (2005), which involves evaluating the reputation of players in a group. Their study demonstrated indirectly reciprocal cooperation based on a discriminating strategy, which only allows cooperation with an individual that has good reputation (Suzuki and Akiyama, 2005).

In our research, we took a different dimension, exploring how the mechanism of pre-commitment can be utilised to promote cooperation in a complex situation like a coordination problem, without using repeated interactions, nor assuming kin relationships nor considering a reputation effect, which are the major factors of cooperation (Axelrod and Hamilton, 1981; Martinez-Vaquero et al., 2017; Nowak, 2006b; Panchanathan and Boyd, 2004; West et al., 2002).

1.1.4 Collective Dynamics

Individually, a single agent can exert only a very small influence on its environment. However, through large numbers, and the expression of cooperative behaviour, the same individual can exert enormous impact over their environment. Hence, while simple cooperative individual appears to abound everywhere (e.g. microbes, bacteria, plants, animals, humans, etc.), but explaining their evolution is challenging because they are often subject to exploitation by rapidly growing non-cooperative individuals. Consequently, the population structure may be critical for this problem because it influences the extent of interaction between cooperative and non-cooperative individuals. That is, it is not enough that cooperative behaviour exists in some individuals but that these individuals must somehow aggregate. Otherwise, it is difficult for cooperative individuals to succeed in competition if they become mixed with non-cooperative ones which can exploit the public good without themselves paying a cost. However, if cooperative individuals are segregated in space and preferentially interact with each other, they may prevail as a collective dynamic that emerges from the collective behaviour (Nadell et al., 2010).

Many advances in the body of knowledge enable the study of collective dynamics particularly as evolutionary dynamics in structured populations. When the fitness of individuals depends on the relative abundance (i.e. frequency-dependent) of the trait in the population, the situation is within the realms of evolutionary game theory (EGT) (Hofbauer and Sigmund, 1998; Sigmund, 2010). EGT is a broad concept that can be used to understand species rivalry in an ecosystem, interactions between hosts and parasites, viruses and cells, and the spread of ideas and behaviours among humans. With this perspective, there are many recent advances that foster the study of fundamental laws particularly stochastic approaches in finite populations. In our research, the EGT method is adopted to study the evolutionary dynamics and interactions among individuals in a finite population (Hauert et al., 2007; Imhof et al., 2005; Nowak et al., 2004). In this type of setting, an individual's payoff represents their fitness or social success (Hofbauer and Sigmund, 1998; Sigmund, 2010). The most successful individuals are imitated more often by other individuals. In each time step, an individual A with fitness f_A adopts the strategy of another individual B with fitness f_B using the pairwise comparison rule, a popular and standard approach to implementing social learning in EGT (Traulsen et al., 2006). Namely, the probability p is given by the Fermi function:

$$p_{A,B} = \left(1 + e^{-\beta(f_B - f_A)}\right)^{-1}. \tag{1.1}$$

The parameter β represents the 'imitation strength' or 'intensity of selection', i.e., how strongly the individuals base their decision to imitate on fitness difference between themselves and the opponents. For $\beta = 0$, we obtain the limit of neutral drift – the imitation decision is random. For large β, imitation becomes increasingly deterministic.

1.2 Technology Adoption and Evolutionary Game Theory

In recent years, rapid technological progress, especially in information and computer technologies, has heightened the strategic importance of new technologies in a competitive marketplace (Huggins and Izushi, 2011). Innovation continues to transform global market and the modern workplace, providing solutions to the challenges that organisations and the society at large encounters and enabling significant competitive advantage to businesses. Sometimes, it is technology adoption that differentiates a firm and without which it could not be present in the market (Zhu and Weyant, 2003). With the emergence of the Covid 19 pandemic, technology has played a major role in all industries, for instance technology aiding employees to work remotely with the innovation of future work, automating various business processes with artificial intelligence (AI) (Roberts et al., 2021). Technology was also used in Covid 19 containment and mitigation strategies (Whitelaw et al., 2020). Up until now, new technology products are still developed at lighting speed in a fiercely competitive and rapidly changing digital world. Yet these innovations are only successful if they are adopted (Frambach and Schillewaert, 2002).

Adopting new technologies allows businesses to offer what no one is offering, boosting revenue streams while providing value to customers. It also presents them as innovators and risk-takers in front of their customers and investors, opening new doors to a wider market and more investment. However, the decision to adopt or invest on a technology arises with challenges. Reluctance of organisations to adopt or invest on a new technology can result in significant costs, such as through loss of competitive advantage and potential revenue (Makkonen et al., 2016).

A vast percentage of changes that occurs in organizations are primarily triggered by globalization, technology innovation acceptance and even the emergence of AI and the global pandemic. Hence, this has spurred a good number of organizations facing the challenge of technology adoption decision-making. The problem is which technologies should be adopted? Managers are constantly faced with the decision-making dilemma of technology adoption or investment. Often, companies might choose to invest in new technologies in order to gain a competitive advantage over their peers (Clemons, 1991; Parsons, 1983; Zhu and Weyant, 2003). These selfish executive priorities may lead to a coordination problem. Ensuring a higher social welfare by providing several technological solutions is ignored if newer technology promises larger profits (Sachs, 2000; Zhu and Weyant, 2003).

In this thesis, we will explore a scenario where two investment firms have a contract to adopt or invest in either a high (benefit) technology or a low (benefit) technology. Investing in a high technology will result in a greater return of investment for the firm, than investing in a low technology. However, there is a need for investment of both low and high technologies for the benefit of the society. In this type of situation where what is invested in determines the outcome, clearly none of the firms would want to invest in a low technology which yields a smaller benefit for the firm. This leads to a dilemma between the investment firms adopting technology. Using methods from evolutionary game theory, we will explore strategies and other supporting mechanisms that would help to achieve efficient coordination amongst the firms adopting technology. We model a coordination game using the technology adoption scenario to show the strategic interactions and decision making amongst firms adopting technology. Using mathematical models, we will explore how arranging pre-commitment can be used as a mechanism to enhance coordination and the overall population welfare in a well-mixed and structured populations for both pairwise and multi-player interaction settings. The study of cooperative actions and pre-commitment in cooperative games for two players and many players is closely related to our research (Han et al., 2013a,b, 2017a; Hasan and Raja, 2013; Sasaki et al., 2015b). Differently, we investigate how pre-commitment can be utilised in promoting cooperation in a coordination problem using technology adoption decision making scenario.

It is noteworthy to state that although our approach is applicable for a wide range of coordination problems (e.g single market product investments), we will frame our models within the technology investment strategic decision-making problem, allowing us to show clarity of our model description. Namely, we describe technology adoption games capturing the competitive market and decision-making process among firms adopting new technologies (Bardhan et al., 2004; Zhu and Weyant, 2003). This research work will perform both theoretical analysis and numerical simulations using stochastic EGT methods as well as agent-based simulations on complex networks (Hofbauer and Sigmund, 1998; Perc et al., 2017; Santos and Pacheco, 2005; Sigmund et al., 2010; Szabó and Fáth, 2007) to model technology adoption decision making behaviours among firms competing to invest in a technology product market.

1.3 Aim and Scope

The focus of this thesis is to study the interactions among firms investing in a competitive technology market. In order to achieve this aim, we will achieve the following objectives:

1. To explore evolutionary game theory methods to model firms' strategic interactions and study the dynamics and evolutionary outcomes of their interactions.
2. To explore mechanisms that allow us to improve coordination.
3. To design a mathematical model that studies human behaviours with respect to technology adoption.

1.4 Thesis Contribution

This section provides a summary of the main contributions of the thesis and highlight the significance of our work. Namely, three major contributions have been achieved, as listed below

1. We provide a novel mechanism that allows pre-commitments to be adopted as a tool for enhancing coordination when its outcomes exhibit an asymmetric payoff structure. Our approach is applicable to addressing complex social dilemma problems such as a (anti-)coordination problem, which is more complex to achieve since there might be several desirable collective outcomes or players might have distinct, incompatible preferences regarding which outcome a mutual agreement should aim to achieve (as a result of asymmetric benefits). Compared to cooperation dilemma games (i.e PD and PGG), where mutual cooperation is the only desirable collective outcome to which all parties are required to commit if an agreement is to be formed (Han et al., 2013a, 2017a; Sasaki et al., 2015b).

   Different works in the past have studied the evolution of coordination, using the so-called Stag Hunt game, see e.g. (Pacheco et al., 2009; Santos et al., 2006a; Sigmund, 2010; Skyrms, 2003), however, to the best of our knowledge, no research has been done on how pre-commitments can be modelled and applied to enhance the outcome of the evolution of coordination.

2. We have proposed a model for a pairwise technology adoption coordination game, then extended and generalized the model to a multi-player interaction, capturing the strategic interaction among any number of players (i.e. firms). The generalised multi-player

game is more complex as more players are involved in the interaction. We further investigated how coordination and cooperation can be enhanced with the application of pre-commitment deal when there are multiple players involved and also when there is a particular market demand.

3. Finally, we have examined the impact of different population structures, capturing homogeneous and heterogeneous network structures on the dynamics of decision-making in the context of a coordination problem. Santos et al. (2006c)'s work on investigating the effect of population structures on different types of two-player social dilemmas including the Prisoner's Dilemma, Stag Hunt and Snowdrift games is closely related to this our contribution. Also Cimpeanu et al. (2022) research explored how safety adoption in the development of AI technology can be enhanced by heterogeneous network structures. And also (Di Stefano et al., 2015, 2020) work on how highly heterogeneous networks, such as SF, constitute the most suitable network topology for the emergence and sustainability of cooperation in a multilayer network. However, these models are different from our coordination game as their works focus on symmetric games. Our work explored an asymmetric coordination game.

   Despite the fact that we have described our model in terms of technology adoption decision making, it is generally relevant to many other coordination issues, such as whenever there are strategic investment decisions to be made (in competitive markets of any products) (Chevalier-Roignant et al., 2011; Zhu and Weyant, 2003).

1.5 Outline of the Thesis

Below we provide a brief summery of the six chapters in the thesis.

1. **Introduction:** The introduction chapter is the first chapter which gives an overview of this thesis. We first commence this chapter by exploring the issues of social dilemma and collective behaviour. We studied cooperation and punishment, the evolution of coordination and anti-coordination games. We explored already existing mechanisms responsible for the emergence of collective behaviours and studied commitment. Furthermore, we looked at technology adoption and evolutionary game theory, exploring the rationale and motivation of this thesis.

2. **Background and Methods:** The second chapter describes the background and methods used in the thesis. We provide some valuable technical detail which we believed to be helpful in understanding the contents of this thesis. We present an overview

of relevant definitions of Game Theory, Evolutionary Game Theory, Well-mixed and Structured Populations. We also provide an extensive literature review that shows past relevant works closely related to our work. We explored here, other mechanisms that have been proposed in the past to promote the emergence and stability of cooperative behaviours among selfish individuals. We looked at relevant contributions, which allow for a better understanding of the thesis. We therefore identified some research gaps and raised some research questions which our work seeks to find answers to.

The next three chapters are the main contributions of this thesis. Each of these chapters corresponds to an already peer-reviewed published and presented worked.

3. **Technology Adoption Model (Two-player Game):** In this chapter we proposed a computational model using evolutionary game theory, that describes a pairwise technology adoption decision making, where two investment firms (or players) compete to make a strategic decision on which technology to adopt. We have first present our model without a pre-commitment or agreement deal, allowing us to see the need and complexity of achieving coordination without any extra mechanism. We further explored the use of commitment in this chapter and showed when commitment is a viable evolutionary mechanism for enhancing coordination among firms.

4. **Multi-Player Technology Adoption Game:** Here, we expanded our two-player technology adoption game in the previous chapter to accommodate multiple players competing for technology adoption. We proposed a new model to investigate how pre-commitments can be applied to improve coordination when its results reveal an asymmetric reward structure, in multiplayer interactions, by utilising methods from evolutionary game theory (EGT). We further explored here how to resolve difficult coordination when there is a need for a group mixture or diversity of group choices.

5. **Structured Population:** Previous chapters focused on well-mixed population setting, however, this chapter investigates on the impact of different population structures, including square lattice and scale-free (SF) networks, capturing typical homogeneous and heterogeneous network structures, on the dynamics of decision-making in the context of coordinating technology adoption. Similar to well-mixed population, we explored here, whether pre-commitments can enhance coordination in structured populations.

6. **Conclusions and General Discussions:** In this chapter, we summarise our work and draw conclusions. We critically review our findings and gave some useful recommen-

dations on how our work can be applied to other domains. We finally propose different areas for future research.

1.6 List of Publications

Here we provide a list of the publications directly related to this thesis. I was the main author, providing the core contributions for each publication. Also, conference abstracts are listed.

Journal Article

1. **Evolution of Coordination in Pairwise and Multi-player Interactions via Prior Commitments** (Ndidi Bianca Ogbo, Aiman Elgarig and The Anh Han)
   In Adaptive Behaviour, 2022;30(3):257-277.
   doi:10.1177/1059712321993166

Peer-reviewed Conference Paper and Abstract

1. **Emergence of Coordination with Asymmetric Benefits via Prior Commitment** (Ogbo Ndidi Bianca and The Anh Han)
   In Artificial Life 2019 Conference, pages 163-170, MIT Press, 2019.
   doi.org/10.1162/isal_a_00157
2. **Shake on it: The role of Commitments and the Evolution of Coordination in Networks of Technology Firms** (Ndidi Bianca Ogbo, Theodor Cimpeanu, Alessandro Di Stefano, The Anh Han)
   In Artificial life 2022 Conference , doi.org/10.1162/isal_a_00524
3. **Evolution of Coordination in Pairwise and Multi-player Interactions via Prior Commitments** (Ndidi Bianca Ogbo, Aiman Elgarig and The Anh Han)
   In Complex Systems Society Conference, 2020. (Abstract).
4. **Arranging Pre-commitment to Enhance Coordination Among Firms Adopting Technology** (Ndidi Bianca Ogbo)
   In Mathematical Model in Ecology and Evolution Conference, 2022. (Abstract)

Chapter 2

Background and Methods

We begin this chapter by first describing the background and methods used in the thesis, including (evolutionary) game theory and agent-based simulations on complex networks. We then review relevant literature on evolutionary dynamics, complex networks, mechanisms that promote cooperation and coordination, in order to frame the thesis contributions. We look at existing models which have been used to study cooperation and coordination problems, which allowed us to identify gaps in the literature and research questions that the thesis aims to address.

2.1 Game Theory

Game theory, used in the modelling of conflict and cooperation, was first introduced as a field by John von Neumann and Oskar Moregenstern in their publication of Theory of Games and Economic Behaviour in 1944 (Von Neumann and Morgenstern, 1994). Ever since then, the logic behind game theoretic thinking continues to be explored. The choice of strategies and the interdependence of people's actions associated with game theoretic reasoning has influenced all social sciences. Game theory is described as the rigorous analysis of situations of strategic interdependence. In this type of situations, a payoff structure faced by a player relies on the decisions or actions made by other parties (i.e. co-players) in the interaction. Hence it leads to a situation Emile Borel called 'psychological uncertainty' (Dimand and Dimand, 1996). The problem of information scarcity and uncertainty is closely connected in this type of game theoretic analysis. Players are faced with uncertainty as they are unaware of the moves taken by their co-players, or actions their co-players are planning to take. Due to this, every player must perform some inference about the moves of others to rationally choose among his or her own potential moves (Dimand and Dimand, 1996).

Game theory studies how players should rationally play games or make a decision. Every player involved in a game would like the game to finish in an outcome that is favorable to them, that is they obtain a large payoff. For instance, a player has influence over the outcome, as his choice of strategy will influence it. However, the outcome is not determined by his choice alone, but also depends upon the choices of all the other players involved in the game. This might result in a situation of conflict versus cooperation. The ability to deal with a tactical interaction among players is what makes game theory an interesting field of study. Players involved in such an interaction might try to predict their opponent's strategy before they make any move. Several real-world games have been captured using game theory interactions, such as football, basketball, chess, checker, war, and politics which are spheres of life that involves people trying to outsmart their rivals (Sarkar, 2016).

Game theory has found successful applications in myriad fields and disciplines, for the analyses of strategic and tactical interactions. Businesses can utilise game theory to out-think competition from rivals. Companies pursuing cooperative strategies are playing a game, likewise political candidates seeking to win an election, members of congress trying to pass or defeat a bill and nations striving to compete in international arena. The application of game theory in many important circumstances has continued to offer solutions right from the early days. Many of the theoretical applications in the 1980s resolved issues in industrial organisation, for instance, the application of commitment and timing in patent races and pre-emptive investment (Fudenberg and Levine, 2016). Milgrom and Roberts (1982) utilised the logic of game theory to limit pricing and many of Tirole (1988)'s influential industrial organisation books majorly applied game theory to his work. Other applications of game theory have continued to follow, including resolving issues ranging from auctions to market organisation, and to monetary, fiscal and even environmental issues (Fudenberg and Levine, 2016). According to Sarkar (2016), the description of a game needs to specify the following:

1. **Players**: A player may be an individual, but it may also be a more general entity like a company, an organisation, a nation, or a biological species. They are players of a game if they are involved in strategic interaction where their decisions affect each other's well-being or happiness. Game theory assumes that players are self-interested individuals. Self-interested behaviour among players does not avert cooperation, however, cooperation happens when there will be benefits obtained from cooperation rather than from competing. Players do not act without self-interest, it could be even a 'warm glow', which is still seen as feeling fulfilled from enhancing the well-being of another. This means that an action that may appear to be altruistic may also involve some form of self-interest.

2. **Strategies**: Strategies are actions or plans of actions available to the players. The strategy set or space defines the scope of what the players can do in the game. Each player has some possible strategies, that is courses of action which he or she may choose to follow.

3. **Outcome**: The preferred strategies chosen by each player in the game would determine the outcome of the game.

4. **Payoffs**: All the outcomes of the strategic interactions of a game are numerical payoffs, one to each player. Payoffs are what the players obtain from the game subject to realization of each of the outcomes. A player's payoff reflects the player's stake in the game. The assumption of self-interested players implies that the players strive to maximize their own payoffs.

2.2 Evolutionary Game Theory

Evolutionary game theory, briefly discussed in Chapter 1, is a mathematical framework conceived by John Maynard Smith and George Robert Price in their seminal work on the logic of animal behaviour (Smith and Price, 1973). It is an extension of game theory to evolving populations in biology that helps us understand the effects of selective pressures on the population dynamics of interacting agents in a population (Bukkuri and Brown, 2021). Agents or players may have different strategies that affect their interactions with one another, where the strategies could be anything from behavior traits such as aggression to body size or cell transporter expression. Evolutionary game theory allows us to derive mathematical examination of population dynamics of agents' behaviours over time.

Before embarking on analysing evolutionary game theory, it is worth noting the key difference between game theory and evolutionary game theory. Game theory was originally developed to provide a framework for determining a player's optimal strategies when an individual's success depends on their choice of strategy and that of other players. This is most apparent in zero sum games in which one player's winnings necessarily becomes another player's losses. However, in a less extreme sense, this conflict is also present in non-zero sum games since what maximizes payoffs for one player does not necessarily do so for another. In a classical game theory, players have the option of selecting their strategies and it is assumed that players act rationally, in their own self-interest (Basu, 1994; Colman, 2003). A common question asked by classical game theorists is "in a situation, what should a rational player do?", that is which strategy or which frequencies of mixed strategies will grant the player with the higher payoff, assuming that the competitors are rational players as well? In this setting, both ecological and evolutionary dynamics are absent (Bukkuri and Brown, 2021).

To integrate these dynamics, evolutionary game theory built upon the framework of game theory by replacing the assumptions of rationality and self-interest with population dynamics and stability associated with Darwinian fitness. Darwin considered strategic interactions where fitness is dependent on the frequency of a type within a population, which became a major theme of evolutionary game theory (Hodgson and Huang, 2012; Hofbauer and Sigmund, 1998; Sigmund, 2010). The central question asked by evolutionary game theorists is "given a population with interacting phenotypes, how will their population dynamics change over time?" (Bukkuri and Brown, 2021). The table below displays the difference between a classical game theory and evolutionary game theory.

Table 2.1 Classical game theory and evolutionary game theory

Attributes	Classical Game Theory	Evolutionary Game Theory
Emphasis	Players	Strategies
Payoffs	No Dynamical Link with Strategy Frequency	Dynamical Link with Strategy Frequency
Players	Fixed	Dynamic
Population	Static	Dynamic
Choices	Rationality	Teleonomy

Evolutionary game theory (EGT) takes a different route to the classic analysis of games. Here, the population of players using different strategies are simulated and a process similar to natural selection is used to determine how the population evolves.

Let us consider an n-player game with the i-th player has strategy space denoted by S_i. An EGT approach would be to model each agent by a population of players. The population for the i-th agent would then be partitioned into groups $E_{i_1}, E_{i_2}, \ldots, E_{i_k}$ (k might be different for each population). Individuals in group E_{i_j} would all play the same (possibly mixed) strategy from S_i. The next step, then, would be to randomly play members of the populations against each other. The sub-populations that performed most successfully would grow, and those that did not do so would shrink. The process of playing members of the populations randomly and refining the populations based on performance would be repeated indefinitely. Ideally the evolution would converge to some stable state for each population, which would represent a (possibly mixed) strategy best response for each agent. A special case is the symmetric two-player game. In a symmetric game payoff matrices and actions are identical for both agents. These games can be modelled by a single population of individuals playing against each other. When the game being played is asymmetric, a different population of players must be used to simulate each agent.

2.3 Evolutionary Dynamics

In this thesis work, we perform theoretical analysis and numerical simulations using EGT methods for finite, well-mixed populations (Hauert et al., 2007; Imhof et al., 2005; Nowak et al., 2004). In populations of a finite size, the dynamics of evolution are stochastic rather than deterministic. If two mutants are equally fit, one of them will eventually seize control while the other might go extinct. An advantageous mutation has a certain chance of succeeding.

Let Z be the size of the population. In such a setting, individuals' payoff accumulated from their interactions represents their *fitness* or social *success*, and evolutionary dynamics is shaped by social learning (Hofbauer and Sigmund, 1998; Sigmund, 2010), whereby the most successful individuals will tend to be imitated more often by the other individuals. In the current work, social learning is modelled using the so-called pairwise comparison rule (Traulsen et al., 2006), a standard approach in EGT, assuming that an individual A with fitness f_A adopts the strategy of another individual B with fitness f_B with probability p given by the Fermi function,

$$p_{A,B} = \left(1 + e^{-\beta(f_B - f_A)}\right)^{-1}.$$

The parameter β represents the 'imitation strength' or 'intensity of selection', i.e., how strongly the individuals base their decision to imitate on fitness difference between themselves and the opponents. For $\beta = 0$, we obtain the limit of neutral drift – the imitation decision is random. For large β, imitation becomes increasingly deterministic.

In the absence of mutations or exploration, the end states of evolution are inevitably monomorphic: once such a state is reached, it cannot be escaped through imitation. We thus further assume that, with a certain mutation probability, an individual switches randomly to a different strategy without imitating another individual. In the limit of small mutation rates, the dynamics will proceed with, at most, two strategies in the population, such that the behavioural dynamics can be conveniently described by a Markov Chain, where each state represents a monomorphic population, whereas the transition probabilities are given by the fixation probability of a single mutant (Hauert et al., 2007; Imhof et al., 2005; Nowak et al., 2004). The resulting Markov Chain has a stationary distribution, which characterises the average time the population spends in each of these monomorphic end states. It has been shown to have a range of applicability which goes well beyond the strict limit of very small mutation (or exploration) rates (Han et al., 2012a; Hauert et al., 2007; Rand et al., 2013b; Sigmund et al., 2010; Sigmund, 2010; Zisis et al., 2015).

Now, for both two-player and N-player settings, the probability to change the number x of individuals using strategy A by $\pm$ one in each time step can be written as (Traulsen et al., 2006)

$$T^{\pm}(k) = \frac{Z-x}{Z}\frac{x}{Z}\left[1+e^{\mp\beta[\Pi_i(x)-\Pi_j(x)]}\right]^{-1}. \tag{2.1}$$

The fixation probability of a single mutant with a strategy i in a population of $(Z-1)$ individuals using j is given by (Nowak et al., 2004; Traulsen et al., 2006)

$$\rho_{j,i} = \left(1+\sum_{i=1}^{Z-1}\prod_{j=1}^{i}\frac{T^{-}(j)}{T^{+}(j)}\right)^{-1}. \tag{2.2}$$

Considering a set $\{1,...,q\}$ of different strategies, these fixation probabilities determine a transition matrix $M = \{T_{ij}\}_{i,j=1}^{q}$, with $T_{ij,j\neq i} = \rho_{ji}/(q-1)$ and $T_{ii} = 1-\sum_{j=1,j\neq i}^{q} T_{ij}$, of a Markov Chain. The normalised eigenvector associated with the eigenvalue 1 of the transposed of M provides the stationary distribution described above (Imhof et al., 2005), describing the relative time the population spends adopting each of the strategies.

2.3.1 Risk-dominance conditions (pairwise ad multi-player games)

An important measure to determine the evolutionary dynamic of a given strategy is its risk-dominance against others. For the two strategies i and j, risk-dominance is a criterion which determine which selection direction is more probable: an i mutant is able to fixate in a homogeneous population of agents using j or a j mutant fixating in a homogeneous population of individuals playing i. In this case, for instance, comparing the two strategies i and j, to know which direction the transition is stronger or more probable, an i mutant fixating in a population of individuals using j, or a j mutant fixating in the population of individuals using i. If the first was more probable than the latter then we say that i is *risk-dominant* against j (Nowak et al., 2004; Sigmund, 2010), which holds for any intensity of selection and in the limit for large population size Z when

$$\sum_{k=1}^{N}\Pi_{i,j}(k) \geq \sum_{k=0}^{N-1}\Pi_{j,i}(k) \tag{2.3}$$

This condition is applicable for both two-player games, $N=2$, and when N-player games with $N>2$ (Gokhale and Traulsen, 2010; Sigmund, 2010). It will allow us to derive analytical conditions such as when commitment proposing is an evolutionarily viable strategy, being risk-dominant against all other strategies in the population.

2.4 Structured Population

2.4.1 Well-Mixed Population (Complete Graph)

The classic foundation of evolutionary game theory is based on differential equations, which define deterministic dynamics in well-mixed and indefinitely large populations (Hofbauer and Sigmund, 1998; Nowak et al., 2010; Sigmund, 2010). Infinitely large, well-mixed populations are an idealised version of the real world, though they are a useful simplification in the world of differential equations which are utilised in many evolutionary game theory models (Axelrod, 1984; Maynard-Smith, 1982).

For well-mixed populations, any two individuals interact with the same probability and is the reference point for any analysis of how a population structure affects evolution. Evolutionary dynamics depends on the population's structure that underlies interactions of individuals. The state of a population and its environment would affect the pattern of interactions amongst individuals in that population. Evolutionary dynamics have been traditionally studied in the context of a homogeneous, well-mixed population.

However, it is usually not the case that any interaction between any two individuals has the same probability to take place. For instance, a population's spatial distribution makes interactions between neighbours more likely than interactions between people who are farther apart. A population's spatial distribution makes connections between neighbours more feasible than connections between people who are farther apart. Friends will likely connect more frequently than strangers in human societies due to social network. These insights produced spatial methods for evolutionary game dynamics (Barabasi, 2014; Nowak and May, 1992, 1993) and later to evolutionary graph theory (Lieberman et al., 2005; Ohtsuki and Nowak, 2006; Ohtsuki et al., 2006).

2.4.2 Lattice Network

Interactions among evolutionary game players are important in studying their evolutionary behavior. Evolutionary dynamics of group interactions are often assumed on well mixed populations of structured populations. However, the study of the dynamics of group interactions is often not entirely in equilibrium but dynamic processes, e.g. biological, economical and social sciences.

If there is a departure from the assumptions of well-mixed populations, then there are some issues to be considered. Notably,

1. Which criterion determines how group configurations are sampled?

2. What kind of population sampling is used to implement replication competition among strategies?

In this regard, lattice networks represent simple topologies which are very useful to game theoretical models. Although they appear different to actual social networks, they provide rather useful considerations for exploring the consequences of a structure on the evolution of cooperation. The lattice network is identified as a uniform field for all competitive strategies when the network reciprocity is known. Network reciprocity, one of the five essential mechanisms for resolving social dilemmas according to Nowak (2006b), has drawn significant interest because, despite its basic premise (that is, "playing with neighbours on an underlying network and copying a strategy from them"), the model nonetheless appears to offer a workable explanation for how cooperation promotes survival in any practical situation (Tanimoto, 2017).

Spatial distribution of a population makes the interaction among neighbors more frequent than interactions between distant individuals. For spatial models, the fixed interaction network is defined by the points of a lattice and the edges between those points whose distance does not exceed a given value. Additionally, many variations of lattices corresponding to different interaction behaviour can be studied because of the availability of several lattices with specific properties of group interactions, see figure 2.1. This feature allows different interaction roles in the evolutionary roles to be tested (Perc et al., 2013b).

(a) Represents a square lattice where each player has 4 immediate neighbors so there is a group size of 5. The square lattice is the most popular structure with von Neumann neighborhood with four closest neighbors. There is a larger square lattice, the Moore neighborhood, where each player has 8 immediate neighbors so the group size is 9.

(b) Represents a honeycomb lattice with 3 immediate neighbors so there is a group size of 4.

(c) Represents a Kagome lattice with 4 immediate neighbors so there is a group size of 5. The Kagome lattice has overlapping triangle shapes which makes it more robust against group interactions.

(d) Represents a triangular lattice with 6 immediate neighbors so there is a group size of 7. The triangular lattice has overlapping triangles which makes it more robust against group interactions.

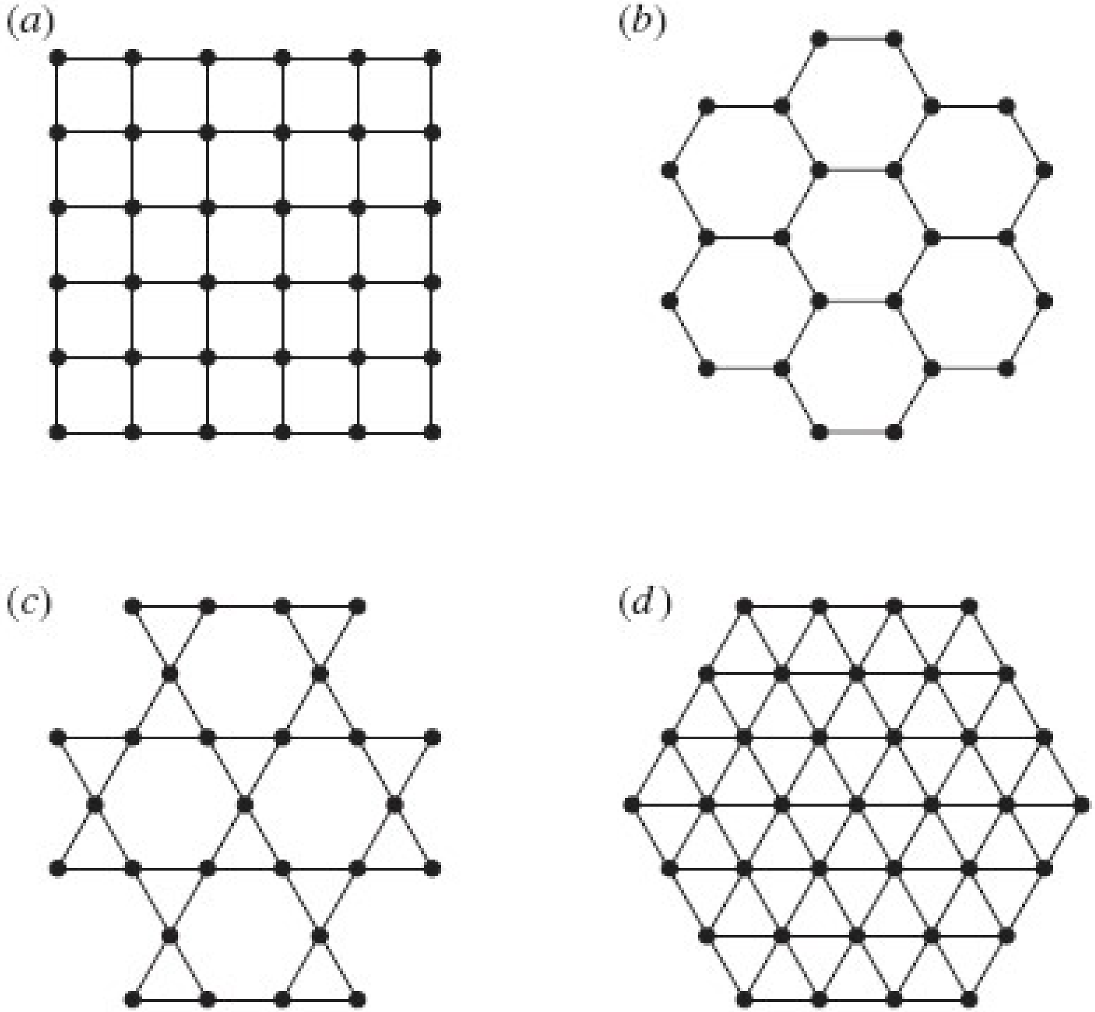

Fig. 2.1 Schematic of different types of lattices (Perc et al., 2013a)

Simulations on a square lattice with agents that imitate the behavior of their neighbor with the highest payoff demonstrated a significant level of cooperation in the prisoner's dilemma (Nowak and Sigmund, 1992). Since their work, evolutionary game has been studied on lattices and complex networks which show that lattice networks significantly promote collective cooperation among individuals (Shu et al., 2017).

2.4.3 Scale-Free Networks

In reality, populations are often heterogeneous where some individuals have more interactions (i.e. contacts) than others (Santos et al., 2006c). The connectivity can range from small degrees of association exhibiting Gaussian distribution, to large heterogeneity with degree distributions exhibiting a power-law behavior. Power-law networks include several significant characteristics, including the presence of hubs, a significant number of nodes with minimal connections, and a typical small-world behaviour (Artico et al., 2020). It is observed that for all cooperation dilemmas, increasing heterogeneity favors the emergence of cooperation (Santos et al., 2006c), such that long-term cooperative behavior easily resists short-term non-cooperative behavior. Therefore, it may be beneficial to extend the study to other forms of interconnection that conform to a network structure referred to as scale-free network (Perc et al., 2013b; Zhang et al., 2015). Networks in the real world are dynamic and heterogeneous. The evolving of networks occurs with new nodes (i.e. individuals) enter and create connections (i.e. interactions) to nodes that already exist. A network is a collection of connected objects such as individuals in a population. Objects are referred to as nodes (or vertices) and drawn as points and the connections between points are called edges.

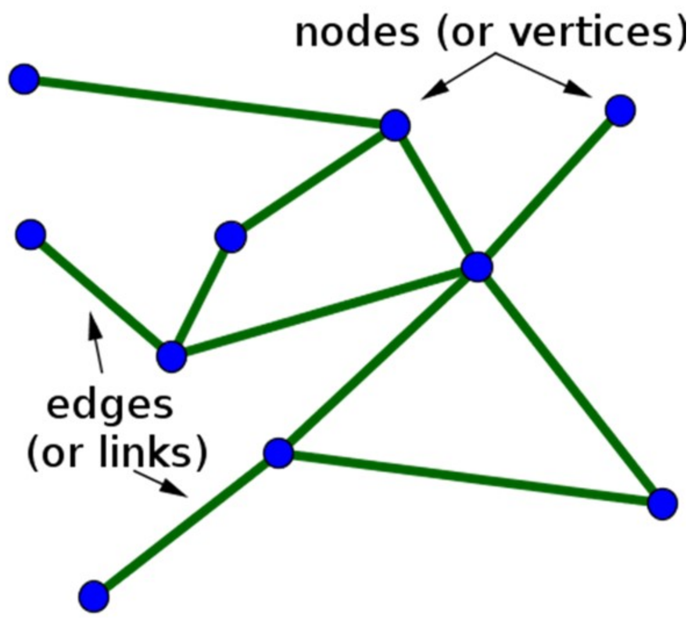

Fig. 2.2 A simple network

In reality, most nodes have a relatively small degree, but a few nodes will have very large degree (being connected to many other nodes)(Barabasi and Albert, 1999). Nodes with degree feature as hubs connections to many other nodes. Scale free networks are represented by the presence of large hubs. A hub is a node that is highly interconnected to other nodes in

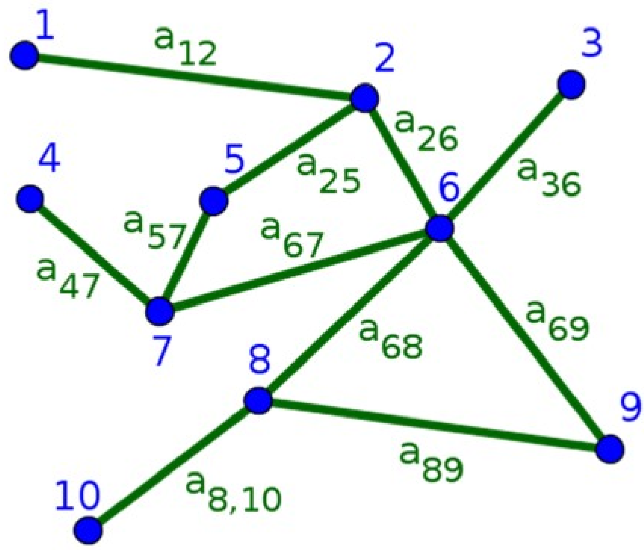

Fig. 2.3 Network with ten nodes and eleven edges

the network. With nodes in the network, the degree distribution will exhibit a long tail, which means the presence of nodes carrying a greater degree than the rest of the nodes present.

One of these models is the Barabasi and Albert (BA) model which is among the most well-known models used to explore extremely complicated, diverse networks. One of the BA model's key characteristics is that it adheres to a preferential attachment rule, has a low clustering coefficient and a power law degree distribution (Barabasi and Albert, 1999; Barabasi, 2014). A scale free network is one with a power-law degree distribution.

Despite the computation inconvenience, it is desirable to define networks with power-law because the distribution has the same function at all scales and so is referred to as scale free. The study of scale-free networks is prevalent in network science, which explores how scale-free structure shapes dynamic running over a network. Scale-free networks are also extensively used as a substrate for network based numerical simulations and experiments, which has been framed for providing a common basis for understanding all networks. Various researchers have carried out significant work on how network structural heterogeneity can affect the evolution of cooperation (Broido and Clauset, 2019; Cimpeanu et al., 2019a; Santos et al., 2008; Serafino et al., 2021).

The application of the power law is contested that it is difficult to decide if real-world networks are indeed scale free (Broido and Clauset, 2019). There are some controversies about the power law and how prevalent it is in empirical network. Early analyses resulted in the widespread acceptance that power law degree distribution being scale free are ubiquitous. Recently, more statistical techniques have emerged that doubt the extent of scale-free universality. Broido and Clauset (2019) argue that scale-free networks are rare after they fitted a power law model to the degree distribution of a variety of networks. It is clear that there exists a great deal of structural diversity between real world networks which is worth exploring since the approach of using scale-free structures has many advantages.

1. It provides a systematic procedure applicable to any network and treats all data sets equivalently.

2. It provides a method of assessing different networks by characterizing their empirical ubiquity.

2.5 Overview of Related Work

The problem of promoting the evolution of cooperative behaviour amongst populations of self-interested individuals has been studied across diverse fields of behavioural, social and computational sciences (Han, 2013; Nowak, 2006a; Perc et al., 2017; Sigmund, 2010; West et al., 2007). Numerous mechanisms that can promote the emergence and stability of cooperative behaviours among these selfish individuals have been proposed and analysed. They include kin and group selection (Hamilton, 1964; Traulsen et al., 2006), direct and indirect reciprocities(Han et al., 2012c; Krellner and Han, 2020; Ohtsuki and Iwasa, 2006; Okada, 2020; Sigmund and Nowak, 2005) spatial networks (Perc et al., 2013b; Santos et al., 2006b) reward and punishment (Boyd et al., 2003, 2010; Fehr and Gachter, 2000; Hauert et al., 2007; Sigmund et al., 2001b) and pre-commitments (Han et al., 2013a, 2016; Martinez-Vaquero et al., 2017; Nesse, 2001a; Sasaki et al., 2015b).

A highly relevant mechanism to this thesis work that has been utilised to promote cooperation is costly (peer) punishment in a one-shot interaction. In this mechanism, a punisher will pay a cost to punish another player who defects (Boyd et al., 2003; Egas and Riedl, 2008; Fehr and Gachter, 2000, 2002; Guala, 2012; Hauert et al., 2007). Differently from the application of commitment, costly punishment does not demand for a prior agreement deal from co-players before the interaction. Rather, players will reactively punish players that defect (if they can be identified) after the interaction has commenced. Costly punishers can evolve in a well-mixed population only if punishment is cost effective, i.e. the punished agent will incur a sufficiently large cost compared to that of the punisher, as shown by both theoretical and experimental studies (Anderson and Putterman, 2006; Boyd et al., 2003; Carpenter, 2007; Egas and Riedl, 2008; Han, 2016; Nikiforakis and Normann, 2008; Sigmund et al., 2001b; Wu et al., 2009). The effectiveness of punishment is, however, diminished by second-order free riders who do not cover the cost of punishment (Hauert et al., 2007; Ozono et al., 2016, 2017; Sigmund et al., 2010).

The public goods game is a popular framework numerous researchers have used to study human behaviour, where agents make a decision to contribute to a public account, the higher an agent's contribution to the public account the higher the group payoff. However, every agent also has an incentive to free ride and not contribute, hence the social dilemma (Nikiforakis and Normann, 2008). Results from studies show that the issue of free riding in a public goods game is pervasive and leads to the under provision of the public goods (Ledyard, 1994; Lerat et al., 2013; Ostrom, 1990a). To resolve free riding, various solutions have been experimented by researchers, one of such solutions which has gained significant attention is the use of a decentralized or peer punishments (this means individuals can punish each other without the intervention of a central authority) to discipline free riders in social dilemma experiments (Han and Lenaerts, 2016a; Powers et al., 2012; Sigmund et al., 2010). The use of such a punishment opportunity in a public goods games have increased cooperation amongst appropriators significantly.

Here, we tackle the coordination of agents to achieve a collective goal despite their individual preference. A Coordination game describes an incentive structure that rewards conformity, as such any player that does deviate would lead to a lower payoff for the whole population (Bayer et al., 2022). In the past different works have been explicitly carried out on coordination games. In a two-player game, the competition between a payoff-dominant and risk-dominant gained a lot of attention. With two equilibrium in a game, the selection issue is problematic. The selection problem in a coordination game relies on the payoff dominance and risk dominance (Harsanyi and Selten, 1990; Raducha and San Miguel, 2022).

On solving the issue of coordination, Cooper et al. (1992) carried out some experimental work on nonbinding and pre-play communication in a coordination game. Results from the experiment have shown that in the absence of prior communication between agents in a game, coordination failure is likely to occur, since there is no cooperative strategy. The result further shows that when players are given the chance to communicate before selecting an action, coordination failure will be reduced as prior communication would enable players to choose a desired outcome. This aligns with the previous work of DeJong et al. (1989), where experimental evidence shows that pre-play communication tackles coordination issues in a battle of the sexes game. In both the theoretical and analytical studies carried out, the issue of coordinating agents was reduced with pre-play communication but not completely eliminated as there is no binding agreement. Rabin's model of behaviour also analysed the results of pre-play communication in two-person games with complete information, in which players have the opportunity to communicate how they should play a game. That is, players create a new game where the sender (one player) can send a free message to the receiver (the other player) before engaging in the game. The issue is whether the chance to communicate affects results (Sobel, 2017). His key findings are that even copious communication cannot guarantee equilibrium results in the underlying game, as there is no binding agreement among players (Costa-Gomes, 2002; Rabin, 1994).

Less attention has been given to coordination in interactive decision-making problems in the past compared to cooperation in the Prisoner's Dilemma and Public Goods Games in which unilateral defection will lead to a better payoff than a mutual cooperation (Balliet et al., 2011; Colman and Gold, 2017;2018). Thomas et al. (2014) refer to coordination as mutualistic cooperation and cooperation of social dilemma type as altruistic cooperation. How agents can coordinate to achieve pay-off dominant outcomes, both in games with multi-Nash equilibrium and also in common-interest games (a single outcome payoff dominates all other outcomes)? Some researchers earlier proposed theories that involve alteration of the game specification for instance by engaging in repetitions (Aumann and Sorin, 1989) or communication among players as previously stated (Anderlini, 1999; Rabin, 1994) as some of the measures of reducing the problem of coordination to some extent (Cooper et al., 1992). Team reasoning is another theory that has been studied to resolve coordination problem. According to team reasoning theory, coordination issues of Stag Hunt type are resolved by players when they adopt a distinctive mode of strategic reasoning from preferences to strategy choices (Colman and Gold, 2017;2018). Common questions asked is: What do I want? and, what is my basic understanding of the complexity of the game and my expectations of what co-player's actions will be? What should I do to achieve this? In team reasoning, the unit of agency is removed from individuals to the pair, or more generally to the group of players, where each player is given the opportunity to ask what do we want and what should I do to play my part in achieving this? In team reasoning, players would first look for an outcome that would best benefit the pair or group of agents. Where this outcome exists and is unique, players would then participate and play their component strategies of the jointly optimal strategy (Colman and Gold, 2017;2018). Team reasoning may not be feasible where there is no uniquely best outcome for the group. Illustrated here is how team reasoning proffers solutions to coordination issue. In Aumann's Stag Hunt game, a team reasoning player notes that the (C, C) strategy profile is uniquely optimal for the player pair, because it offers the best possible payoff to both, and no other strategy profile will result in either player having a payoff as good as the payoff in (C, C). If both players adopt the team reasoning mode, then both will select and play their C strategies (Colman and Gold, 2017;2018). Team reasoning is best for resolving any common-interest game with a single payoff dominant outcome.

The Stag Hunt game describes a social interaction like an example of a scenario that involves a butcher and a baker deciding whether to coordinate their actions and sell hot dogs (Thomas et al., 2014). In the Stag Hunt game above, the outcome (C, C) is a Nash

Table 2.2 Payoff matrix for Stag Hunt Game

		Player 2	
		Cooperate	Defect
Player 1	Cooperate	$(9,9)$	$(0,8)$
	Defect	$(8,0)$	$(7,7)$

Table 2.3 Aumann's Stag Hunt Game, with R > T > P > S

		Player 2	
		Cooperate	Defect
Player 1	Cooperate	(R,R)	(S,T)
	Defect	(T,S)	(P,P)

equilibrium as the C strategies are best outcomes for each other. Neither player could get a better payoff by choosing differently against a co-player's choice of C. Against a C chooser, a player will get 9 by choosing C but only 8 by choosing D and it follows that neither player has a reason to regret choosing C if the co-player chooses it too. It is tempting to think that players who by definition seeks to maximize their own payoffs, will coordinate themselves to choose C in this game because the (C, C) equilibrium is better for all players than the (D, D) equilibrium (Colman and Gold, 2017;2018). The problem in this setting is that C is not an unconditionally best choice for the player, it is best only if the co-player chooses to play C as well. Coordinating these players to jointly take an action remains the hurdle in this type of scenarios in which our work seeks to tackle. Utilising team reasoning explains coordination by allowing groups to act as agents, if individual players would identify with the group (Lahno and Lahno, 2018). The group can be instrumentally rational and have outcomes that are good which can be achieved through rational decision-making of the individual players, given that they identify with the group. This raises the question of whether or not it is possible for people to identify with a group for instrumental reasons, as well as how they choose to identify with it (Colman and Gold, 2017;2018). Players first search for an outcome that would be best for the pair or group of players; if such an outcome exists and is unique, they then identify and play their component strategies of the jointly optimal strategy profile, and if there is no uniquely best outcome for the group, then team reasoning may not be feasible. Team thinking only seems feasible when members have a connection to the group.

2.6 Pre-commitment

Commitment, which allows the expression of an intention, has been applied in solving the issue of cooperation recently (Han et al., 2013a, 2017a; Sasaki et al., 2015b). People engage in commitment deals with others when they give up options with the aim of influencing others. Commitments usually rely on some form of incentive that is necessary to ensure that the action is in the agent's interest and thus be carried out (Gintis, 2001; Han and Lenaerts, 2016b; Nesse, 2001a), with some penalty for defaulting. The introduction of pre-commitment for resolving technology adoption coordination is the centre of this thesis. We explore how arranging a prior agreement or pre-commitment deal can be used as a mechanism for enhancing the population social welfare in a complex coordination problem, in both pairwise and multi-player interaction settings. This is studied both on a well-mixed and on structured populations. Closely related to our work is the study of pre-commitments used as mechanisms for the evolution of cooperation and in determining the outcome of strategic interactions (Han et al., 2017a). Ever since Schelling (1990), commitment has been a widely adopted concept in economics. Individuals can benefit from the opportunity to credibly bind themselves to certain actions or alternatively to remain flexible longer than their opponents (CARUANA and EINAV, 2008). Commitment is typically modelled through dynamic games in which one of the players is given a chance to make an initial binding action, allowing him to commit first (Han and Pereira, 2013; Han et al., 2017a).

Pre-commitments have been applied mostly in cooperative dilemmas and shown to enhance cooperation significantly if they are sufficiently enforced and the cost of setting up the pre-commitment deal is justified given the benefits derived from the interactions (Cherry and McEvoy, 2013; Ostrom, 1990a). The use of commitment-based strategies in understanding social behaviours is important that natural selection may have shaped specialised signalling capacities to enable this (Back and Flache, 2008; Nesse, 2001a; Santos et al., 2011; Skyrms, 2010).

The implementation of the pre-commitment strategies in different settings have been proven to be an antidote to social conflicts (Han et al., 2013a). As earlier stated, one major goal of this thesis is to explore through Evolutionary Game Theory (Hofbauer and Sigmund, 1998; Sigmund et al., 2010) how pre-commitments can be utilised to enable the emergence of coordination among technology firms. This will be explored for both a pairwise and multiplayer interactions with asymmetric benefits. According to Han et al. (2013a), to make a commitment deal reliable, a commitment proposer pays an arrangement cost. If the co-player agrees with the deal, then the proposer assumes that the opponent will adopt the agreed choice, yet there is no guarantee that this will actually be the case. In a situation whereby the co-player accepts the commitment though later does not honour it, she has to compensate the honouring co-player at a personal cost. Marriage is an example of a commitment that is widely recognised. Participants in a marriage contract give up options to leave someone else, gain security and a chance for a deeper relationship that may be impossible otherwise, as it may be impossible to ascertain a partner's intention of remaining faithful without the commitment of marriage. Arranging a commitment deal would help enhance cooperation even in situations where agents may not want to be cooperative. Also, an employment contract e.g. where the employer states the terms and conditions of the job is another form of a commitment deal. The employee is obligated to work according to the terms of the job or risk being fired. With these in place, both the employee and employer know what to expect and actions that can be taken if things go otherwise. A commitment deal helps to ensure that people bind to an agreement or face penalty depending on how the agreement is defined and the set rules.

To the best of our knowledge, there had been no work that studied how EGT can be applied in solving a coordination problem such as our technology adoption model which has an asymmetric payoff or benefit to be shared among players involved. Past works mostly utilized EGT to solve mutual cooperation problems where the outcome is symmetric. The dynamics of our technology adoption game is complex and therefore require some extra form of coordination among players. Thus we proposed to use pre-commitment in our technology adoption model to enhance coordination among the players. There is a research gap in this area which our work hopes to study and bridge.

2.7 Research Questions

From the above described literature review and background, we have identified some gaps in the literature which will be addressed in our work. Our work seeks to answer these research questions outlined below:

1. How can pre-commitments be utilised in achieving coordination and how to model them using an evolutionary game?

2. How can asymmetric benefits that might occur in technology adoption be resolved through costly commitment formation?

3. Whether and when is it advantageous to arrange and accept to engage in a costly commitment deal?

4. How does the dynamics and evolutionary outcomes of coordination change when moving from a pairwise (two-firm) competition to multi-firm one?

5. How does the population structure (such as homogeneous vs heterogeneous ones) affect the dynamics and evolutionary outcomes of technology adoption coordination, in presence or absence of pre-commitments?

Chapter 3

Technology Adoption Model (Two-Player Game)

In this chapter, we propose an evolutionary game model describing a pairwise technology adoption decision making, where two investment firms (or players) compete within a same product market who need to make strategic decision on which technology to adopt. We first present our model where a pre-commitment (agreement deal) is absent and then extend the model to explore whether pre-commitments would be a viable evolutionary mechanism for enhancing coordination among the firms.

3.1 Introduction

The design of mechanisms that can help achieve coordination in populations of self-regarding agents continues to be recognised as a major challenge within several areas of social, life and engineering sciences. It is ubiquitous in real-world situations, human organisations, technological innovations and social networks (Han et al., 2019; Ostrom, 1990a; Pitt et al., 2012; Sigmund et al., 2001a).

Several mechanisms that can promote the emergence and stability of collective behaviours among such individuals, have been proposed, see again detailed discussion in the previous chapter. They include kin and group selection, direct and indirect reciprocities, spatial networks, reward and punishment (Nowak, 2006b).

Recently, the capacity to create, and commit to, prior agreements (Frank, 1988; Han et al., 2015c, 2017a; Nesse, 2001c) has been proposed as an evolutionarily viable strategy inducing cooperative behaviour in the context of cooperation dilemmas; namely, the Prisoner's Dilemma (PD) (Han et al., 2013a) and the Public Goods Game (PGG) (Han et al., 2017a). It provides an alternative to different forms of punishment against inappropriate behaviour and of rewards to stimulate the appropriate one (Martinez-Vaquero et al., 2015; Powers et al., 2012; Sasaki et al., 2015b). These works have solely focused on the roles of commitments for enhancing mutual cooperation among self-interested individuals. However, commitments can be adopted as a tool for enhancing other types of collective behaviour such as coordination (Barrett, 2016; Nesse, 2001c; Ostrom, 1990a), which our work seeks to address. In the context of cooperation dilemma games such as the PD and PGG (Nowak, 2006b), mutual cooperation is the only desirable collective outcome to which all parties are required to commit if an agreement is to be arranged. In contrast, in a coordination problem, there might be multiple optimal or desirable collective outcomes and players might have distinct, incompatible preferences regarding which outcome a mutual agreement should aim to achieve (e.g. due to asymmetric payoffs).

The issue of coordination which our work seeks to address presents a choice between conflicting preferences of different agents which must be made on some conditions set. Considering technology adoption decision-making, it is quite a challenge to tackle coordination among different firms to achieve a common goal for the social welfare of the population.

The research question here is to identify the processes involved in technology adoption using EGT. To answer the question, this chapter will systematically describe our technology adoption model, showcasing the players' strategic interactions.

3.2 Model description

In our work, we consider a situation in which two firms (players) are able to compete against one another within a common product market. They must first choose which technology to invest in strategically. A low benefit (L) or high benefit (H) technology might be chosen as an investment option. The adoption of a high technology will result in a high return on investment as opposed to adopting a low technology, which would result in the firm obtaining a low profit on investment.

The outcome of the players' interaction in this scenario is described in terms of costs and benefits of investments, using the cost-benefit analysis which measures the benefits of a decision or taking action minus the costs associated with taking that action. In our model, we describe both the cost of adopting a high technology and low technology as c_H and c_L respectively. Cost here, is the value or money that the firms will spend to adopt or invest in either a high technology or low technology. We also ascribed α (alpha) to mean the competitive level of the market. Where two firms adopt the same technology, they both share the benefit. Hence, obtaining only a partial benefit. Further description of the notations used in our model is shown in table 3.1 below.

3.2.1 Notations

For easy representations, different notations are utilised in the design and the development of our technology adoption model. The table below lists the notations used and further gives a description of the various notations used in our model.

Table 3.1 Description of Notations

Notations Used	Description
H	Represents high benefit technology
L	Represents low benefit technology
b_H	Benefit of adopting/investing in a high technology
b_L	Benefit of adopting/investing in a low technology
c_H	Cost of adopting/investing in a high technology
c_L	Cost of adopting/investing in a low technology
α	Competitive level of the market

Considering the cost and benefit of investment to this game, the resulting profits to each firm for the alternative strategies taken are given by the payoff matrix displayed below. The two strategies of firm A correspond to the two rows and the two strategies of firm B correspond to the two columns of the matrix. The entries of the matrix represent their payoffs when they choose their strategies.

$$\begin{array}{cc} & \begin{array}{cc} H & L \end{array} \\ \begin{array}{c} H \\ L \end{array} & \begin{pmatrix} \alpha b_H - c_H & b_H - c_H \\ b_L - c_L & \alpha b_L - c_L \end{pmatrix} \end{array} := \begin{array}{cc} & \begin{array}{cc} H & L \end{array} \\ \begin{array}{c} H \\ L \end{array} & \begin{pmatrix} a & b \\ c & d \end{pmatrix} \end{array} \tag{3.1}$$

The above matrix satisfies the following conditions:

- H always lead to a higher benefit than L, that is $b_H > b_L$ and also leads to a greater net benefit, that is b_H - $c_H > b_L - c_L$
- Also, $\alpha < 1$ represents the competitiveness level when two firms adopt the same technology, i.e. they obtain only a partial benefit.
- It satisfies that $b > a$ and $c > d$ whenever $\alpha < 1$. The payoff matrix corresponds to the parameters satisfying either of this order (since $b > c$): $b > a > c > d$ or $b > c > a > d$.

The payoff $b_H - c_H$ above represents the benefit obtained in full when one of the two firms decides to adopt a high technology and the other a low technology. In this case, the payoff $b_H - c_H$ is given to the firm who adopts a high technology. This payoff has the highest benefit possible among the payoffs.

On the contrary, the payoff $\alpha\, b_H - c_H$, represents a partial benefit obtained from adopting a high technology. This occurs when both firms A and B adopt a high technology. α here indicates their competitive level, as they both receive partial benefit or return of investment for adopting the same technology.

Also, the payoff $b_L - c_L$ is a full benefit payoff received when one firm adopts a low technology and the other firm adopts a high technology. This payoff is for the firm that adopts the low technology which will lead to a lower profit gained. Lastly, the payoff $\alpha\, b_L - c_L$ is obtained when both firms together adopt a low technology. They both receive a partial benefit for adopting the same technology.

In our work, to illustrate the two different orderings of payoff entries above, we numerically study two configurations, namely, game 1 and game 2, below.

1. For game 1 ($a = 2$, $b = 5$, $c = 1$, $d = 0$) i.e, when $\alpha = 0.5$, $c_L = c_H = 1$, $b_H = 6$, $b_L = 2$.

2. For game 2 ($a = 0.5$, $b = 2$, $c = 1$, $d = 0$) i.e, when $\alpha = 0.5$, $c_L = c_H = 1$, $b_H = 3$, $b_L = 2$.

The payoff matrices for these games (game 1 and 2) are given as:

$$\begin{array}{cc} & \begin{array}{cc} H & L \end{array} \\ \begin{array}{c} H \\ L \end{array} & \begin{pmatrix} 2 & 5 \\ 1 & 0 \end{pmatrix} \end{array} \text{ and } \begin{array}{cc} & \begin{array}{cc} H & L \end{array} \\ \begin{array}{c} H \\ L \end{array} & \begin{pmatrix} 0.5 & 2 \\ 1 & 0 \end{pmatrix} \end{array} \tag{3.2}$$

3.2.2 Without Commitment

It is clear from this scenario that it will always be in their individual interest to outsmart the other firm by adopting a high-quality technology which will offer them a higher profit. Each of these firms will want to go for a high-fast quality technology, with the hope that the other firm goes for a low-slow quality technology. Where both firms adopt same technology, there will be a partial benefit for both firms, see payoff matrix 3.1.

Given this, we explored how players here can be coordinated to maximise profit. Clearly, we see from the payoff matrix 3.1 that the players would benefit more when they are coordinated to adopt different technologies. From the first payoff matrix, both players choosing strategy H and H, or H and L is the Nash equilibrium. Individually, the players may fail to take an action that would be in their collective interest, hence the coordination problem our work aims to address here.

It is noteworthy to state that although we have designed our model in terms of technology adoption decision making, it is generally applicable to several other coordination problems, for instance wherever there are strategic investments decisions to make (in competitive markets of any products) and even in other interactions that requires strategic decision-making.

3.2.3 In the Presence of Commitment

The application of commitment deal as we have earlier discussed remains one of the methods used to promote the emergence of cooperation even in a coordination dilemma such as our technology adoption game (Han et al., 2013a, 2017b). Although commitment may not have gained much attention, here we studied both analytically, numerically and also carrying out simulations on how commitment can help to enhance the coordination of firms in technology adoption investment.

After our first interactions on a two-player game where firms compete for a particular technology adoption to adopt and invest in, we have realised that individual interests will always prevail in this setting. Each of these players (firms) will always think rationally by putting their investments where they are guaranteed of a huge profit margin than where they will get a lesser profit, especially as they are aware of the outcome of their choices. Although they cannot control the choice of their opponent, but they would choose what they consider as best choice for themselves.

Now, the problem we gather from this setting is that if both players go by their choice of adopting, they will most likely adopt a high technology with the hope that the other party adopts a low technology. We see a dilemma here on the choice of adoption or technology to invest here. This may also result in both players adopting a high technology, since no one would want to adopt a low technology with a lesser benefit. In a population where there is a need for the adoption of a high and low technology, all firms choosing to adopt a particular technology that is, a high technology in this case will not be good for the welfare of the overall population. Someone will have to adopt a low technology, but the issue is who? Which of these firms clearly seeing that adopting a higher technology would result to a higher benefit would intentionally go for adopting a low technology with lower benefit without any condition, agreement or coercing to do so? Note that, in our technology adoption game, we have assumed and set our parameters so that when both firms adopt same technology, they will have a partial benefit as the benefit of adopting the technology will be shared between the two firms. We have set this because we are modelling a case whereby there are a variety of different technologies (high and low technology) in the market. If for instance, we consider a scenario whereby all firms should adopt same technology (i.e. it is optimal for the population collectively to adopt high technology), the dynamics of our technology adoption game will change as we will set the parameters to favour adoption of same technology rather than different technologies. This scenario occurs when α is sufficiently high.

We hereby see a need to extend our technology adoption model to allow players to have the option of arranging a prior commitment deal before their interaction (Han et al., 2013a). We considered a case whereby one of the players in the game would act as a commitment proposer and ask the co-player to adopt a different technology. That is they both go into a strategic interaction and agreement, where a strategist intending to adopt a High quality technology (respectively L) would ask the co-player to adopt a Low quality technology (respectively H). We denote these commitment proposing strategies as HP and LP, respectively. Similar to previous models of commitments (for Prisoner's Dilemma Game and Public Goods Game) (Han et al., 2013a, 2017b), to ensure that the commitment deal is reliable, a commitment proposer is required to pay a cost (ε) for arranging the commitment deal. If the co-player accepts the terms of the commitment deal, then the commitment proposer assumes that the opponent will adopt the agreed choice, although there is no guarantee that the co-player will comply with the terms and conditions of the agreement. However, whenever a co-player refuses to commit, the HP and LP which are the commitment proposes would play H in the game, that is they chose to adopt a high technology whenever co-player refuses to accept a commitment proposal. In the case where a co-player accepts a commitment deal but later fails to honour the deal by keeping to the agreement, the co-player is required to compensate the honouring co-player at a personal cost δ. In our model, in line with (Han et al., 2013a, 2017a), we implicitly assumed a third party (e.g. an external institution) who ensures that the compensation cost δ is paid by dishonouring players. This compensation cost is set to be higher than the cost of arranging the commitment deal so that the commitment proposal who pays the cost of arranging a commitment does not entirely lose out when a co-player dishonours an agreement.

Differently from previous models on Prisoner's dilemma and public goods game where an agreed outcome leads to the same payoff for all the parties involved in the agreement (mutual cooperation benefit), in our current technology adoption model with commitment such an outcome would result to different payoffs for the parties involved. Therefore, we have designed in this commitment model that as part of the agreement made between the players, the HP would compensate after the game an amount $\theta 1$ to accepted player that honours the agreement, while the LP would request a compensation $\theta 2$ from such an accepted co-player.

Besides the HP and LP, we also consider a minimal model with the following basic strategies in this commitment version:

- We mapped out the non-proposing acceptors namely the HC and LC, who always commit when being proposed a commitment deal wherein they are willing to adopt any technology proposed (even when it is different from their intended choice), they always honour the adopted agreement, but do not propose a commitment deal themselves. They play their intended choice, i.e H and L, respectively, when there is no agreement in place.

- The Non-acceptors which are the HN and LN, who do not accept a commitment deal. They play their intended choice during the game and they also do not propose commitment deal to others in the game. They generally do not accept commitment nor propose a commitment deal.

- Another category called the false committers, specifically the HF and LF, who accept a commitment proposal when approached but make the opposite choice when the game is actually played. The goal of the HF and LF is to take advantage of players who offer to make commitments without having to bear the repercussions. Thus, after accepting a commitment deal from the proposers, they violate it by acting in a way that is inconsistent with the terms of the agreement.

Similar to the commitment models for the PD game (Han et al., 2013a), it should be noted that some potential strategies have been left out of the analysis because, in every possible configuration of the game, at least one of the strategies dominates them. This means that leaving them out of the analysis would not affect the results. For instance, individuals who propose a commitment (i.e paying a cost ε), but do not follow through on it (and must pay the compensation when dealing with acceptors who do so) would be dominated by the comparable non-proposers.

Bringing everything together, the model is made up of eight strategies that work together to generate the following payoff matrix, which depicts the typical average payoffs that each strategy will experience when it interacts with one of the other seven strategies (where we denote $\lambda = \theta_1 + \theta_2$, $\lambda_1 = b - \varepsilon - \theta_1$, $\lambda_2 = c - \varepsilon + \theta_2$, $\lambda_3 = a - \varepsilon + \delta$ and $\lambda_4 = d - \varepsilon + \delta$, purely for the purpose of being represented very clearly).

We first designed a model where the commitment proposer LP plays their default choice L when co-player refuses their commitment proposal. LP in this instance is a commitment proposal that asks a co-player to adopt or invest on a High technology (H) while they the LP's adopt a low technology (L). The LP's strategy pays for the cost of the commitment deal (if the co-player agrees), adopts a low technology and requests from co-player who adopts a high technology for share of benefit $\theta 2$, as they have adopted a high profit technology which gives them a higher return of investment than the LP's. If co-player refuses the commitment proposal from LP, play here plays their default choice, which is adopting a low technology (L). The payoff matrix designed for this interaction is given as:

$$\begin{array}{c} \\ \text{HP} \\ \text{LP} \\ \text{HN} \\ \text{LN} \\ \text{HC} \\ \text{LC} \\ \text{HF} \\ \text{LF} \end{array} \begin{array}{c} \begin{array}{cccccccc} \text{HP} & \text{LP} & \text{HN} & \text{LN} & \text{HC} & \text{LC} & \text{HF} & \text{LF} \end{array} \\ \begin{pmatrix} \frac{b+c-\varepsilon}{2} & \frac{2b-\varepsilon-\lambda}{2} & a & b & \lambda_1 & \lambda_1 & \lambda_3 & \lambda_3 \\ \frac{2c-\varepsilon+\lambda}{2} & \frac{b+c-\varepsilon}{2} & c & d & \lambda_2 & \lambda_2 & \lambda_4 & \lambda_4 \\ a & a & a & b & a & b & a & b \\ c & c & c & d & c & d & c & d \\ c+\theta_1 & b-\theta_2 & a & b & a & b & a & b \\ c+\theta_1 & b-\theta_2 & c & d & c & d & c & d \\ a-\delta & d-\delta & a & b & a & b & a & b \\ a-\delta & d-\delta & c & d & c & d & c & d \end{pmatrix} \end{array}. \tag{3.3}$$

Differently from the first payoff, upon exploring, we further designed a model where its payoff matrix considers when co-player refuses LP commitment proposer. The LP's plays their most favourable choice (H) in this game instead of sticking to playing their default choice (L) as seen in the first payoff matrix. LP is considered to make the smart choice here compared to the first payoff matrix. This payoff matrix where the LP plays the most favourable choice (H) when a co-player refuses an agreement deal. This choice is adopted in our technology adoption model. Adopting this, we have defined our model for the LP's to always adopt a high technology (that is, plays H) whenever they encounter rejection from co-players upon proposing a commitment deal. The payoff matrix for this model where LP's plays H when they are refused commitment deal is given as:

$$\begin{array}{c} \\ \text{HP} \\ \text{LP} \\ \text{HN} \\ \text{LN} \\ \text{HC} \\ \text{LC} \\ \text{HF} \\ \text{LF} \end{array} \begin{array}{c} \begin{array}{cccccccc} \text{HP} & \text{LP} & \text{HN} & \text{LN} & \text{HC} & \text{LC} & \text{HF} & \text{LF} \end{array} \\ \begin{pmatrix} \frac{b+c-\varepsilon}{2} & \frac{2b-\varepsilon-\lambda}{2} & a & b & \lambda_1 & \lambda_1 & \lambda_3 & \lambda_3 \\ \frac{2c-\varepsilon+\lambda}{2} & \frac{b+c-\varepsilon}{2} & a & b & \lambda_2 & \lambda_2 & \lambda_4 & \lambda_4 \\ a & a & a & b & a & b & a & b \\ c & c & c & d & c & d & c & d \\ c+\theta_1 & b-\theta_2 & a & b & a & b & a & b \\ c+\theta_1 & b-\theta_2 & c & d & c & d & c & d \\ a-\delta & d-\delta & a & b & a & b & a & b \\ a-\delta & d-\delta & c & d & c & d & c & d \end{pmatrix} \end{array}. \tag{3.4}$$

Here, we will further explain how some of the strategies in the payoff matrix are derived. Which is given as:

- HP AND HP

  When two commitment proposers interact in a game, they both have a 50% chance of paying the cost of setting up the agreement. Also, 50% chance of acting as the receiver in the game. Therefore, 50% of the time the first HP may either be the commitment proposer or receiver on average. Only one of them need to pay the cost of arranging a commitment.

  50% if the first HP is a proposer, it gets b - ε - θ_1

  50% if the first HP is a receiver, it gets c + θ_1

  Therefore, the average payoff of HP when playing with another HP is given as:

  $\frac{1}{2}(b-\varepsilon-\theta_1+c+\theta_1) = \frac{1}{2}(b+c-\varepsilon)$.

  Note that we considered an *an agreement to be fair* if both parties obtain the same benefit when they honour it (after having taken into account the cost of setting up the agreement). For that, we can show that θ_1 and θ_2 must satisfy $\theta_1 = \frac{b-c-\varepsilon}{2}$ and $\theta_2 = \frac{b-c+\varepsilon}{2}$ [1], and thus, both parties obtain $\frac{b+c-\varepsilon}{2}$.

  With these conditions, it also ensures that the payoffs of HP and LP when interacting with each other are equal.

- LP AND HP

  Similar to HP interacting with another HP, when two commitment proposers are involved in a game they both have a 50% chance of paying the cost of setting up the agreement, which is acting as the proposer.

  50% of the time LP may either be the commitment proposer or receiver

  50% if the LP is a proposer it gets c - ε + θ_2, while HP gets b – θ_2

  Therefore, the average payoff when LP is playing with HP is given as:

  $\frac{1}{2}(c-\varepsilon+\theta_2+b-\theta_2) = \frac{1}{2}(c+b-\varepsilon)$.

- HN AND HN

  The payoff matrix for HN if it interacts with another HN in the game is A. This is achieved as the conditions for HN states that they do not propose nor accept commitment proposal in a game. They play their default choice H.

[1] These can be obtained for instance by comparing the payoffs of HP and HC when they interact, i.e. $b-c-\theta_1 = c+\theta_1$. Solving this equation we would obtain $\theta_1 = \frac{b-c-\varepsilon}{2}$. Similarly for θ_2.

- HC AND HP

  When HC and HP are involved in a game, the payoff for HC is c + θ_1 accepts proposals from the commitment proposing strategies like the HP's and LP's but they do not propose to co-players .

  HC accepts to play L, which the payoff is c and gets θ_1 (shared benefit from HP who proposed). Hence, the payoff of HC when playing with the HP strategy is c + θ_1.

- HFAKE AND HP

  From the conditions given, the HFAKE strategy accepts a commitment proposal but dishonours the agreement by playing the opposite.

  Therefore, when HFAKE and HP play a game. The HP strategy proposes to HFAKE to play L. HFAKE accepts but dishonour the agreement by playing H which is the opposite of what HP proposes and against their agreement. HFAKE pays δ (compensation cost) for defecting in the game.

  Hence, the payoff for HFAKE when played with HP is a – δ.

  Note that in our model, in line with previous commitment models (Han et al., 2013a, 2017a), we implicitly assumed a third party (e.g. an external institution) who ensures that the compensation cost δ is paid by dishonouring players.

3.3 Summary of Methods

Evolution happens in populations of reproducing individuals and the composition of a population structure can have effect on which traits evolve in that population (Allen et al., 2017). Evolutionary dynamics remains an important aspect in this study. Thus, we first start by conducting theoretical analysis and numerical simulations using Evolutionary Game Theory methods for finite population size (Imhof et al., 2005; Nowak et al., 2004). In this situation, each person's payoff corresponds to their level of fitness or social success, and social learning shapes evolutionary dynamics (Hofbauer and Sigmund, 1998; Rendell et al., 2010; Sigmund, 2010; Traulsen and Nowak, 2006), whereby the most successful individuals in the population will tend to be imitated more often by the other individuals. The cumulative payoff from all encounters imitates an individual's fitness or social success within the context of evolutionary game theory (EGT). Any participant in a game has the potential to alter their approach by adopting the approach of another player with a probability that is determined by the Fermi probability distribution. A strategy that, for instance, has a greater average reward or fitness than another will be more frequently imitated by that strategy. See chapter two, section 2.3.

- **Average Payoff for the Two Player Game**
  Let N be the size of the population. Denote $\pi_{A,B}$ the payoff a strategist A obtains in a pairwise interaction with strategist B (defined in the payoff matrices in equations (3.2) and (3.4)). Suppose there are at most two strategies in the population, say, k individuals using strategy A ($0 \leq k \leq N$) and $(N-k)$ individuals using strategies B. Thus, the (average) payoff of the individual that uses A and B can be written as follows, respectively,

$$\begin{aligned} \Pi_A(k) &= \frac{(k-1)\pi_{A,A} + (N-k)\pi_{A,B}}{N-1}, \\ \Pi_B(k) &= \frac{k\pi_{B,A} + (N-k-1)\pi_{B,B}}{N-1}. \end{aligned} \tag{3.5}$$

  Now, the probability to change the number k of individuals using strategy A by $\pm$ one in each time step can be written as(Traulsen et al., 2006)

$$T^{\pm}(k) = \frac{N-k}{N}\frac{k}{N}\left[1 + e^{\mp\beta[\Pi_A(k) - \Pi_B(k)]}\right]^{-1}. \tag{3.6}$$

  The fixation probability of a single mutant with a strategy A in a population of $(N-1)$ individuals using B is given by (Nowak et al., 2004; Traulsen et al., 2006)

$$\rho_{B,A} = \left(1 + \sum_{i=1}^{N-1}\prod_{j=1}^{i}\frac{T^-(j)}{T^+(j)}\right)^{-1}. \tag{3.7}$$

Considering a set $\{1,...,q\}$ of different strategies, these fixation probabilities determine a transition matrix $M = \{T_{ij}\}_{i,j=1}^{q}$, with $T_{ij,j\neq i} = \rho_{ji}/(q-1)$ and $T_{ii} = 1 - \sum_{j=1,j\neq i}^{q} T_{ij}$, of a Markov Chain. The normalised eigenvector associated with the eigenvalue 1 of the transposed of M provides the stationary distribution described above (Imhof et al., 2005), describing the relative time the population spends adopting each of the strategies.

Risk-dominance An important measure to compare the two strategies A and B is which direction the transition is stronger or more probable, an A mutant fixating in a population of individuals using B, $\rho_{B,A}$, or a B mutant fixating in the population of individuals using A, $\rho_{A,B}$. That is, comparing the two strategies A and B, to know which direction the transition is

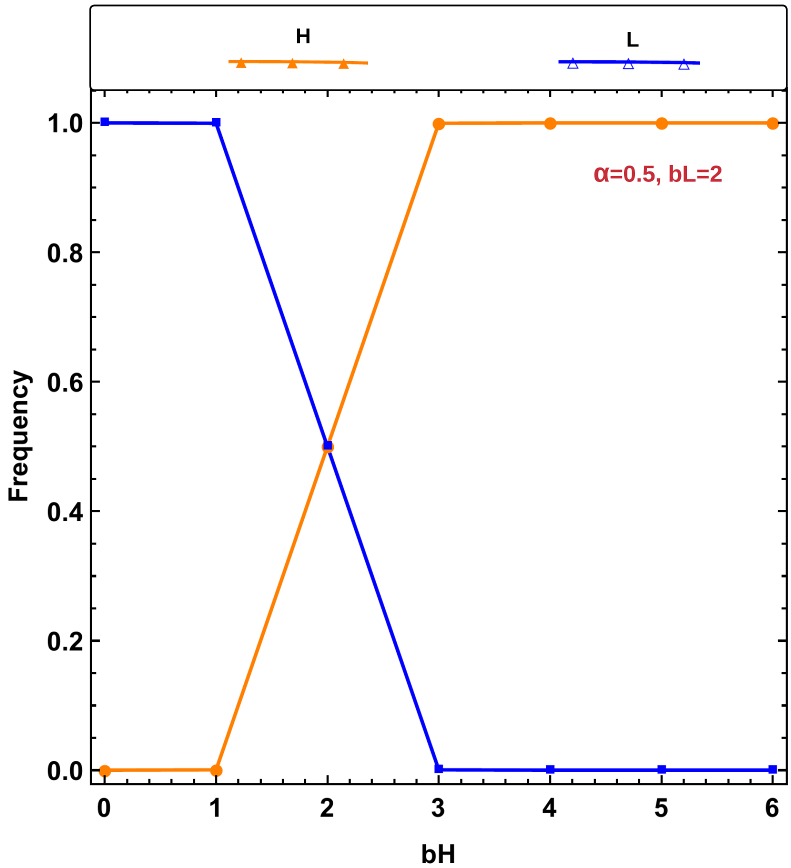

Fig. 3.1 **Effect of b_H varied when commitment is absent**. In general, we observed that when b_H is significantly low, the population would adopt a low technology and when b_H is sufficiently high, the population would be dominated by the high technology adopters. Parameters: $c_H = 1$, $c_L = 1$, $b_L = 2$, $\alpha = 0.5$

stronger or more probable, an A mutant fixating in a population of individuals using B, or a B mutant fixating in the population of individuals using A. If the first was more probable than the latter then we say that A is risk-dominant against B (see again Chapter 2, Section 2.3).

$$\pi_{A,A} + \pi_{A,B} > \pi_{B,A} + \pi_{B,B}. \tag{3.8}$$

3.4 Results

3.4.1 When Commitment is Absent

From our analysis and simulations of the technology adoption games 1 and 2, we observe here how players would make their decision on technology adoption when there is no form

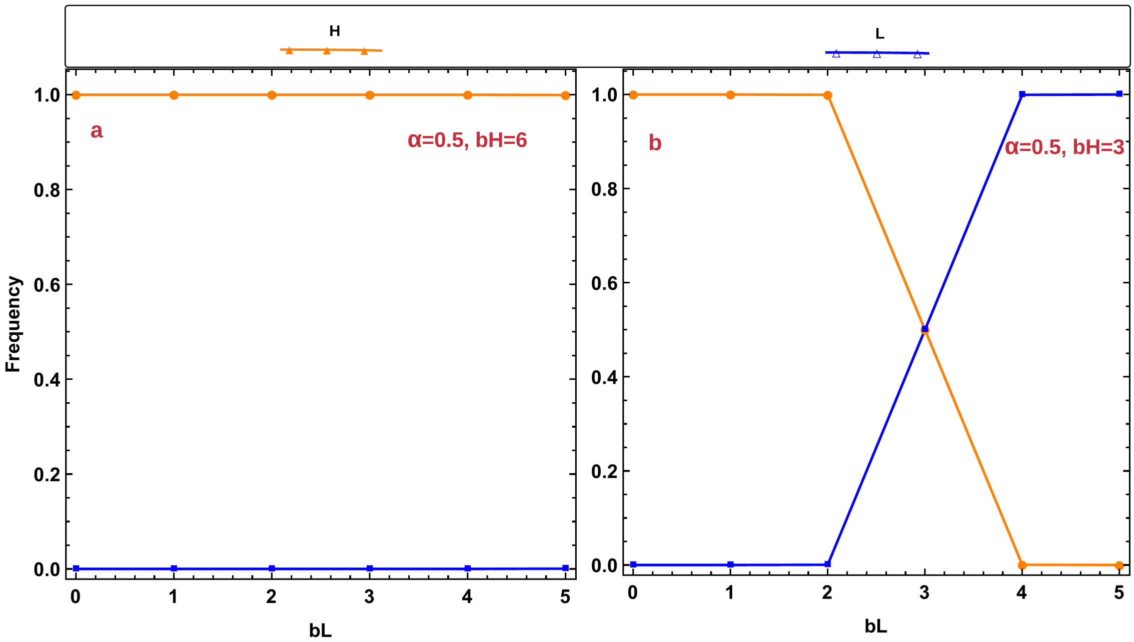

Fig. 3.2 **Effect of b_L varied when commitment is not present** We varied here the value of b_L in two different game configurations. We observed from the left panel that at all points of b_L, the H strategy has a higher frequency than the L strategy, given that we have a moderate competitive level at $\alpha = 0.5$ and a high benefit of adopting $b_H = 6$, the population would always want to adopt a high technology in this case. We see some difference in our result from the right panel. Parameters: in all panels $c_H = 1$, $c_L = 1$, $\alpha = 0.5$; Panel a) $b_H = 6$ (i.e. $b = 5$) and panel b) $b_H = 3$ (i.e. $b = 2$).

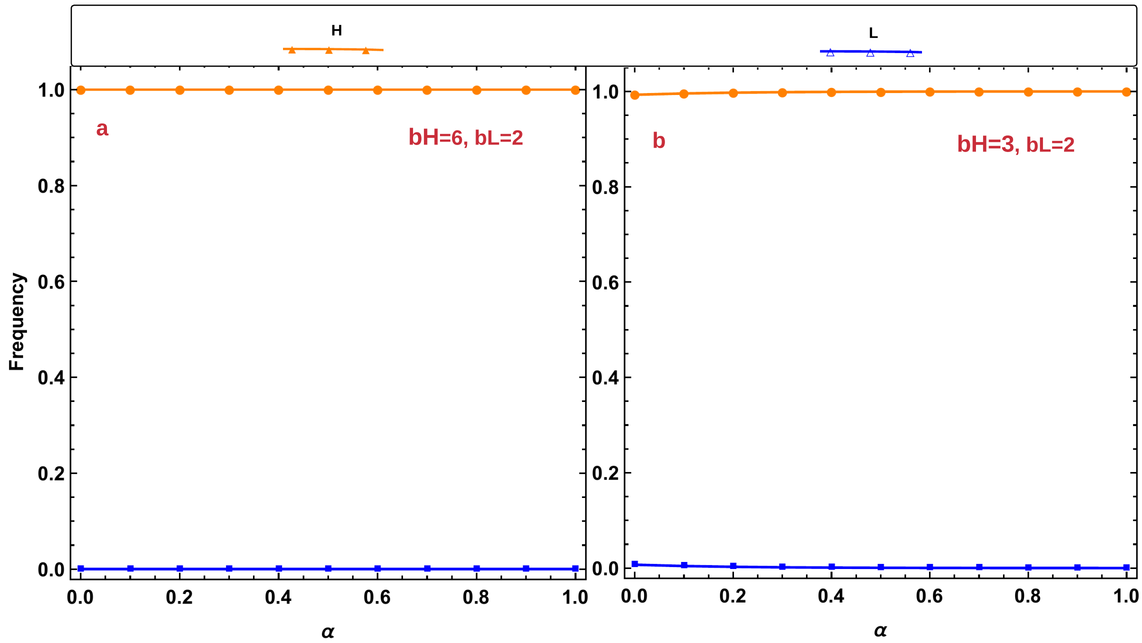

Fig. 3.3 **Effect of α when commitment is not present**. In general, we observed that at all points of α in both games, the H strategy dominate the population as seen in panel a and b. This means, whether the market is competitive or not, the H strategy will always dominate the population. α here shows the level of competitiveness of the market. Parameters: in all panels $c_H = 1$, $c_L = 1$, $b_L = 2$, $\alpha = 0.5$; Panel a) $b_H = 6$ (i.e. $b = 5$) and panel b) $b_H = 3$ (i.e. $b = 2$).

of commitment or agreement deal in place. We see that the default choice for players will always be to choose the H strategy, which is the adoption of a high technology as it promises a higher return of investment than adopting a low technology. When both players choose to adopt a high technology, they get a partial benefit which is represented in panel a and b in figure 3.3. However, even with the partial benefit obtained, panel a and b shows that players will still choose to adopt a high technology, which shows a need to coordinate these players to act collectively and in the overall best interest of the population. The player's problem in this game is how to coordinate their choices. Are there any mechanism that can be utilised to enhance coordination amongst the players? Prior agreements (Frank, 1988; Han et al., 2015c, 2017a; Nesse, 2001c) has been proposed as an evolutionary viable strategy inducing cooperative behaviour in the context of cooperation dilemmas; namely, the Prisoner's Dilemma (PD) (Han et al., 2013a) and the Public Goods Game (PGG) (Han et al., 2017a). Although their works focused on the roles of commitments for enhancing mutual cooperation among self-interested individuals. Prior agreement/commitment can also be utilised for enhancing coordination (Barrett, 2016; Nesse, 2001c; Ostrom, 1990a), as we further explore in our technology adoption game. We investigate how coordination can be achieved even in a complex game where all players have their own self-interest but still needs coordination to achieve a common goal for the social welfare.

3.4.2 Conditions for the viability of commitments

First of all, using pair-wise analysis (using Equation 3.8) it can be shown that if:

$$\theta_1 + \theta_2 < b - c$$

then HP is preferred (i.e. risk-dominant, see Methods) to LP. Otherwise, LP is risk-dominant against HP.

We now derive the conditions regarding the commitment parameters for which HP and LP are viable strategies, i.e. when they are risk-dominant against all other non-proposing strategies. Namely, using Equation 3.8 we can derive that HP and LP are risk-dominant against all other six non-proposing strategies, respectively, if and only if

$$\begin{aligned}
&\varepsilon < \min\{b+c-2a, 3b-c-2d, \frac{3b-c-2a-4\theta_1}{3},\\
&\quad \frac{3b-c-2d-4\theta_1}{3}, \frac{b+c-2a+4\delta}{3}, \frac{b+c-2d+4\delta}{3}\},\\
&\varepsilon < \min\{b+c-2a, 3b-c-2d, \frac{3c-b-2a+4\theta_2}{3},\\
&\quad \frac{3c-b-2d+4\theta_2}{3}, \frac{b+c-2a+4\delta}{3}, \frac{b+c-2d+4\delta}{3}\}.
\end{aligned} \tag{3.9}$$

Note that each element in the *min* expressions above corresponds to the condition for one of the six non-proposing strategies HN, LN, HC, LC, HF, LF, respectively.

Thus, we can derive the conditions for θ_1, θ_2 and δ:

$$\begin{aligned}
\theta_1 &< \frac{1}{4}\left(3b-c-3\varepsilon-2\max\{a,d\}\right),\\
\theta_2 &> \frac{1}{4}\left(b-3c+3\varepsilon+2\max\{a,d\}\right),\\
\delta &> \frac{1}{4}\left(3\varepsilon-b-c+2\max\{a,d\}\right).
\end{aligned} \tag{3.10}$$

In particular, for fair agreements, i.e. $\theta_1 = (b-c-\varepsilon)/2$ and $\theta_2 = (b-c+\varepsilon)/2$, we obtain

$$\begin{aligned}
\varepsilon &< \min\{3b-c-2d, b+c-2\max\{a,d\}\},\\
\delta &> \frac{1}{4}\left(3\varepsilon-b-c+2\max\{a,d\}\right).
\end{aligned} \tag{3.11}$$

Since the first inequality can be simplified further, we obtain

$$\begin{aligned}
\varepsilon &< b+c-2\max\{a,d\},\\
\delta &> \frac{1}{4}\left(3\varepsilon-b-c+2\max\{a,d\}\right).
\end{aligned} \tag{3.12}$$

Note that $3b-c-2d > b+c-2\max\{a,d\}$, which is due to $b > c$ and $\max\{a,d\} \geq d$.

In general, these conditions indicate that for commitments to be a viable option for improving coordination, the cost of arrangement ε must be sufficiently small while the compensation associated with the contract needs to be sufficiently large (see already Figure 3.8 for numerical validation). Furthermore, for the first condition to hold, it is necessary that $b+c > 2\max\{a,d\}$. It means that the total payoff of two players when playing the TD game is always greater when they can coordinate to choose different technologies, than when they both choose the same technology.

Moreover, the conditions in Equation 3.12 can be expressed in terms of α and the costs and benefits of investment, as follows (see again the payoff matrices in Equation 3.1)

$$\alpha < 1 + \min\{\frac{c_H + b_L - c_L - \varepsilon}{2b_H}, \frac{c_L + b_H - c_H - \varepsilon}{2b_L}\},$$
$$\alpha < 1 + \min\{\frac{c_H + b_L - c_L - 3\varepsilon + 4\delta}{2b_H}, \frac{c_L + b_H - c_H - 3\varepsilon + 4\delta}{2b_L}\},$$

which can be rewritten as

$$\alpha < 1 + \min\{\frac{c_H + b_L - c_L - \gamma}{2b_H}, \frac{c_L + b_H - c_H - \gamma}{2b_L}\}, \tag{3.13}$$

where $\gamma = \max\{\varepsilon, 3\varepsilon - 4\delta\}$.

This condition indicates under what condition of the market competitiveness and the costs and benefits of investing in available technologies, commitments can be an evolutionarily viable mechanism. Intuitively, for given costs and benefits of investment (i.e. fixing c_L, c_H, b_L, b_H) , a larger cost of arranging a (reliable) agreement, ε, leads to a smaller threshold of α where commitment is viable. Moreover, given a commitment system (i.e. fixing ε and δ), assuming similar costs of investment for the two technologies, then a larger ratio of the benefits obtained from the two technologies, b_H/b_L, leads to a smaller upper bound for α for which commitment is viable.

Remarkably, our numerical analysis below (see already Figure 3.4) shows that the condition in Equation 3.13 accurately predicts the threshold of α where commitment proposing strategies (i.e. HP and LP) are highly abundant in the population, leading to improvement in terms of the average population payoff compared to when commitment is absent (Figure 3.5).

3.4.3 Numerical Results

We calculate the stationary distribution in a population of eight strategies, HP, LP, HN, LN, HC, LC, HF and LF, using methods described above. In Figure 3.4, we show the frequency of these strategies as a function of α, for different values of ε and game configurations. In general, the commitment proposing strategies HP and LP dominate the population when α is small while HN and HC dominate when α is sufficiently large. That is, commitment proposing strategies are viable and successful whenever the market competitiveness is high, leading to the need of efficient coordination among the competing players/firms to ensure high benefits. Notably, we observe that the thresholds of α below which HP and LP are dominant, closely corroborate the analytical condition described in Equation 3.13, in all cases. Namely, for the parameter values in the first and second rows of Figure 3.4, $\alpha \approx 0.66,\ 0.58,\ 0.5$ and $\alpha \approx 0.81,\ 0.67,\ 0.5$, for $\alpha = 0.1, 1,\ 2$, respectively. That explains the consistent dominance of HP and LP when α is small, and that of HN and HC when α is large (see again at the risk dominant conditions).

This observation is robust for varying commitment parameters, i.e. the cost of arranging commitment, ε, and the compensation cost associated with commitment, δ, see Figure 3.8. Namely, we show the total frequency of commitment strategies (i.e. sum of the frequencies of HP and LP) for varying these parameters and for different values of α. It can be seen that, in general, the commitment strategies dominate the population whenever ε is sufficiently small and δ is sufficiently large. This observation is in accordance with previous commitment modelling works for the cooperation dilemma games (Han et al., 2013a, 2015c, 2017a). Furthermore, we observe that in the current coordination problem, that the smaller α is, these commitment strategies dominate the population for wider range of ε and δ. Our additional results show that these observations are robust with respect to other game configurations.

Now, in order to determine whether and when commitments can actually lead to meaningful improvement, in Figure 3.5, we compare the average population payoff or social welfare when a commitment is present and when it is absent. In general, it can be seen that when α is sufficiently small (below a threshold), the smaller it is, the greater improvement of social welfare is achieved through the presence of a commitment deal. Moreover, the smaller the cost of arranging commitments, ε, the greater improvement is obtained. On the other hand, when α is sufficiently large, little improvement can be achieved, especially when b_H/b_L is large (which is in accordance with the analytical results above). We can observe that the thresholds for which a notable improvement can be achieved is the same as the one for the viability of HP and LP (i.e. as described in Equation 3.13).

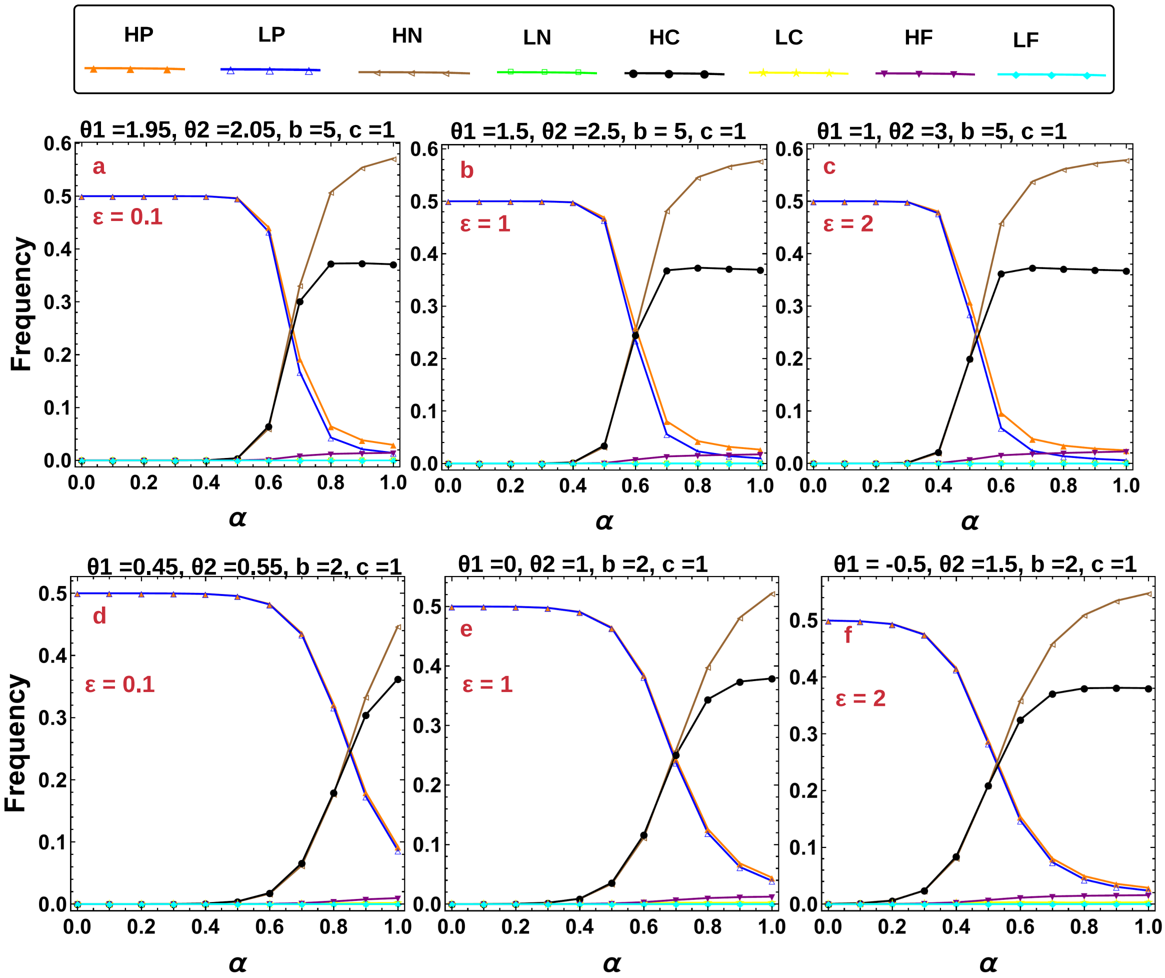

Fig. 3.4 **Frequency of the eight strategies, HP, LP, HN, LN, HC, LC, HF and LF, as a function of** α, for different values of ε and game configurations. In general, the commitment proposing strategies HP and LP dominate the population when α is small while HN and HC dominate when α is sufficiently large. The thresholds of α for which HP and LP dominate, in all cases, are in accordance with the analytical condition described in Equation 3.13. Parameters: in all panels $c_H = 1$, $c_L = 1$, $b_L = 2$ (i.e. $c = 1$); Top row) $b_H = 6$ (i.e. $b = 5$) and bottom row) $b_H = 3$ (i.e. $b = 2$); Other parameters: $\delta = 6$; $\beta = 0.1$; population size $N = 100$; Fair agreements are used, where θ_1 and θ_2 are given by $\theta_1 = (b - c - \varepsilon)/2$ and $\theta_2 = (b - c + \varepsilon)/2$. The HN and HC strategies dominate the population when α is sufficiently large as they play H and do not bear the cost of arranging a commitment deal. When the market is less competitive, that is α is large, it is more beneficial to not engage in a commitment deal. Thus, α is a key parameter in determining when players should engage in a commitment deal or not.

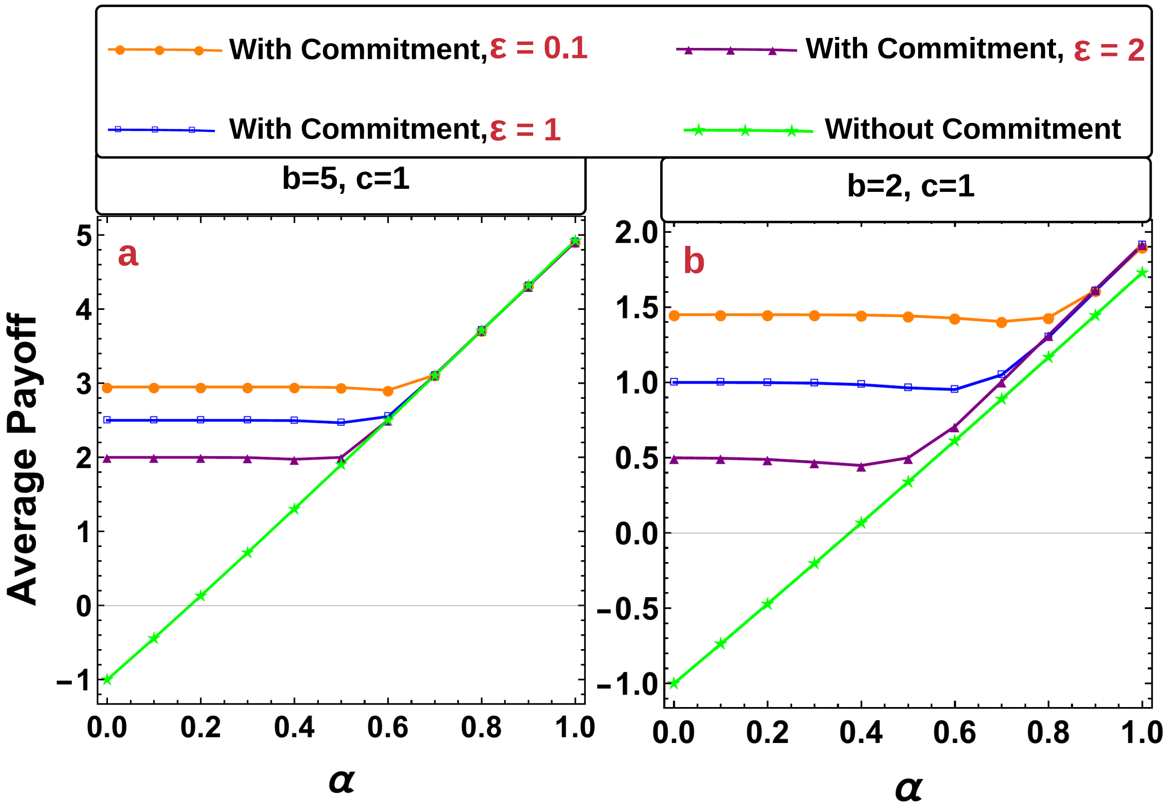

Fig. 3.5 **Average population payoff as a function of α, when commitment is absent and when it is present, for different values of ε.** In general, we observe that when α is small, significant improvement in terms of the average population payoff can be achieved through prior commitments, while when α is sufficiently large, little improvement can be achieved, especially when b_H/b_L is small (compare panels a and b). Parameters: in all panels $c_H = 1$, $c_L = 1$, $b_L = 2$ (i.e. $c = 1$); in panel a) $b_H = 6$ (i.e. $b = 5$) and in panel b) $b_H = 3$ (i.e. $b = 2$); Other parameters: $\delta = 6$; $\beta = 0.1$; population size $N = 100$; Fair agreements are used, where θ_1 and θ_2 are given by $\theta_1 = (b - c - \varepsilon)/2$ and $\theta_2 = (b - c + \varepsilon)/2$.

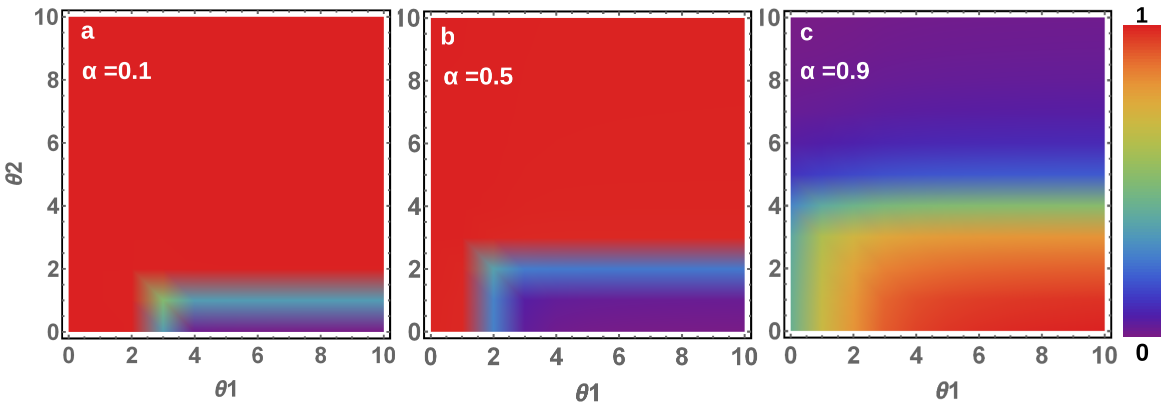

Fig. 3.6 **Average population payoff as a function of θ_1 and θ_2 for different values of α.** When α is small (panels a and b), the highest average payoff is achieved when θ_1 is sufficiently small and θ_2 is sufficiently large, while for large α (panel c), it is the case when θ_1 is sufficiently large and θ_2 is sufficiently small. Parameters: in all panels $c_H = 1$, $c_L = 1$, $b_L = 2$ (i.e. $c = 1$), and $b_H = 6$ (i.e. $b = 5$). Other parameters: $\delta = 4$, $\varepsilon = 1$; $\beta = 0.1$; population size $N = 100$.

3.4.4 Results for different values of θ_1 and θ_2

We now consider what would happen if HP and LP can customise the commitment deal they want to propose, i.e. any θ_1 and θ_2 can be proposed (instead of always being fair). Namely, Figure 3.6 shows the average population payoff varying these parameters, for different values of α. We observe that when α is small, the highest average payoff is achieved when θ_1 is sufficiently small and θ_2 is sufficiently large, while for large α, it is reverse for the two parameters. That is, in a highly competitive market (i.e. small α), commitment proposers should be strict (HP keeps sufficient benefit while LP requests sufficient payment, from their commitment partners), while when the market is less competitive (i.e. large α), commitment proposers should be more generous (HP proposes to give a larger benefit while LP requests a smaller payment, from their commitment partners). Figure 3.7 and figure 3.8 confirms that this observation is robust for different values of α, ε, δ, β and game configurations.

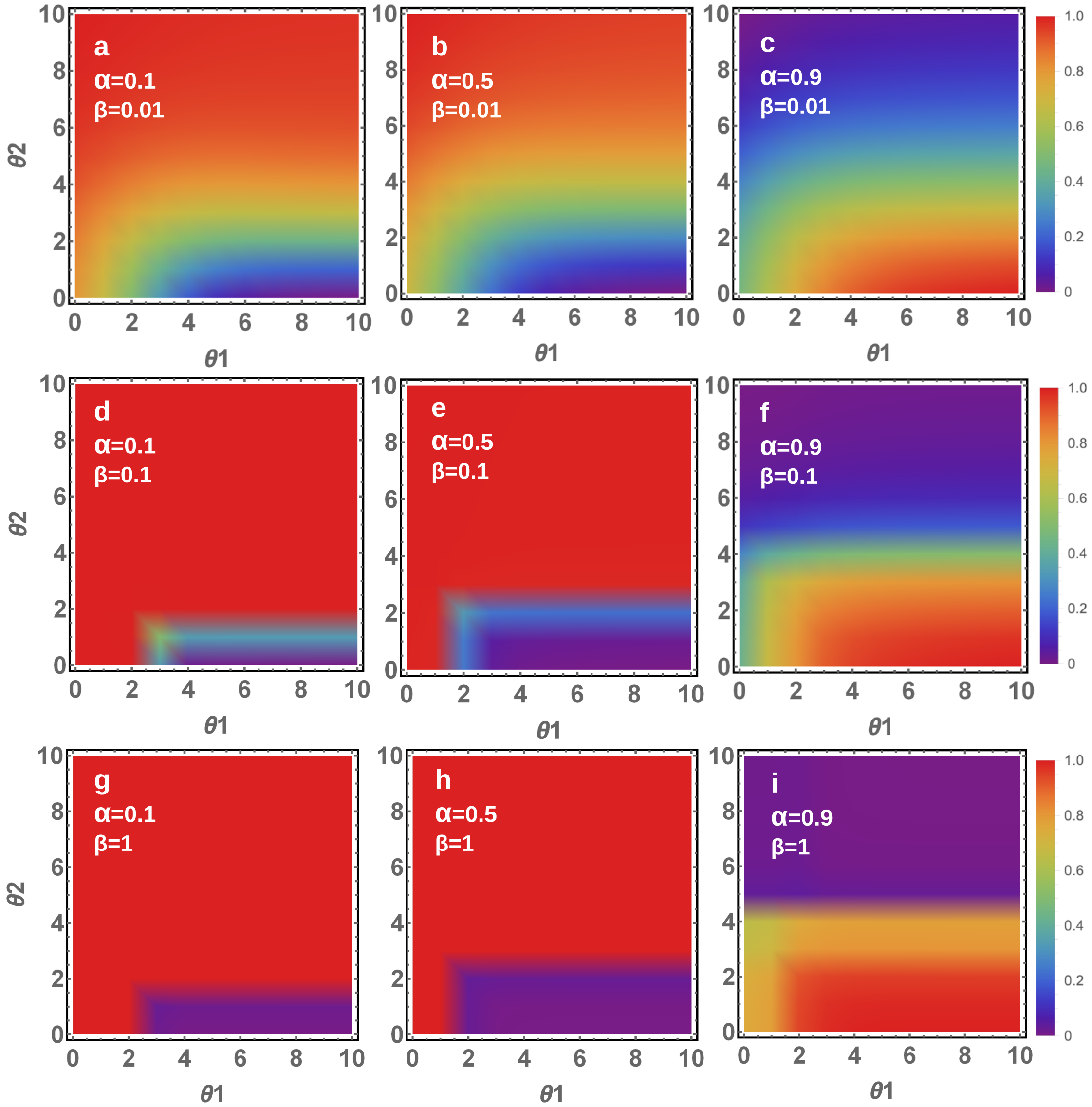

Fig. 3.7 **Average population payoff as a function of θ_1 and θ_2**, for different values of α and β (for pairwise TD games). When α is small (panels a and b), the highest average payoff is achieved when θ_1 is sufficiently small and θ_2 is sufficiently large, while for large α (panel c), it is the case when θ_1 is sufficiently large and θ_2 is sufficiently small. Figure 4 also shows that for a small value of β, the highest average payoff is achieved when α is very minimal compared to other panels with higher value of β (compare panel a, d and g). Parameters: in all panels $c_H = 1$, $c_L = 1$, $b_L = 2$ (i.e. $c = 1$), and $b_H = 6$ (i.e. $b = 5$). Other parameters: $\delta = 4,\ \varepsilon = 1$; $\beta = 0.01,\ 0.1$ and 1; population size $Z = 100$.

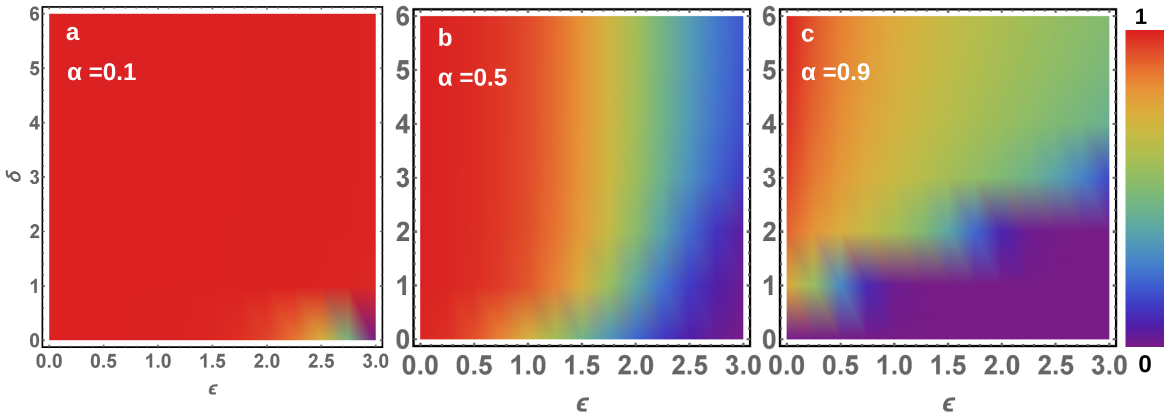

Fig. 3.8 **Total frequency of commitment strategies (i.e. sum of the frequencies of HP and LP), as a function of ε and δ**, for different values of α. In general, the commitment proposing strategies dominate the population whenever ε is sufficiently small and δ is sufficiently large. Furthermore, the smaller α, these commitment strategies dominate for a wider range of ε and δ, especially when α is smaller. Parameters: in all panels $c_H = 1$, $c_L = 1$, $b_L = 2$ (i.e. $c = 1$), and $b_H = 6$ (i.e. $b = 5$). Other parameters: $\beta = 0.1$; population size $N = 100$; Fair agreements are used, where θ_1 and θ_2 are given by $\theta_1 = (b - c - \varepsilon)/2$ and $\theta_2 = (b - c + \varepsilon)/2$.

Stationary Distribution: Here we studied the stationary distribution and fixation probabilities that shows the transition direction between the eight strategies. In Figures 3.9 and 3.10, the population spends most of the time with the commitment proposing strategies (HP and LP), where the competitive level is either very fierce or intermediate, that is $\alpha = 0.1$ and $\alpha = 0.5$ and the cost of arranging the commitment is very minimal ($\varepsilon = 0.1$). We see the reverse when the competitive level of the market is very low ($\alpha = 0.9$). In this case, there is more transition to the non-proposing strategies (HN and HC) as seen in Figure 3.11. Note that although the cost of arranging the commitment deal is very minimal in Figure 3.11, there is a stronger transition towards the non-proposing strategies (HN and HC) as a result of the low competitive level ($\alpha = 0.9$). It means that if there is no significant competition, regardless of whether the cost of arranging the commitment deal is sufficiently small, it is not beneficial to arrange a commitment deal. The results are in line with our risk dominance analysis.

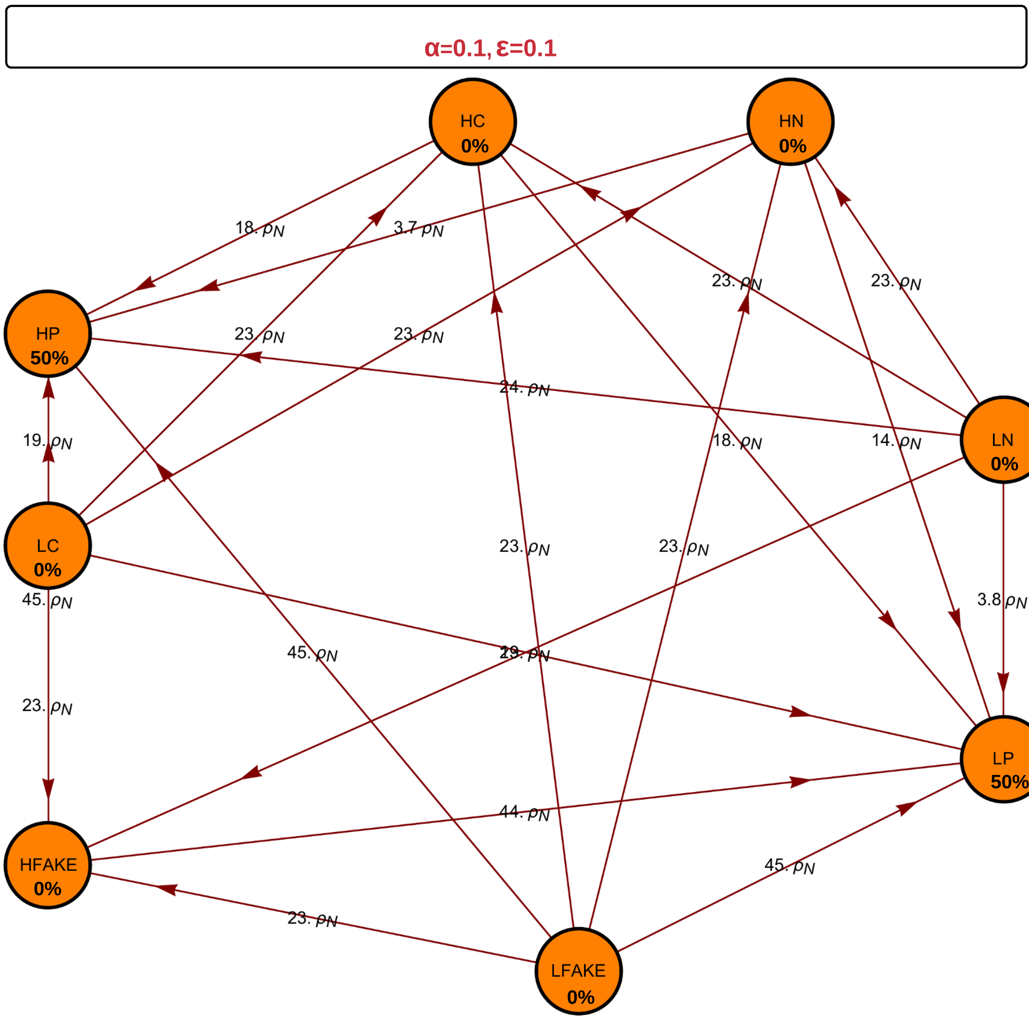

Fig. 3.9 **Stationary distribution and transitions directions among the eight strategies. The arrows displayed show the direction where the transition probability is stronger for the indicated values of α and ε.** In general, when α is small, indicating a fierce market competition, and the value of ε is small, there is a high transition from the other strategies to the commitment proposing strategies (HP and LP). This means, it is beneficial for the players to coordinate themselves in this case. Parameters: $\alpha = 0.1$, $\varepsilon = 0.1$, $\theta_1 = 0.45$, $\theta_2 = 0.55$, $c_H = 1$, $c_L = 1$, $b_L = 2$ (i.e. $c = 1$), and $b_H = 3$ (i.e. $b = 2$). Other parameters: $\beta = 0.1$; population size $N = 100$.

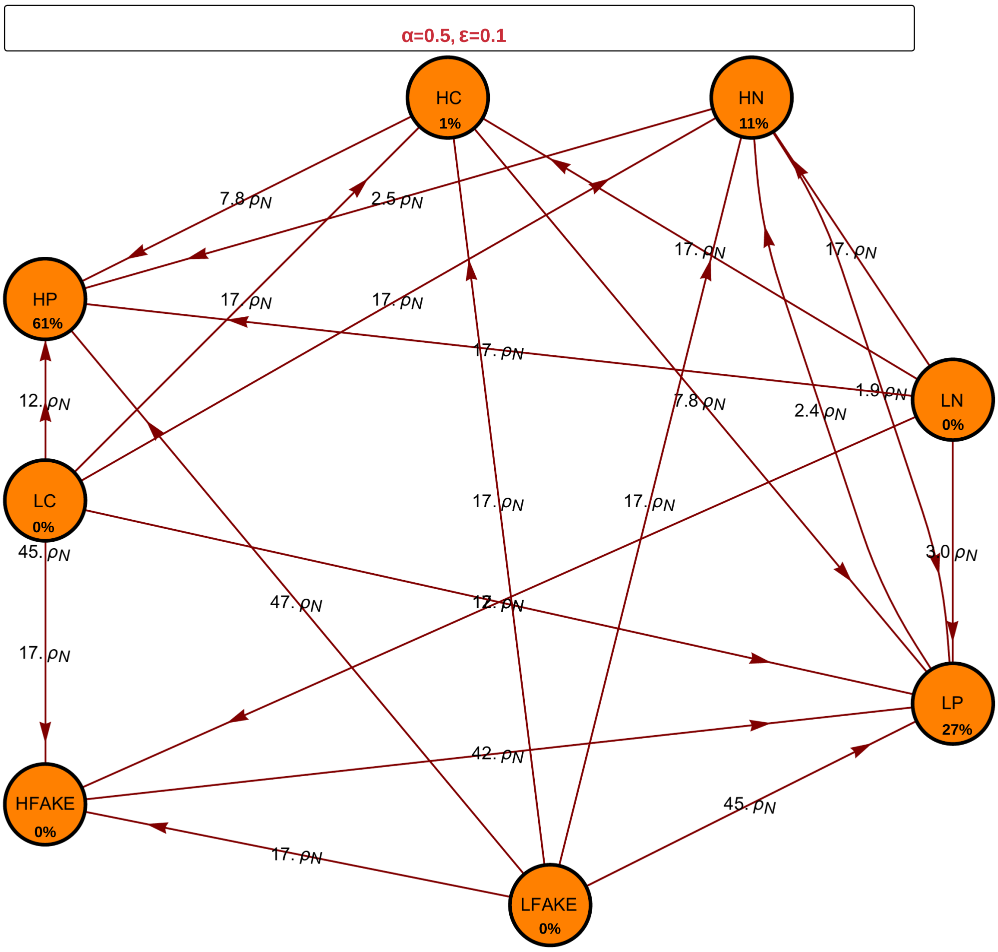

Fig. 3.10 **Stationary distribution and transitions directions among the eight strategies. The arrows displayed show the direction where the transition probability is stronger for the indicated values of α and ε.** In general, when α is intermediate, that is $\alpha = 0.5$ and the value of ε is small, there is a high transition from the other strategies to the commitment proposing strategies, especially a high transition to the HP strategy at 61% and then to the LP strategy at 27%. The non-proposing strategy HN has a transition probability of 11% as there is transition from other strategies to the HN strategy, however, the HP and LP strategies have a higher transition. This means that at an intermediate market competition with a small cost of arranging commitment deal, commitment is still beneficial. Parameters: $\alpha = 0.5$, $\varepsilon = 0.1$, $\theta_1 = 0.45$, $\theta_2 = 0.55$, $c_H = 1$, $c_L = 1$, $b_L = 2$ (i.e. $c = 1$), and $b_H = 3$ (i.e. $b = 2$). Other parameters: $\beta = 0.1$; population size $N = 100$.

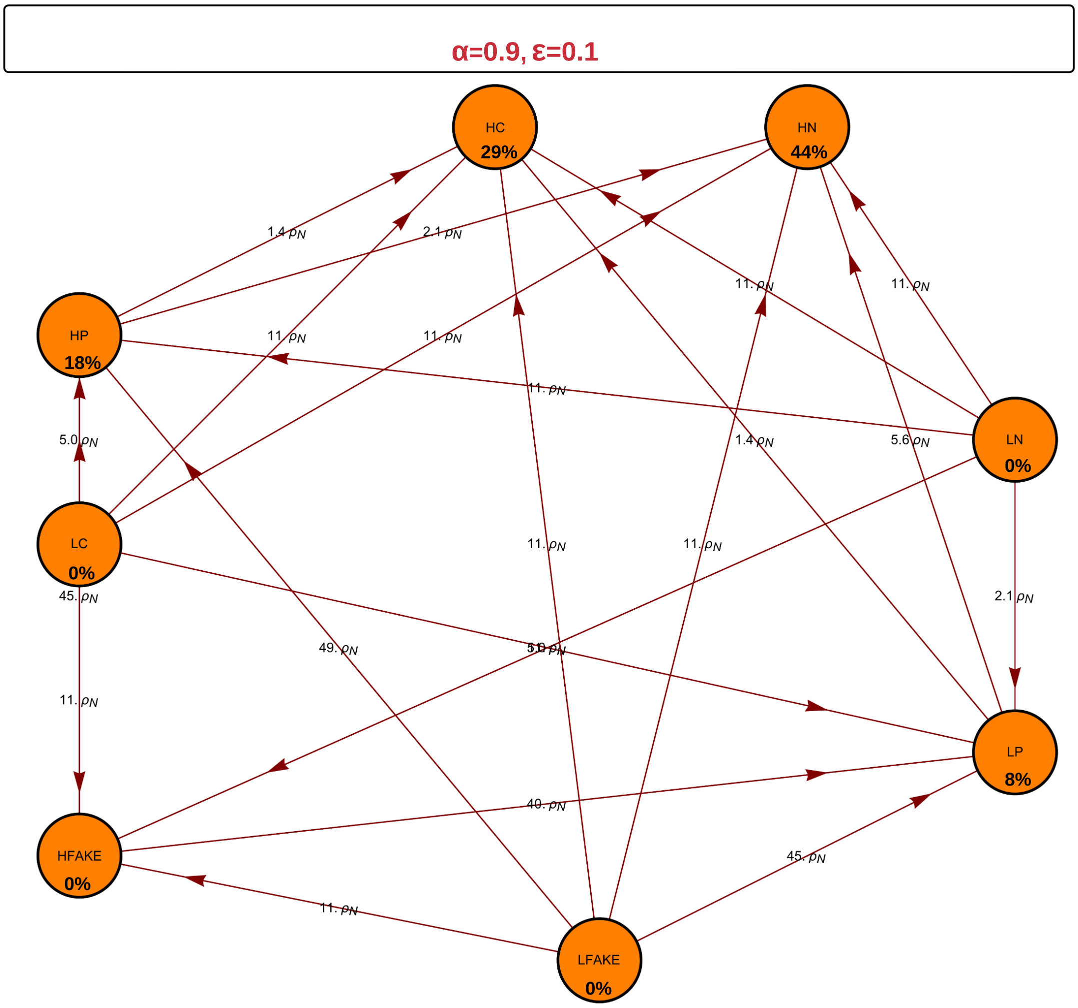

Fig. 3.11 **Stationary distribution and fixation probabilities Transitions direction among the eight strategies, the arrows show the direction where the transition probability is stronger in all strategies**. We observed here that when α is large ($\alpha = 0.9$, which means there is no market competition) and the value of ε is small, there is a higher transition from the other strategies to the non-proposing strategies (HN and HC) compared to the commitment proposing strategies (HP and LP) as shown above. Parameters: $\alpha = 0.9$, $\varepsilon = 0.1$, $\theta_1 = 0.45$, $\theta_2 = 0.55$, $c_H = 1$, $c_L = 1$, $b_L = 2$ (i.e. $c = 1$), and $b_H = 3$ (i.e. $b = 2$). Other parameters: $\beta = 0.1$; population size $N = 100$.

3.5 Discussion

In summary, this chapter describes a novel model showing how prior commitments can be adopted as a tool for enhancing coordination when desirable coordination outcomes exhibit an asymmetric payoff structure, see results from Figures 3.4 and 3.5. For that, we described a technology adoption game where technology investment firms would achieve the best collective outcome if they can coordinate with each other to adopt different technologies, with a parameter α capturing the competitiveness level of the product market and how beneficial it is to achieve coordination. In such a context, there are multiple desirable outcomes and players have distinct preferences in terms of which outcome should be agreed upon, thus leading to a larger behavioural space than in the context of cooperation dilemmas (Han et al., 2013a, 2017a). We have shown that whether commitment is a viable mechanism for promoting the evolution of coordination, strongly depends on α: when α is sufficiently small, prior commitment is highly abundant leading to significant improvement in terms of social welfare, compared to when commitment is absent. Importantly, we have derived the analytical condition for the threshold of α which the success of commitments is guaranteed.

Furthermore, whenever commitment proposers are allowed to freely choose which deal to propose to their co-players, our results show that, in a highly competitive market (i.e. small α), commitment proposers should be strict (i.e. sharing less benefits), while when the market is less competitive, commitment proposers should be more generous. That is, in a highly competitive market, the commitment proposing strategies can get sufficient benefit for themselves, while when the market is less competitive, the commitment proposing strategies can propose to be more liberal in sharing and requesting of benefit from their co-players. Also, if the cost of arranging a commitment is sufficiently small, better improvement is achieved. With these results, arranging a pre-commitment has been demonstrated in our model to be an essential tool in coordinating for payoffs which are asymmetric.

Moreover, we demonstrate that agreements for coordination (with asymmetric benefits) exhibit more complex decision points than in previous models on cooperation dilemmas, leading to a larger behavioural space and a larger set of strategies.

Our analytical and numerical results clearly show that pre-commitment is an evolutionarily viable mechanism that can be applied to achieve coordination in complex games like our technology adoption game. Our analysis has further demonstrated that this mechanism can be used as a viable tool for promoting the evolution of diverse collective behaviours among self-interested individuals, beyond the context of cooperation dilemmas where there is only one desirable collective outcome (Nesse, 2001c).

In the next chapter, we will consider how the mechanism can be extended and generalised to solve collective problems where there are a large number of desirable outcomes or equilibria, when the number of players in an interaction increases (Duong and Han, 2015; Gokhale and Traulsen, 2010).

Chapter 4

Multi-Player Technology Adoption Game

In this chapter, we took further steps from the previous chapter by proposing a new model to investigate how pre-commitments can be applied to improve coordination when its results reveal an asymmetric reward structure, in multiplayer interactions, by utilising methods from evolutionary game theory (EGT). Our analysis, both analytically and via numerical simulations, shows that whether pre-commitments would be a viable evolutionary mechanism for enhancing coordination and the overall population social welfare strongly depends on the collective benefit and severity of competition, and more importantly, how asymmetric benefits are resolved in a pre-commitment deal.

4.1 Introduction

From the dynamics of bacterial populations to the development of social behaviour, evolutionary game theory has proven successful in explaining a variety of phenomena. However, it has frequently concentrated on a two-player game that illustrates how people interact with one another, numerous intraspecies and interspecies interactions take place between organisms at the same time (Venkateswaran and Gokhale, 2019). Typically, social dilemmas are depicted by two-player two-strategy games with each player having the option of cooperating or defecting (Macy and Flache, 2002). For example in the pairwise social dilemma games described in previous chapters, mutual cooperation results to a reward R for each player, while mutual defection a punishment P; when a cooperator encounters a defector, the cooperator obtains a sucker's payoff S and the defector gets the temptation T. Even though this illustration is straightforward, numerous interactions outside of dyadic settings happen in the real world and frequently involve more than two individuals. Therefore, there is a need to move from two-player games to multi-player games. A move from a two-player interaction to a multi-player game where multiple players are involved yields richer dynamics closer to natural settings (Gokhale and Traulsen, 2010; Han et al., 2012b; Venkateswaran and Gokhale, 2019).

There has been extensive research done on the dynamics of evolutionary games involving two players and two strategies (Hofbauer and Sigmund, 1998; Maynard-Smith, 1982). However, less attention has been given to evolutionary dynamics of more general multiplayer games (Broom et al., 1997). Recently, the multiplayer games have begin to gain some interest (Broom et al., 1997; Gokhale and Traulsen, 2010; Huang et al., 2020), this is likely due to the abundance of biological and social settings where interactions commonly occur among a group of persons. A rising number of scholars are now focusing their attention on researching multi-player games and multi-strategy games as a result of this (Duong and Han, 2016; Gokhale and Traulsen, 2010; Huang et al., 2019; Peña et al., 2016; Tarnita et al., 2011; Wu et al., 2013a).

According to Broom et al. (1997), the most general form of multiplayer games, a straightforward generalization of the payoff matrix concept, leads to a significant increase in the complexity of the evolutionary dynamics compared to the simplicity of a two-player model. Although the evolution of cooperation is an important and illustrative example, typically it does not lead to very complex dynamics. On the other hand, intuitive explanations for more general games are less straightforward, but only they illustrate the full dynamical complexity of multiplayer games (Broom et al., 1997). Multiplayer games show a great dynamical complexity that cannot be captured based on pairwise interactions (Gokhale and Traulsen, 2010).

4.2 Model description

4.2.1 Multi-player Game Without Commitments

Here, we extend and generalise the two-player technology adoption game described in the previous chapter (Bianca and Han, 2019) to the multi-player setting. We start by describing our multi-player model in the absence of pre-commitment and then extend it to allow players to have an option of arranging a commitment deal before the interaction/game.

In particular, we describe a N-player ($N > 2$) version of our technology adoption (TD) model. Again, as before, we will introduce the model in the context of technology investment market decision making. In a group (of size N) with k players of type H (i.e., $N-k$ players of type L), the expected payoffs of playing H and L can be written as follows

$$\begin{aligned}\Pi_H(k) &= \alpha_H(k)b_H - c_H,\\ \Pi_L(k) &= \alpha_L(k)b_L - c_L,\end{aligned} \tag{4.1}$$

where $\alpha_H(k)$ and $\alpha_L(k)$ represent the fraction of the benefit obtained by H and L players, respectively, which depend on the composition of the group, k. For two-player TD model, both are equal to α. To generalize for N-player TD interactions, they should also depend on the demand for high technology (H) in the group, describing what is the maximal number of players in the group that can adopt H without reducing their benefit due to competition. Let us denote this number by μ (where $1 \leq \mu \leq N$). For example, intermediate values of μ indicate a high level of group diversity is needed for optimal coordination. When $\mu = N$, it means there is a significant market demand of the high benefit technology so that all firms can adopt it without leading to competition.

Hence, we define

$$\alpha_H(k) = \begin{cases} 1, & \text{if } k \leq \mu, \\ \frac{\alpha_1 \mu}{k} & \text{otherwise,} \end{cases} \tag{4.2}$$

$$\alpha_L(k) = \begin{cases} 1, & \text{if } k \geq \mu, \\ \frac{\alpha_2 (N-\mu)}{N-k} & \text{otherwise.} \end{cases} \tag{4.3}$$

The rationale of these definitions is that whenever $k \leq \mu$, full benefits from adopting H can be obtained, and moreover, if $k > \mu$, the larger k the stronger the competition is among H adopters. Similarly for L adopters. The parameters α_1 and α_2 stand for the intensities of competition for investing in H and in L, respectively. For simplicity we assume in this paper $\alpha_1 = \alpha_2 = \alpha$. Note that for $N = 2$ we recover the two-player model given in Equation (3.1) in the previous chapter, given that the current α is scaled (by 2) compared to the value of α in the pairwise game, solely for the purpose of a clear presentation.

The optimal group payoff is achieved when there are exactly μ players adopting H and the rest adopting L, leading to an average payoff for each member given by

$$A := \frac{\mu(b_H - c_H) + (N-\mu)(b_L - c_L)}{N}.$$

4.2.2 Multi-player TD in Presence of Commitments

We can define the N-player game version with prior commitments in a similar fashion as in the two-player game. Commitment proposing strategists (i.e. HP and LP players) will propose before an interaction that the group will play the optimal arrangement (so that every player obtains an average payoff A). For simplicity, we assume that the committed players adopt the fair agreement, i.e. every member will obtain the same payoff after compensation is made to those adopting L. As such, we do not need to consider who will adopt H or L, as all would receive the same payoff at the end. Moreover, whenever a player in the group refuses to commit, commitment proposers will adopt H.

4.3 Summary of Methods

For convenience, we provide here a summary of the finite population evolutionary dynamics used for multi-player games. We assume that an individual A with fitness f_A adopts the strategy of another individual B with fitness f_B with probability p given by the Fermi function,

$$p_{A,B} = \left(1 + e^{-\beta(f_B - f_A)}\right)^{-1}.$$

The parameter β represents the 'imitation strength' or 'intensity of selection', i.e., how strongly the individuals base their decision to imitate on fitness difference between themselves and the opponents.

Below, we describe how payoffs are calculated in a N-player setting

In the case of N-player interactions, suppose the population includes x individuals of type i and $Z-x$ individuals of type j. The probability to select k individuals of type i and $N-k$ individuals of type j, in N trials, is given by the hypergeometric distribution as follows (Gokhale and Traulsen, 2010; Sigmund, 2010)

$$H(k,N,x,Z) = \frac{\binom{x}{k}\binom{Z-x}{N-k}}{\binom{Z}{N}}.$$

Hence, in a population of x i-strategists and $(Z-x)$ j strategists, the average payoff of i and j are given by

$$
\begin{aligned}
\Pi_{ij}(x) &= \sum_{k=0}^{N-1} H(k,N-1,x-1,Z-1)\pi_{ij}(k+1) = \sum_{k=0}^{N-1} \frac{\binom{x-1}{k}\binom{Z-x}{N-1-k}}{\binom{Z-1}{N-1}}\pi_{ij}(k+1), \\
\Pi_{ji}(x) &= \sum_{k=0}^{N-1} H(k,N-1,x-,Z-1)\pi_{ji}(k) = \sum_{k=0}^{N-1} \frac{\binom{x}{k}\binom{Z-1-x}{N-1-k}}{\binom{Z-1}{N-1}}\pi_{ji}(k).
\end{aligned}
\tag{4.4}
$$

Now, similar to the two-player setting, in a N-player setting, the probability to change the number x of individuals using strategy i by $\pm$ one in each time step can be written as (Traulsen et al., 2006)

$$
T^{\pm}(k) = \frac{Z-x}{Z}\frac{x}{Z}\left[1+e^{\mp\beta[\Pi_i(x)-\Pi_j(x)]}\right]^{-1}. \tag{4.5}
$$

Furthermore, the fixation probability of a single mutant with a strategy i in a population of $(Z-1)$ individuals using j is given by (Nowak et al., 2004; Traulsen et al., 2006)

$$
\rho_{j,i} = \left(1+\sum_{i=1}^{Z-1}\prod_{j=1}^{i}\frac{T^{-}(j)}{T^{+}(j)}\right)^{-1}. \tag{4.6}
$$

Now, considering a set $\{1,...,q\}$ of different strategies, these fixation probabilities determine a transition matrix $M = \{T_{ij}\}_{i,j=1}^{q}$, with $T_{ij,j\neq i} = \rho_{ji}/(q-1)$ and $T_{ii} = 1-\sum_{j=1,j\neq i}^{q} T_{ij}$, of a Markov Chain. The normalised eigenvector associated with the eigenvalue 1 of the transposed of M provides the stationary distribution described above (Imhof et al., 2005; Sigmund, 2010), describing the relative time the population spends adopting each of the strategies.

Risk-dominance in N-player games. An important measure to determine the evolutionary dynamic of a given strategy is its risk-dominance against others. For the two strategies i and j, risk-dominance is a criterion which determine which selection direction is more probable: an i mutant is able to fixating in a homogeneous population of agents using j or a j mutant fixating in a homogeneous population of individuals playing i. In the case, for instance, the first was more probable than the latter then we say that i is *risk-dominant* against j (Nowak et al., 2004; Sigmund, 2010) which holds for any intensity of selection and in the limit for large population size Z when

$$
\sum_{k=1}^{N}\Pi_{i,j}(k) \geq \sum_{k=0}^{N-1}\Pi_{j,i}(k) \tag{4.7}
$$

Table 4.1 List of parameters in the models.

Parameters description	Notation
Cost of investing in high technology, H	c_H
Cost of investing in low technology, L	c_L
Benefit of investing in high technology, H	b_H
Benefit of investing in low technology, L	b_L
Competitive level of the market	α
Group size (in N-player TD games)	N
Optimal number of H-adopters in a group of N players	μ
Cost of arranging a commitment	ε
Compensation paid by dishonouring commitment acceptors	δ
Compensation paid by HP to honouring commitment acceptors	θ_1
Compensation paid to LP by commitment acceptors	θ_2

4.4 Results

We provide here analytical and numerical simulation results for our N-player version of our technology adoption model. Table 4.1 summarises the key parameters, for ease of following.

4.4.1 Payoff Derivation in N-player TD game

Compared to cooperation dilemmas such as PD and PGG, fake strategies make less sense in the context of coordination games since they would not earn the temptation payoff by adopting a different choice from what being agreed. To focus on the group effect and the effect of the newly introduced parameter μ, we will consider a population consisting of HP, LP, HN, LN, HC and LC (i.e. excluding fake strategies). As shown in the two-player game analysis, the fake strategies (i.e. HF and LF) are not viable options in TD games and can be ignored. It is equivalent to consider to the full set of strategies with a sufficiently large δ.

First of all, we derive the payoffs received by each strategy when encountering specific other strategies (see a summary in Table 4.2). Namely, $\Pi_{ij}(k)$ and $\Pi_{ji}(k)$ denote the payoffs of a strategist of type i and j, respectively, in a group consisting of k player of type i and $N-k$ players of type j. The first column of the table lists all possible strategies which can be used by player i (focal player), where as the second column shows strategies of co-players (opponents). The third column shows the payoffs of focal players.

Table 4.2 Average payoffs of focal strategy i when facing strategy j, in a group of k former and $N-k$ latter strategists.

Focal Player (i)	Opponent (j)	$\Pi_{i,j}(k)$
HP, LP	HP, LP	$A-\varepsilon/N$
HP, LP	HC, LC	$A-\varepsilon/k$
HP, LP	HN	$\Pi_H(N)$ (for $k<N$)
HP, LP	LN	$\Pi_H(k)$ (for $k<N$)
HN	HP, LP, HN, HC	$\Pi_H(N)$
HN	LN, LC	$\Pi_H(k)$
LN	HP, HN, HC	$\Pi_L(k)$
LN	LN, LC	$\Pi_L(N)$
LN	LP	$\Pi_L(k)$
HC, LC	HP, LP	A (for $k<N$)
HC	HN, HC	$\Pi_H(N)$
HC	LN, LC	$\Pi_H(k)$
LC	HN, HC	$\Pi_L(k)$
LC	LN, LC	$\Pi_L(N)$

4.4.2 Analytical conditions for the viability of commitment proposers in N-player TD game

We now derive the conditions under which HP is risk-dominant against the rest of strategies. Since we assume fair agreements, the conditions for LP would be equivalent to those for HP in terms of risk-dominance. For ease of following the derivations below, we recall that A denotes the optimal group payoff achieved when there are exactly μ players adopting H and the rest adopting L, that is, $A := \frac{1}{N}\left(\mu(b_H-c_H)+(N-\mu)(b_L-c_L)\right)$.

HP is risk-dominant against HC if

$$\sum_{k=1}^{N}\Pi_{HP,HC}(k) \geq \sum_{k=0}^{N-1}\Pi_{HC,HP}(k),$$

which can be written as

$$\sum_{k=1}^{N}\left(A-\frac{\varepsilon}{k}\right) \geq \Pi_H(N)+\sum_{k=1}^{N-1} A.$$

Hence we obtain

$$\varepsilon \leq \frac{A-\Pi_H(N)}{H_N}, \tag{4.8}$$

where $H_N = \sum_{k=1}^{N}\frac{1}{k}$.

Similarly, HP is risk-dominant against LC if

$$\varepsilon \leq \frac{A-\Pi_L(0)}{H_N}. \tag{4.9}$$

For risk-dominance of HP against HN,

$$\sum_{k=1}^{N}\Pi_{HP,HN}(k) \geq \sum_{k=0}^{N-1}\Pi_{HN,HP}(k),$$

which equivalently can be written as

$$A-\frac{\varepsilon}{N} \geq \Pi_H(N),$$

or,

$$\varepsilon \leq N\big(A-\Pi_H(N)\big). \tag{4.10}$$

which can be rewritten as

$$A-\frac{\varepsilon}{N}+\sum_{k=1}^{N-1}\Pi_H(k) \geq \sum_{k=0}^{N-1}\Pi_L(k),$$

or

$$\varepsilon \leq N\left(A+\sum_{k=1}^{N-1}\Pi_H(k)-\sum_{k=0}^{N-1}\Pi_L(k)\right). \tag{4.11}$$

In short, in order for commitment proposers to be risk-dominant against all other strategies, it requires that ε is sufficiently small, namely, smaller than minimum of the right hand sides of Equations (4.8)-(4.11).

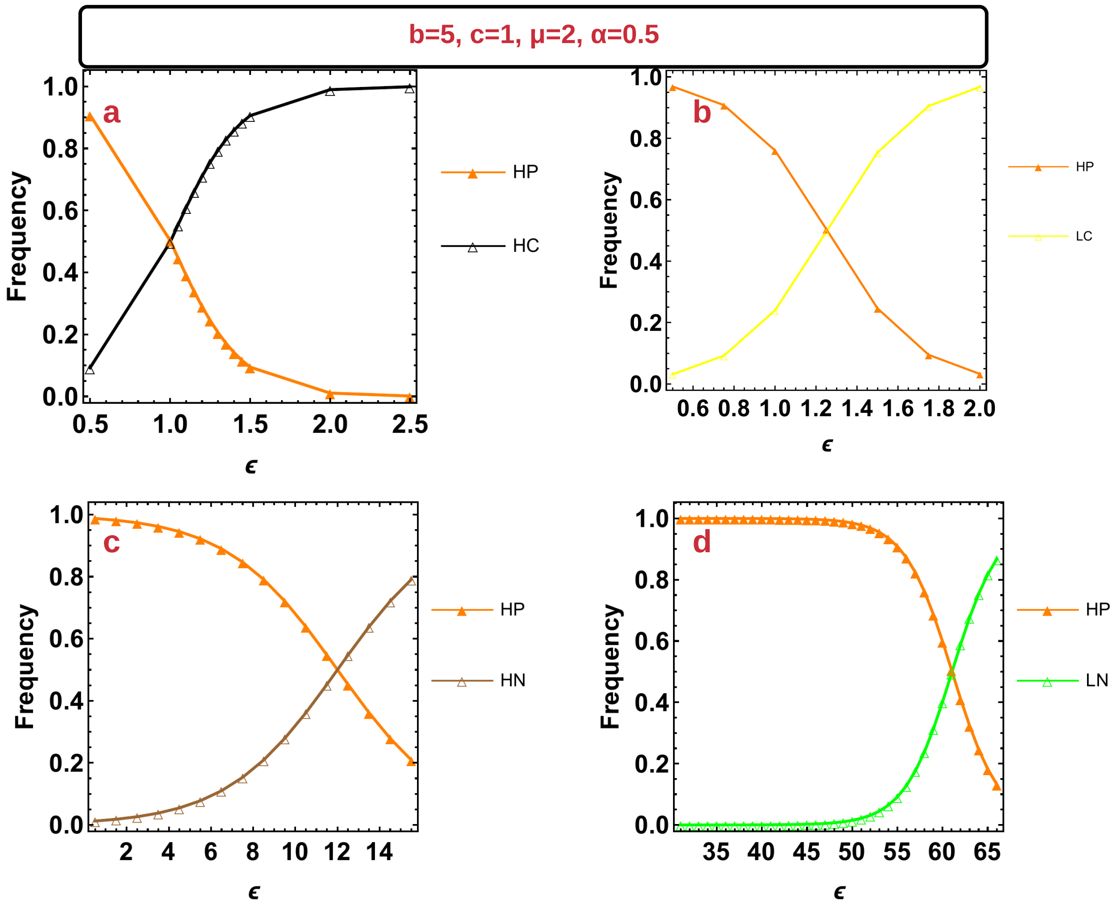

Fig. 4.1 **Validation for the analytical conditions under which HP is risk dominant against strategy HC, LC, HN and LN**. In all cases, with a small value of ε, the HP strategy dominated other players. This result of this figure is in close accordance with our equations derived above. Namely, the risk-dominance thresholds of ε for HP (LP) playing against HC, LC, HN and LN, are, 1.05, 1.31, 12.0 and 58.75, respectively. We notice a small difference between numerical and theoretical results, since the latter ones are approximated for larger population sizes. Parameters: in all panels, $N = 5$, $c_H = 1$, $c_L = 1$, $b_H = 6$ (i.e. $b = 5$), $\mu = 2$, and $\alpha = 0.5$.

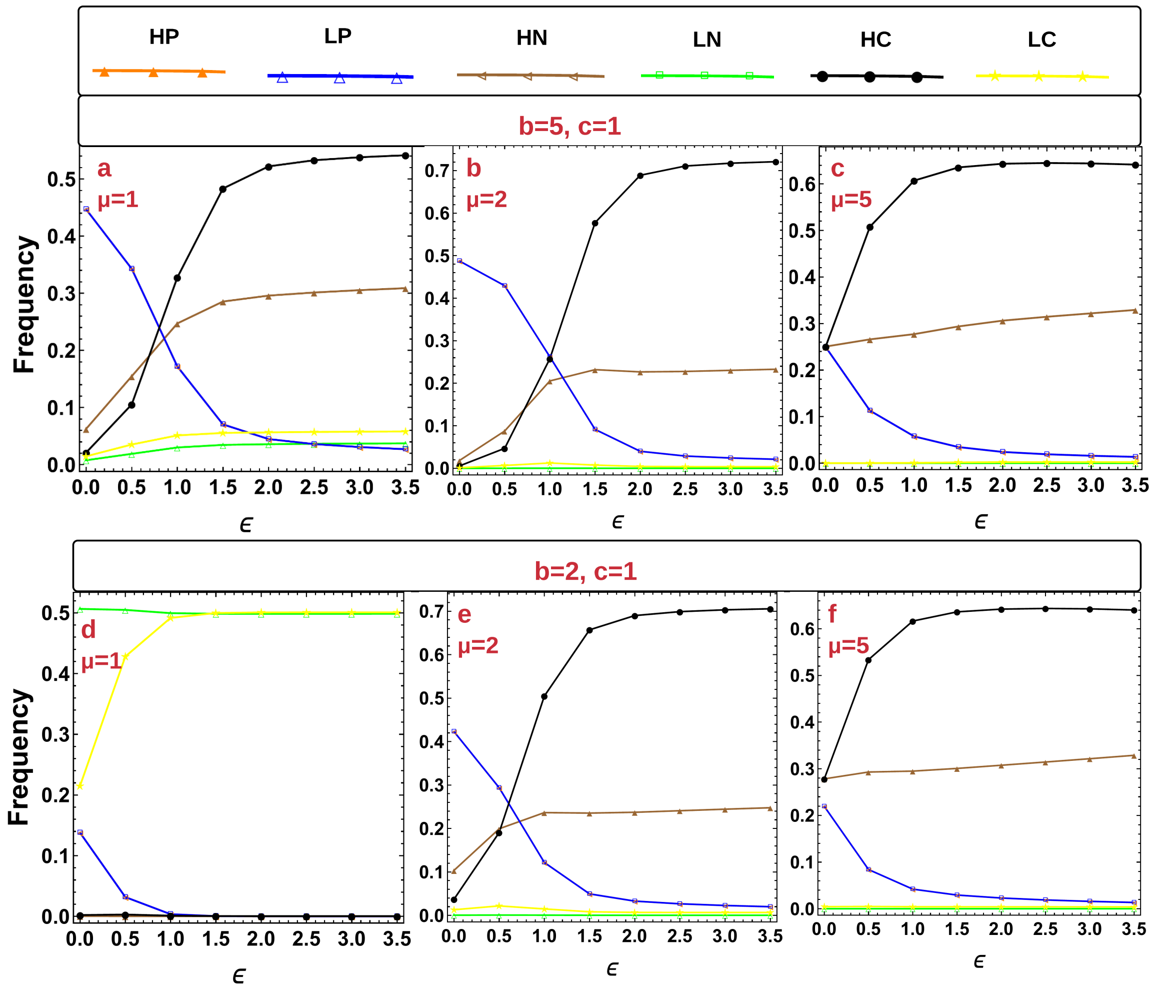

Fig. 4.2 **Frequency of the six strategies HP, LP, HN, LN, HC and LC, as a function of ε in a N-player game with commitment, for different values of μ.** In the N-player game, the new parameter μ describes the market demand for a high technology, which was set to 1 in the pairwise game. HP and LP have a high frequency for sufficiently small ε for $\mu = 2$ in both games, and also when $\mu = 1$ for the first, easy coordinate situation (first row). When $\mu = 5$, i.e. when all players can adopt H without benefit reduction, HC always dominates and commitment strategies are not successful. This means that when there is a need for a diversity of technology adoption, initiating prior commitments to enhance coordination is important. Parameters: in panel a, b and c) $b_H = 6$ (i.e. $b = 5$) with $\mu = 1, 2, 5$ respectively. Also, in panel d,e and f) $b_H = 3$ (i.e. $b = 2$) with $\mu = 1, 2, 5$ respectively; Other parameters: $N = 5$, $\beta = 0.1$; $\alpha = 0.5$; $c_H = 1$, $c_L = 1$, $b_L = 2$ (i.e. $c = 1$); .

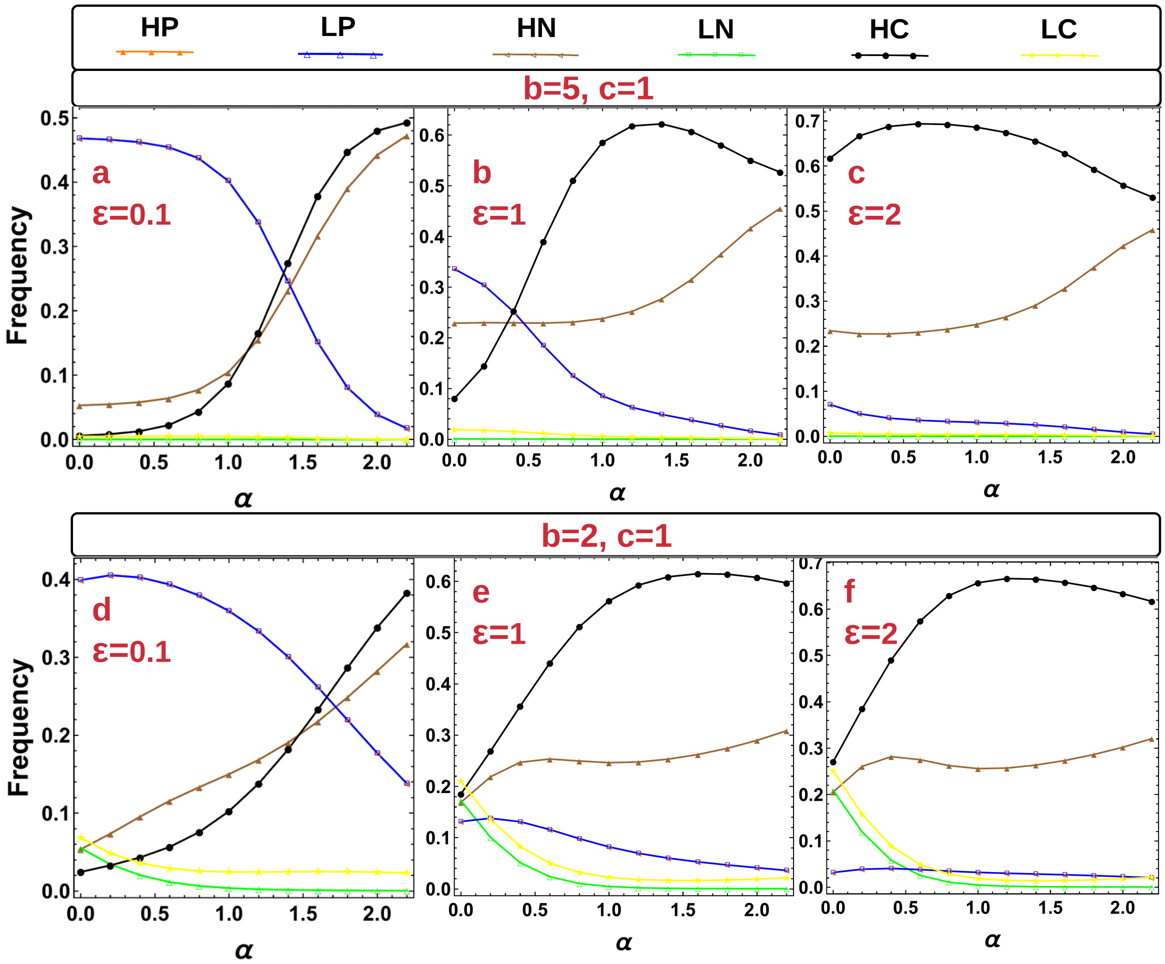

Fig. 4.3 **Frequency of the six strategies HP, LP, HN, LN, HC and LC, as a function of α in a multiplayer game with commitment, for different values of ε and also two different game configurations.** In general, the commitment proposing strategies (HP and LP) decrease in frequency for increasing α. They dominate over other strategies for sufficiently small α and ε. That is, it is more beneficial to engage in a prior commitment deal when the market competition is fierce and the cost of arranging the commitment is very minimal. Also, in both games, the commitment proposers (HP and LP) have the same curve. Parameters: in all panels $c_H = 1$, $c_L = 1$, $b_L = 2$ (i.e. $c = 1$); in panel a, b and c) $b_H = 6$ (i.e. $b = 5$) with $\varepsilon = 0.1,\ 1$ and 2, respectively. Also, in panel d, e and f: $b_H = 3$ (i.e. $b = 2$) with $\varepsilon = 0.1, 1$ and 2 respectively; Other parameters: $N = 5$, $\beta = 0.1$; $\mu = 2$.

4.4.3 Results for other intensities of selection in the N-player game

Comparing Figure 4.4 to Figure 4.3 above, it is clear that the same findings hold true for other values of intensity of selection (β) in the N-player TD game. We have examined different values of β and observed similar results that shows the commitment proposing strategies (HP and LP) dominating the population when the values of α and ε are significantly small in different levels of selection, that is when $\beta = 0.01, 0.1 and 1$. This is to say that, regardless of the intensity of selection, as long as there is a high market competition (α is small) and the cost of setting up the commitment deal (ε) is likewise small, the commitment proposing strategies will always dominate the population. In this case, it is more beneficial for commitment to be arranged by the players.

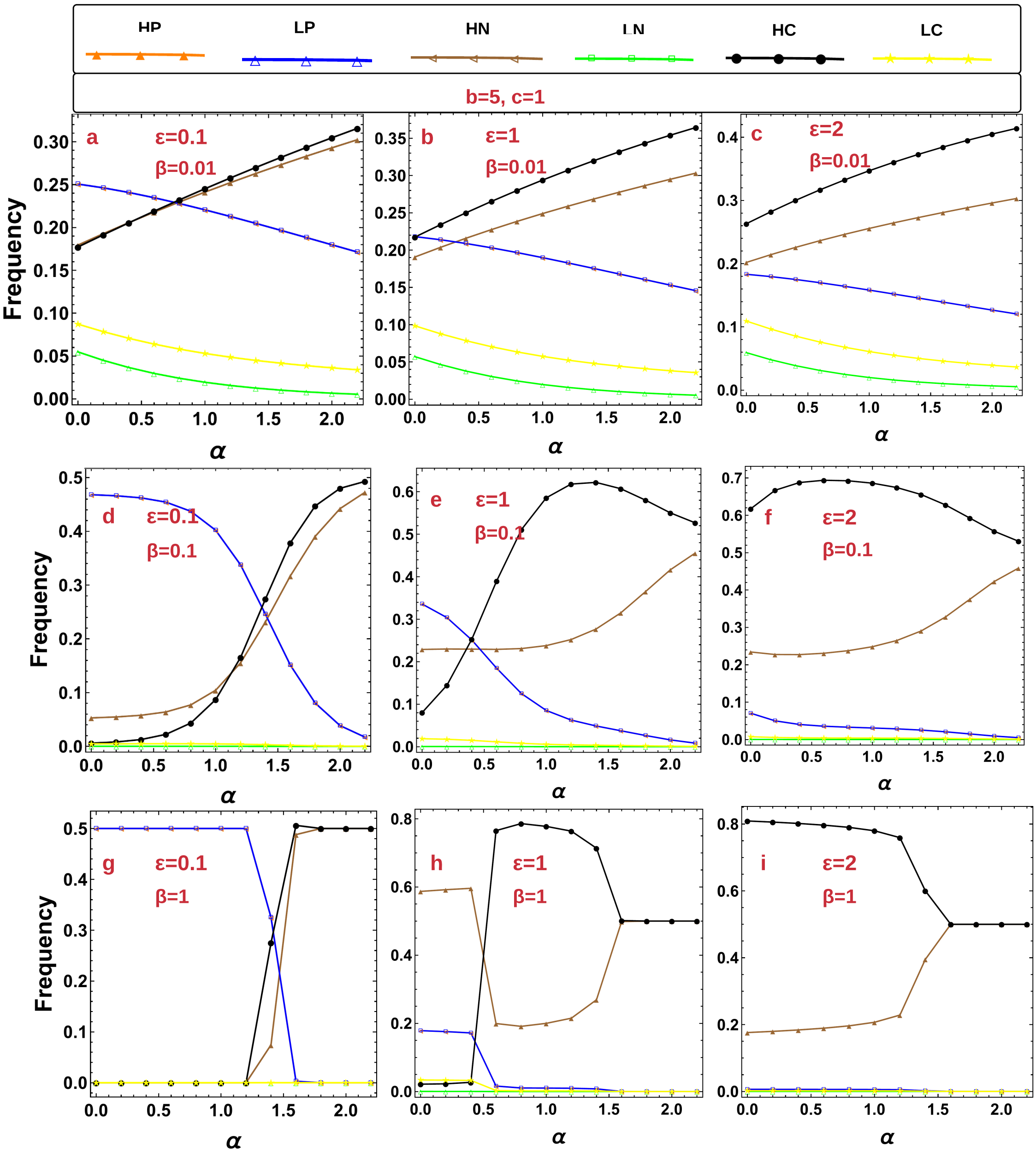

Fig. 4.4 **Frequency of six strategies HP, LP, HN, LN, HC and LC, as a function of α and for different values of ε and β.** The commitment proposing strategies HP and LP dominate the population when the values of α and ε are sufficiently small, in all cases of β. Furthermore, as the value of ε increases, the non-proposing strategies dominate the population. Parameters: in all panels $c_H = 1$, $c_L = 1$, $b_L = 2$ (i.e. $c = 1$), $b_H = 6$ (i.e. $b = 5$); Other parameters: $N = 5$, $\varepsilon = 0.1,\ 1,\ 2$; $\beta = 0.01,\ 0.1,\ 1$.

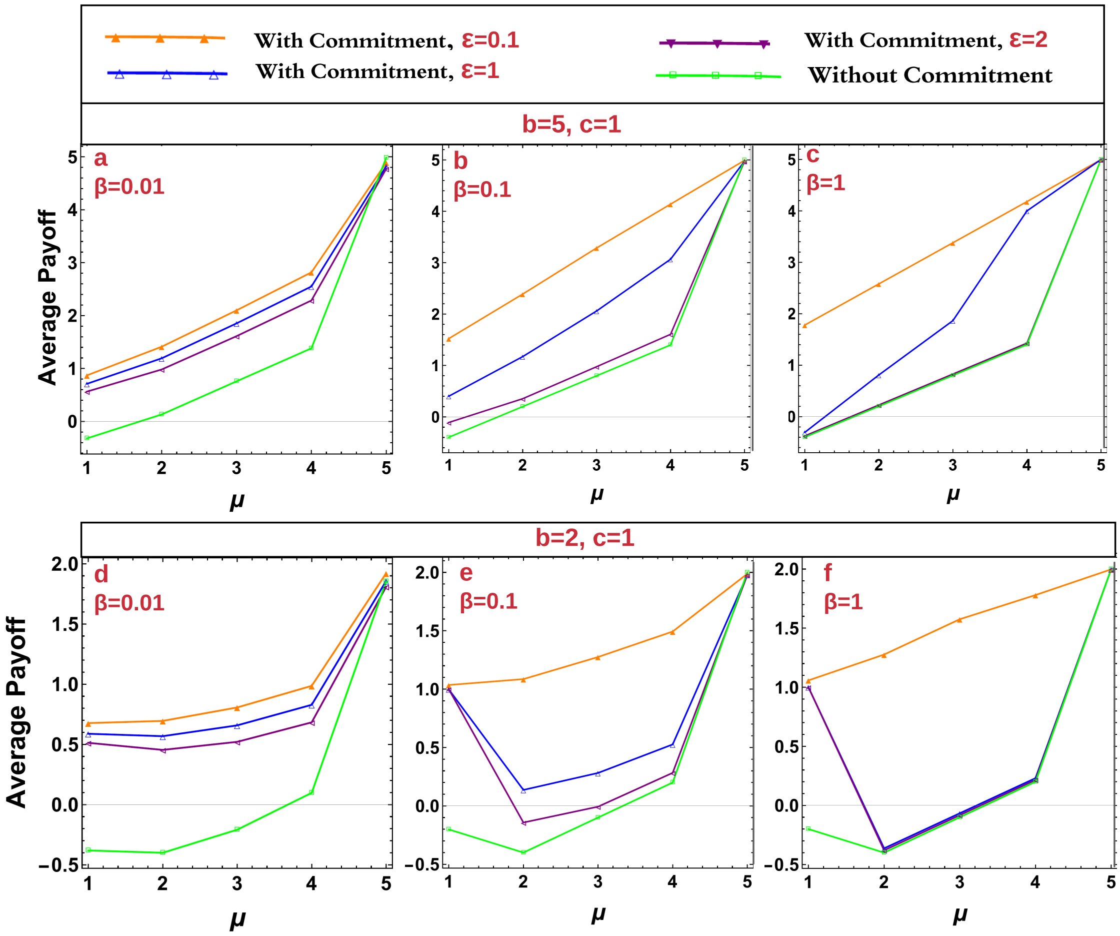

Fig. 4.5 **Average population payoff (social welfare) as a function of μ with different values of ε, showing when commitment is absent against when it is present.** We compare results for different values of β in two game configurations. We observe that whenever $\mu < 5$ (i.e. when there is a need for coordination to avoid competition in the group), arranging a prior commitment is beneficial to the population social welfare. Parameters: in panel a, b and c) $b_H = 6$ (i.e. $b = 5$), in panel d,e and f) $b_H = 3$ (i.e. $b = 2$). Other parameters: $N = 5$, $\alpha = 0.5$, $c_H = 1$, $c_L = 1$, $b_L = 2$. When $\mu < N$ ($N = 5$), it means that there is a need to coordinate among the group players to avoid competition that would result in a lower benefit, prior commitments lead to increase of social welfare. This increase is more significant in the more difficult coordination situation (i.e. the bottom row, which is a different game configuration) and when the cost of arranging commitment is low, which is also slightly more significant for intermediate values of μ and higher values of intensity of selection, β. We have seen in this figure different transitions when varying μ in the two game configurations. Our game 2 exhibits a more difficult coordination problem, thus displaying a non-linear transition compared to game 1.

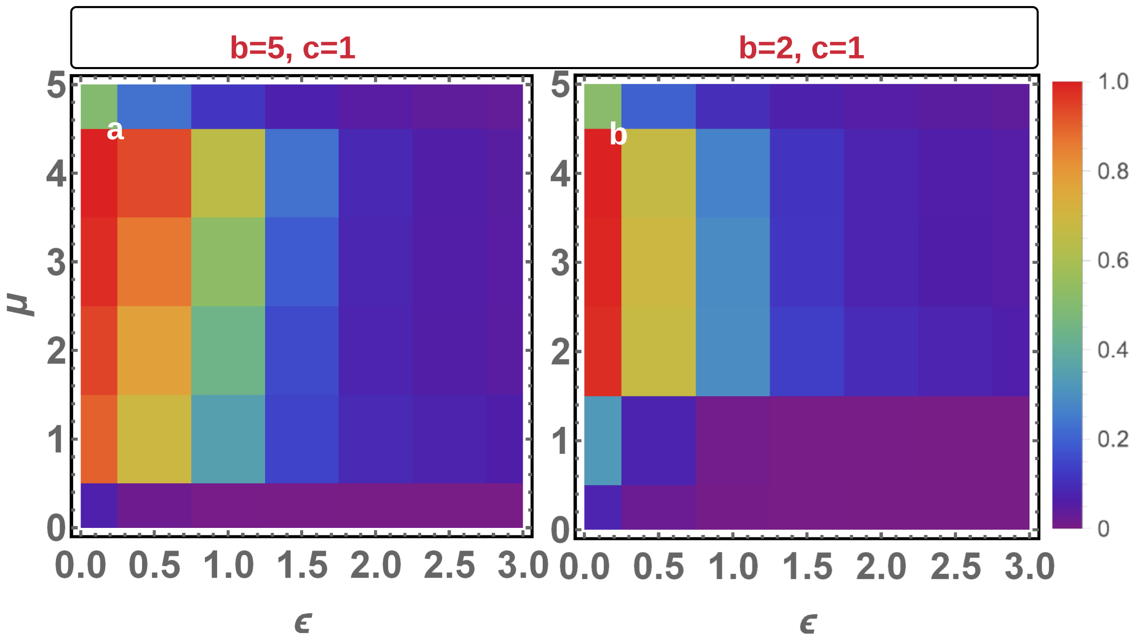

Fig. 4.6 **Total frequency of commitment proposing strategies HP and LP as a function of μ and ε.** In general, the commitment proposing strategies are most successful for intermediate values of μ, especially for a sufficiently small cost of arranging prior commitment ε. Parameters: in all panels, $c_H = 1$, $c_L = 1$ (i.e. $c = 1$), $b_L = 2$. In panel a), $b_H = 6$ (i.e. $b = 5$) and in panel b) $b_H = 3$ (i.e. $b = 2$). Other parameters: $N = 5$, $\beta = 0.1$; $\alpha = 0.5$.

4.4.4 Numerical Results for N-player TD game

We compute stationary distributions in a population of six strategies HP, LP, HN, LN, HC and LC, for the N-player TD game, using the payoffs in Table 4.2 and the Methods described above. To begin with, in Figure 4.2 (see also Figure 4.1), we provide numerical validation for the analytical conditions obtained in the previous section regarding when commitment proposing strategies are evolutionarily viable strategies (being risk-dominant against others). Similar to the pairwise TD game (Chapter 3), we observe that there is a threshold for ε below which it is the case. Moreover, Figure 4.3 shows that the frequencies of these strategies (HP and LP) decrease for increasing α. They dominate the population whenever ε is sufficiently small (e.g. when the value of $\varepsilon = 0.1$ and $\varepsilon = 1$). That is, it is more beneficial to engage in a pre-commitment deal when the market competition is harsher (i.e. small α). These results are robust for different intensities of selection (see Figure 4.4). In general, our results confirm the similar observations regarding the effects of ε and α on the evolutionary outcomes obtained in the pairwise game. However, when the reverse is the case when the cost of arranging commitment ε is adequately large. Also, when there is lesser market competition (that means the value of α is high), the non-proposing strategies dominate the population, even with a very small ε (See figure 4.3, panels a, b, d and e).

We now focus on understanding the effect of the new parameter in the N-player game, μ, on the evolutionary outcomes. Recall that μ indicates the demand for high technology (H) in the group, describing what is the maximal number of players in the group that can adopt H without reducing their benefit due to competition. Figure 4.2 shows the effect of different values of μ on the frequency or evolutionary success of all strategies as a function of ε. When μ is small to intermediate, and the cost of arranging pre-commitment is also small, the commitment proposing strategies are dominant. This suggests that arranging pre-commitments might be more beneficial in such instances. These results also imply that μ is very essential in determining when commitment should be initiated. Apparently, the greater need for a group mixture or market diversity of technologies, indicating a more difficult coordination situation, the greater need for the utilization of commitment to enhance coordination among players is. This observation is even more evident in Figure 4.6, where we examine the success of commitment for varying μ and ε, in regards to two different game configurations. It can be observed that an intermediate value of μ leads to the highest frequency of commitment strategies, especially in the more difficult coordination situation (i.e. the right panel).

We now closely examine the gain in terms of social welfare improvement when using pre-commitments. As shown in Figure 4.5, whenever $\mu < N$ ($N = 5$), i.e. there is a need to coordinate among the group players to avoid competition that induces benefit reduction, prior commitments lead to increase of social welfare. This increase is more significant in the more difficult coordination situation (i.e. the lower row) and when the cost of arranging commitment is low, which is also slightly more significant for intermediate values of μ and higher values of intensity of selection, β.

4.5 Conclusions and Further Discussion

We have studied in this chapter novel evolutionary game theory models demonstrating how pre-commitments can be adopted as an efficient mechanism for enhancing coordination, in multi-player interactions and have compared with previous results from pairwise interaction. For that, we described technology adoption (TD) games where technology investment firms would achieve the best collective outcome if they can coordinate with each other to adopt a mixture of different technologies.

In our two-player game, we have studied a parameter α which captures the competitiveness level of the product market and how beneficial it is to achieve coordination while in our multi-player game, we introduced another parameter μ to capture the optimal coordination mixture or diversity of technology adopters in a group. α parameter which represents the competitive level of the market is also studied in our multi-player game. Apart from the fact that a multi-player game captures more players engaging in an interaction, a significant difference between our two-player and multi-player games is that, in the two-player game we assume that the optimal mixture is where two firms adopt different technologies to avoid conflict. While the μ parameter introduced in the multi-player game captures the optimal coordination mixture or diversity of technology adopters in a group, thus generalising from the two-player game that would correspond the specific case of $\mu = 1$. In the multi-player model, the key parameter μ is ascribed to the market demand of high technology, i.e. what is the optimal fraction of the firms in a group to adopt H. We analytically examine how players can be coordinated when there is a market demand for a particular technology. We show that differently from the two-player game, the newly defined parameter μ leads to a new kind of complexity when trying to achieve group coordination. When there is a high level of diversity in demand (i.e. intermediate values of μ), introducing prior commitment can lead to significant improvement in the levels of coordination and population social welfare.

In the coordination settings, there are multiple desirable outcomes and players have distinct preferences in terms of which outcome should be agreed upon, thus leading to a larger behavioural space than in the context of cooperation dilemmas (Han et al., 2013a, 2015c, 2017a; Hasan and Raja, 2013; Sasaki et al., 2015b). We have shown that whether commitment is a viable mechanism for promoting the evolution of coordination, strongly depends on α: when α is sufficiently small, pre-commitment is highly abundant leading to significant improvement in terms of social welfare (i.e. population average payoff), compared to when commitment is absent. This answers our fourth research question *" Whether and when is it advantageous to arrange and accept to engage in a costly commitment deal?"*. From our analytical and numerical simulations, we see that it is more beneficial for firms to engage in a pre-commitment deal when the market competition is fierce and when the cost of arranging the commitment deal is very minimal, which means when the value of α and ε is sufficiently small. Therefore, when to engage in commitment deal is dependent on the competitive level of the market and the cost of arranging the commitment deal.

Importantly, we have derived the analytical condition for the threshold of α below which the success of commitments is guaranteed for multi-player Technology adoption games. Furthermore, moving from pairwise interaction in our previous chapter to a multi-player setting, it was shown that μ plays an important role for the success of commitment strategies as well. In general, when μ is intermediate, equivalent to a high level of diversity in group choices, arranging pre-commitments proved to be highly important. It led to significant improvement in terms of social welfare, especially in a harsher coordination situation.

In both pairwise interaction from previous chapter and multi-player coordination settings in this chapter, our analysis has shown that the cost of arranging agreement must be sufficiently small, to be justified for the cost and benefit of coordination.

This is in line with previous works in the context of PD and PGG (Han et al., 2013a, 2015c, 2017a). It is due to the fact that those who refuse to commit can escape sanction or compensation. Solutions to this problem have been proposed in the context of PD and PGG, namely, to combine commitment with peer punishment, intention recognition, apology or social exclusion to address non-committers (Han and Lenaerts, 2016a; Han et al., 2015a,c; Martinez-Vaquero et al., 2017; Quillien, 2020) or to delegate the costly process of arranging commitment to an external party (Cherry and McEvoy, 2013; Cherry et al., 2017; Han, 2022).

In distributed and self-organizing multi-agent systems, pre-commitments and agreements have been applied to model and construct desirable right behaviour, such as cooperation, coordination, and fairness. (Chopra and Singh, 2009; Singh, 1991; Winikoff, 2007). These works however do not consider the dynamical aspects of the systems nor under what conditions for instance regarding the relation between costs and benefits of coordination and those of arranging a reliable commitment. Thus, our results provide important insights into the design of such distributed and self-organizing (adaptive) systems to ensure high levels of coordination, in both pairwise and multi-party interactions (Bonabeau et al., 1999; Pitt et al., 2012).

Our next chapter will focus on exploring the impact of different population structures, including square lattice and scale-free (SF) network on the dynamics of decision-making in the context of coordinating technology adoption.

Chapter 5

Structured Population

Arranging pre-commitments of future actions has been shown to be an evolutionary viable strategy in the context of social dilemmas. Previous chapters have focused on the simple well-mixed population setting. In this chapter, starting from a baseline model of a coordination game with asymmetric benefits for technology adoption in the well-mixed setting, we examine the impact of different population structures, including square lattice and scale-free (SF) networks, capturing typical homogeneous and heterogeneous network structures, on the dynamics of decision-making in the context of coordinating technology adoption.

We show that, similarly to the well-mixed analyses, pre-commitments enhance coordination and the overall population payoff in structured populations, especially when the cost of commitment is justified against the benefit of coordination, and when the technology market is highly competitive. When commitments are absent, slightly higher levels of coordination and population welfare are obtained in scale-free than lattice. In the presence of commitments and when the market is very competitive, the overall population welfare is similar in both lattice and heterogeneous networks; though it is slightly lower in scale-free when the market competition is low, while social welfare suffers in a monopolistic setting. Overall, we found that commitments can improve coordination and population welfare in structured populations, but in its presence, the outcome of evolutionary dynamics is, interestingly, not sensitive to changes in the network structure.

5.1 Introduction

Considering today's technology-driven economy, managers often face challenging decisions regarding the adoption of innovative technology. Often, companies might choose to invest in new technologies in order to gain a competitive advantage over their peers (Clemons, 1991; Parsons, 1983; Zhu and Weyant, 2003). These selfish executive priorities may lead to a coordination problem. Ensuring higher social welfare by providing several technological solutions is ignored if newer technology promises larger profits (Sachs, 2000; Zhu and Weyant, 2003). In this setting, commitments have already been shown to promote coordination in the face of technology adoption in homogeneous (namely, well-mixed) populations (Ogbo et al., 2022). However, real-world firms and their interactions are far from homogeneous. Some developers are more influential than others, or can play a more impactful role in the adoption of innovative technologies. These economies are shaped by complex networks of exchange, influence and competition where diversity is ubiquitous. Particular networks of contacts have been shown to promote the evolution of positive behaviours in settings such as cooperation (Chen et al., 2015; Ohtsuki et al., 2006; Perc and Szolnoki, 2010; Perc et al., 2017; Santos et al., 2008), fairness (Cimpeanu et al., 2021; Page et al., 2000; Santos et al., 2017; Szolnoki et al., 2012; Wu et al., 2013b) and trust (Kumar et al., 2020). In the present work, we pay heed to the divide between the previous research and the diversity observed in real-world interactions, and ask whether network topology plays an important role in the coordination of beneficial *technology adoption*.

Technology innovation and collaboration networks (e.g. among firms and stakeholders) are highly heterogeneous (Newman, 2004; Schilling and Phelps, 2007). Firms interact more frequently within their spheres than outside them, forming alliances and networks of followers and collaborators (Ahuja, 2000; Barabasi, 2014). Developers may compete in numerous markets, while others might choose only to invest in a few, and their positions in inter-organisational networks strongly influence not only their behaviours (such as information and resource sharing), but also innovation outcomes (Ahuja, 2000; Shipilov and Gawer, 2020). Therefore, it is paramount to comprehend the roles that spatiality and diversity in the network of contacts play in the formation and stability of commitment-based strategies and the resulting coordination outcome. Therefore, here we depart from well-mixed settings (Ogbo et al., 2022) and examine how network structures shape the dynamics of adoption decisions and commitments.

Several attempts have been made to study the effects of population structures on evolutionary and ecological dynamics. Including approaches like the spatial models in ecology, viscous populations, spatial games and games on graphs (Perc et al., 2017; Santos and Pacheco, 2005; Tarnita et al., 2009). Among these works, by introducing spatial structures, the research work has attracted interest from different fields as significant extensions of traditional evolutionary game theory focusing on well-mixed populations (Su et al., 2019).

Highly relevant to our work, Santos et al. (2006c) investigated the effect of population structures on different types of two player social dilemmas including the Prisoner's Dilemma, Stag Hunt and Snowdrift games. Cooperation is shown to be more prevalent in heterogeneous networks than homogeneous ones (such as square lattice and well-mixed populations). Similarly, Cimpeanu et al. (2022) have shown that safety adoption in the development of AI technology can be enhanced by heterogeneous network structures. This is also in line with what is explored in (Di Stefano et al., 2015, 2020) where it has been shown how highly heterogeneous networks, such as SF, constitute the most suitable network topology for the emergence and sustainability of cooperation in a multilayer network. This is even more marked in the presence of homophily (i.e., the tendency to associate and interact more frequently with similar people), increasing the speed and size of the formation of cooperative groups, and allowing the network to quickly converge to cooperation. Our coordination setting is different from the aforementioned models, as they focus on symmetric games, whereas we address the context in which players need to coordinate to choose different actions (i.e. an asymmetric game) (Ogbo et al., 2022). Our analysis below shows that, surprisingly, the outcomes of our model differ from (Cimpeanu et al., 2022; Santos et al., 2006c) insomuch that heterogeneous networks have little positive impact on, or are even detrimental to coordination and social welfare, compared to homogeneous settings.

Moreover, this observation is partially coherent with other previous works (Gracia-Lázaro et al., 2012a,b) in the context of the Prisoner's Dilemma game, where it has been shown how the population structure has little relevance as a cooperation promoter, and where the presence of a structured population does not promote or inhibit cooperation with respect to well mixed populations. Our results are also in line with (Pena et al., 2009), where authors, by introducing conformity, namely the tendency of humans to imitate locally common behaviours, have shown that when fair quantities of conformity are added in the imitation rules of the players, scale-free networks are no longer powerful amplifiers of cooperation. Such weakening of the cooperation-promoting abilities of scale-free networks is the result of a less biased flow of information in SF topologies, making hubs more susceptible to being influenced by less-connected neighbours.

5.2 Model and Methods

Our technology adoption (TD) game as already described in previous chapters consist of firms competing in a common market, making a decision on investing in a technology (Ogbo et al., 2022). These firms either invest in innovative technology which promises the highest profits (i.e. high technology, denoted by **H**), or to invest in less sophisticated products, resulting in a lower potential benefit (i.e. low technology, **L**). For convenience, recall that the interaction between these firms is described in terms of costs and benefits of the investments by the following payoff matrix (for row player):

$$\begin{array}{c} \\ H \\ L \end{array}\!\!\begin{array}{c} \begin{array}{cc} H & L \end{array} \\ \begin{pmatrix} \alpha b_H - c_H & b_H - c_H \\ b_L - c_L & \alpha b_L - c_L \end{pmatrix} \end{array} = \begin{array}{c} \\ H \\ L \end{array}\!\!\begin{array}{c} \begin{array}{cc} H & L \end{array} \\ \begin{pmatrix} a & b \\ c & d \end{pmatrix} \end{array}, \tag{5.1}$$

5.2.1 Network Topology

Real-world networks are not static and inherently heterogeneous (Barabási and Albert, 1999; Dorogovtsev, 2010; Newman, 2003). Networks evolve with new nodes entering and creating connections to already existing nodes (Dall'Asta et al., 2006). Several works have unveiled how structural *heterogeneity* plays a key role in both the evolution of cooperation (Cimpeanu et al., 2019b; Dercole et al., 2019; Di Stefano et al., 2015, 2020; Poncela et al., 2007) or emergence of fairness (Cimpeanu et al., 2021; Sinatra et al., 2009). To study the effects of heterogeneity on the evolution of coordination and prior commitments, we will study spatially structured populations, as well as a growing network model characterized by *preferential attachment*.

Links in the networks describe both proximity for the purposes of interactions (i.e. whom the agents can interact with), but also for the purposes of social learning (whom the agents can imitate). Thus, the network of interactions coincides with the network of imitation (Ohtsuki et al., 2007). Structured populations converge more readily than heterogeneous populations, and our choice of population sizes and maximum number of generations reflects on these differences.

We model spatially structured populations using a square lattice graph (SL) of size $Z = L \times L$ with periodic boundary conditions— a widely adopted population structure in population dynamics and evolutionary games (for a survey, see (Szabó and Fáth, 2007)). This network adds spatial structure, but each agent can only interact with its four immediate edge neighbours; thus, we can say it is homogeneous in the number of neighbours, unlike real-world networks of firms (Newman, 2004; Schilling and Phelps, 2007). For all of our experiments with this network type, we choose $L = 30$ (i.e. $Z = 900$).

In an effort to introduce a more realistic interaction setting, we turn to SF networks, specifically the popular Barabási and Albert (BA) model (Barabási and Albert, 1999). SF networks constructed using the BA model follow a preferential attachment rule, leading to a typical *power-law degree distribution*. To construct such a network, we start from a small complete graph of size m_0 and gradually introduce new nodes. Each new node selects m other nodes according to a probability proportional to their degree (how connected they are in the network), creating a new link with each of these nodes. This procedure repeats until a network of size Z is obtained. The resultant network follows a power-law degree distribution, which is skewed with a long tail. There are few hubs in the network, which gradually increase in size (number of connections) as the size of the network increases, in a classic *rich-get-richer* setting. The obtained network has average degree $h = 2m$, small clustering (of order $1/N$) and a power-law degree distribution $P(k) \sim k^{-\gamma}$, with $\gamma = 3$. This form of $P(k)$ decays slowly as the degree k increases, thus increasing the likelihood of finding a node with a very large degree.

For all of our experiments with this network type, we seed 10 different networks of size $Z = 1000$, with an average connectivity of $h = 4$. The latter is chosen for ease of comparison against the square lattice graph.

5.2.2 Population Dynamics

We consider a population of agents distributed on a network (see below for different topologies), randomly assigning one of the eight strategies. At each time step or generation, each agent plays the game with its immediate neighbours. The success of each agent (i.e., its fitness) is the sum of the payoffs in all these encounters. Each individual fitness, as detailed below, defines the time-evolution of strategies, as successful choices will tend to be imitated by their peers.

At the end of each generation, a randomly selected agent A with a fitness f_A chooses to copy the strategy of a randomly selected neighbour, agent B, with fitness f_B with a probability p that increases with their fitness difference. As in the well-mixed population settings (in Chapters 3 and 4), we adopt the well-studied Fermi update or pairwise comparison rule, where (Traulsen et al., 2006):

$$p = (1 + e^{\beta(f_A - f_B)})^{-1}. \tag{5.2}$$

In this case, β conveniently describes the selection intensity — i.e., the importance of individual success in the imitations process: $\beta = 0$ represents neutral drift while $\beta \to \infty$ represents increasingly deterministic imitation (Traulsen et al., 2006). Varying β allows capturing a wide range of update rules and levels of stochasticity, including those used by humans, as measured in lab experiments (Grujić and Lenaerts, 2020; Rand et al., 2013b; Zisis et al., 2015). In line with previous network settings and lab experiments, we set $\beta = 1$ in our simulations, ensuring a high intensity of selection (Pinheiro et al., 2012). This update rule implicitly assumes an asynchronous update rule, where at most one imitation occurs at each time-step. With a given probability μ, this process is replaced instead by a randomly occurring mutation. A mutation is equivalent to behavioural exploration, whereby the individual makes a stochastic decision switch to one of the eight available strategies.

We simulate this evolutionary process until a stationary state or a cyclic pattern is reached. As network topology and the number of available strategies affects rates of convergence, we select different maximum numbers of runs for each network type, for robustness. The simulations have been conducted for 15000 generations in the case of lattice and the results are averaged over the final 1000 steps. For BA networks, we run the simulations for 250000 generations (for 8 strategies, with commitment) and 50000 generations (for 2 strategies, no commitment), averaging over the final 25000 steps. Furthermore, to improve accuracy, for each set of parameter values and pre-seeded network (in the case of BA networks), the final results are obtained from averaging 15 independent realizations (replicates), an approach usually adopted in structured population analyses (Perc and Szolnoki, 2010; Perc et al., 2017; Santos et al., 2006c). When shown in figures, the error bars represent the standard deviation of the mean between replicates.

5.3 Results

5.3.1 In absence of pre-commitments

To begin with, we study evolutionary outcomes in the technology adoption (TD) game when arranging commitments is not available as an option. Figure 5.1 shows that for all values of α, i.e. regardless of market competition, players dominantly choose to adopt high technology (i.e. playing H in the TD game). This observation is applied to both lattice and SF networks, with L having a slightly higher frequency in the SF network than lattice when α is sufficiently small (i.e., highly competitive markets). To support the understanding of this observation, we show in Figure 5.2 the evolution of the two strategies H and L over time, for different values of α. We observe that only in SF and when the market competitiveness is high ($\alpha = 0.1$), L players have a chance to survive the dominance of H players, even though they are still in minority. This observation differs from previous findings in homogeneous networks, but is in line with previous works studying cooperation dilemmas in structured populations, where SF networks can lead to higher levels of pro-social behaviours (including cooperation and fairness) than in lattice counterparts (Cimpeanu et al., 2021; Perc et al., 2017; Santos et al., 2006c, 2008). Note that no existing works have studied commitment formation dynamics in the such structured population settings, as in the present work.

In the following, unless stated otherwise, we set $\alpha = 0.5$. As such, there is a clear need for arranging prior commitments among players to enhance coordination. Otherwise, this

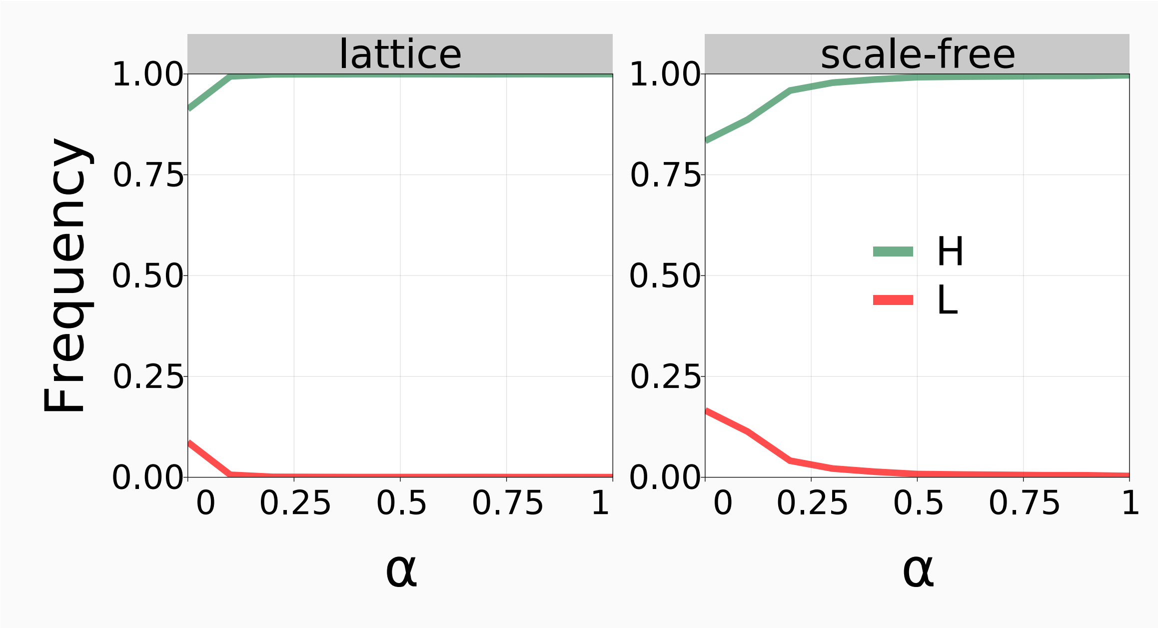

Fig. 5.1 **In the absence of commitments: Depicted are frequencies of H and L as a function of α for lattice (left panel) and scale-free (right panel) networks.** We have compared here when there is no commitment involved in both cases of lattice and scale-free networks. When there is no commitment, we have two strategies where players will either play H (adopt a high technology) or play L (adopt a low technology). We observe that H (adopt a high technology) is dominant, irrespective of the market competitiveness α. L is more frequent in SF than in lattice when α is small. Parameters: in all panels $c_H = 1$, $c_L = 1$, $b_L = 2$, $b_H = 6$ and $\beta = 1$.

would lead to the extinction of firms that would choose to adopt low-benefit technologies (i.e., L players) in the population.

The time evolution in Figure 5.2 has clearly shown that regardless of the competitive level of the market i.e $\alpha = 0.1, 0.5, 0.9$, indicating α is either highly competitive, moderately competitive or less competitive, players would always adopt H technology (except that when α is small, a small number of players would adopt L in SF, compared to none in lattice). Which means their will be no adopters of L technology in this instance, hence the need for coordinating players to have a blend of both H and L technologies in the population.

5.3.2 In presence of pre-commitments

We now examine whether arranging pre-commitments can improve coordination outcomes, and whether these outcomes change for different population structures (homogeneous versus heterogeneous networks). We analyse evolutionary outcomes in a population with eight strategies (see Model and Methods), for varying different key factors. Firstly, Figure 5.3

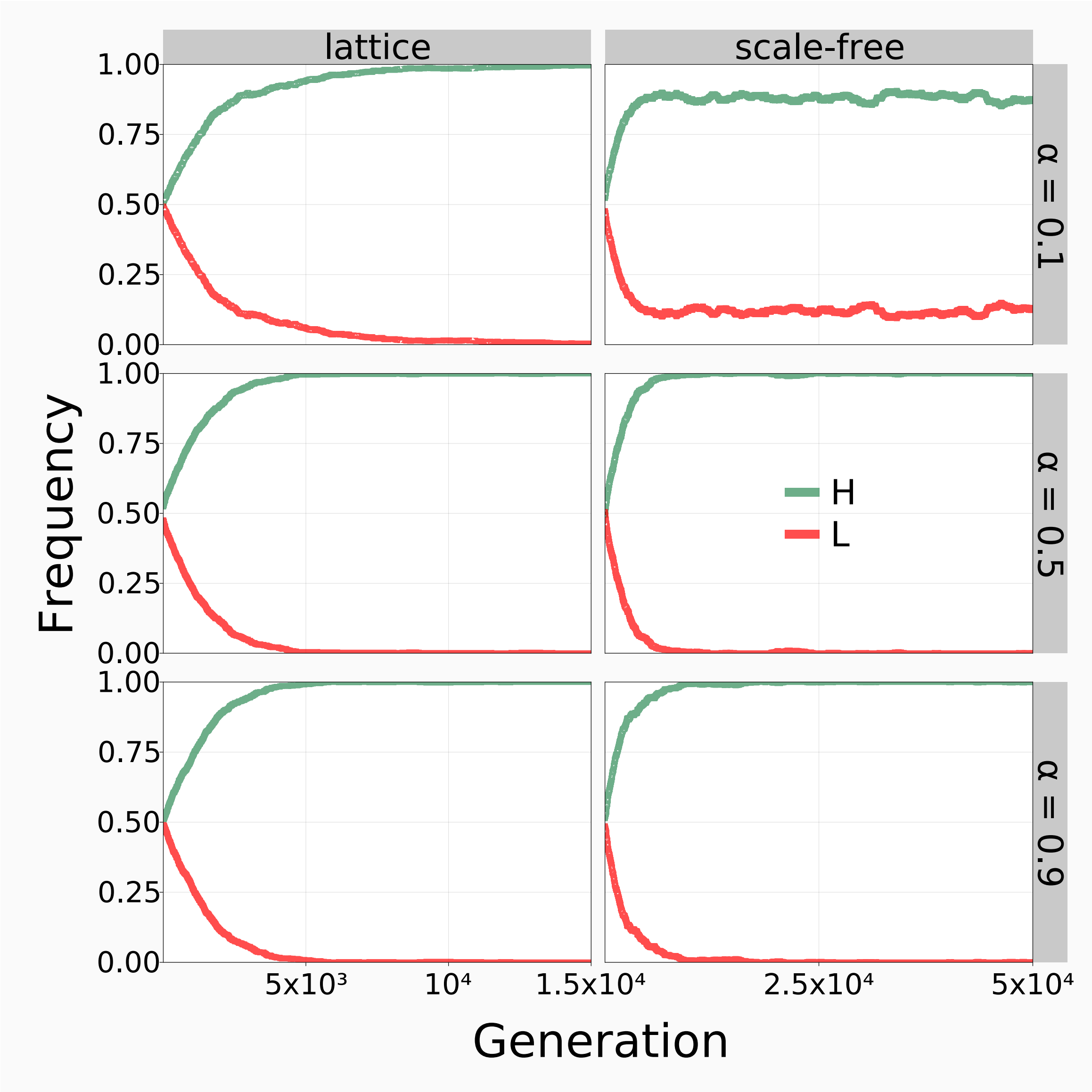

Fig. 5.2 **Time-evolution of frequencies of two strategies H and L in the absence of commitments**, for different levels of competitiveness: high ($\alpha = 0.1$), medium ($\alpha = 0.5$) and low ($\alpha = 0.9$). Only when the market competitiveness is high ($\alpha = 0.1$) and in case of SF (first row), L players have a non-negligible (but still rather small) frequency. Other parameters' values are the same as in Figure 1.

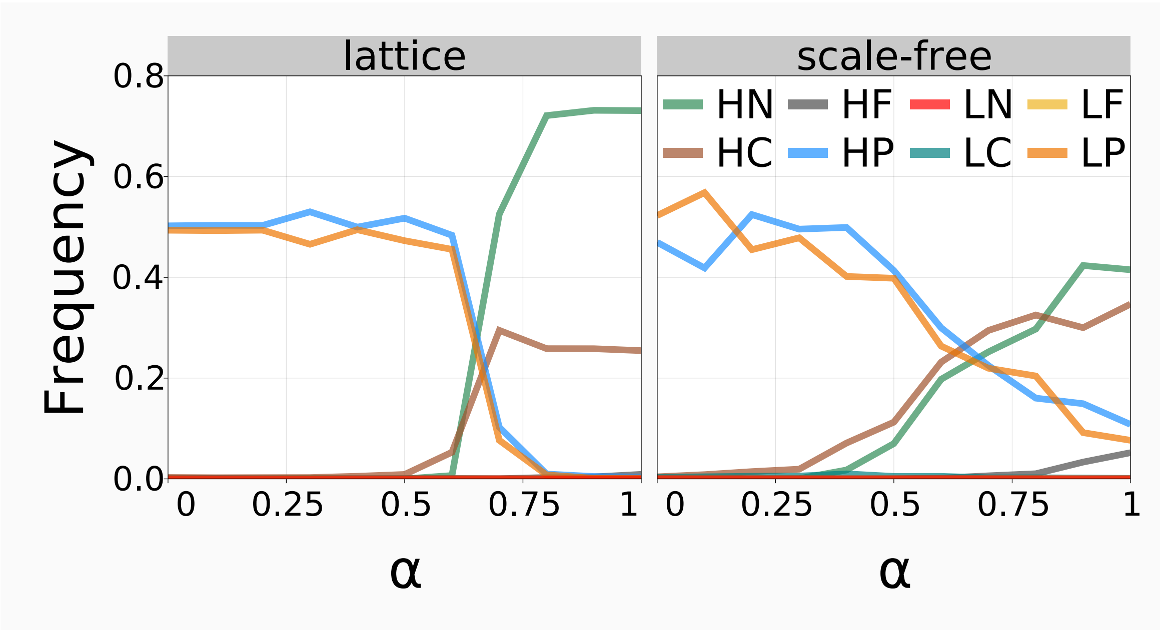

Fig. 5.3 **Frequencies for the eight strategies (HP, LP HN, LN, HC, LC, LF, HF) as a function of α for lattice (left panel) and scale-free (right panel) networks.** In both types of network, we observe that when α is small, indicating a highly competitive market, the commitment proposing strategies (HP and LP) dominate the population. When α is large, the non-commitment strategies HN and HC dominate the population. Comparing the two types of network, commitment proposers have higher frequencies in SF than in lattice when α is sufficiently large. Parameters: in all panels $c_H = 1$, $c_L = 1$, $b_L = 2$, and $b_H = 6$, $\beta = 1$; $\mu = 0.001$; $\varepsilon = 0.1$; $\delta = 6$. Fair agreements are applied, where θ_1 and θ_2 are given by $\theta_1 = (b - c - \varepsilon)/2$ and $\theta_2 = (b - c + \varepsilon)/2$.

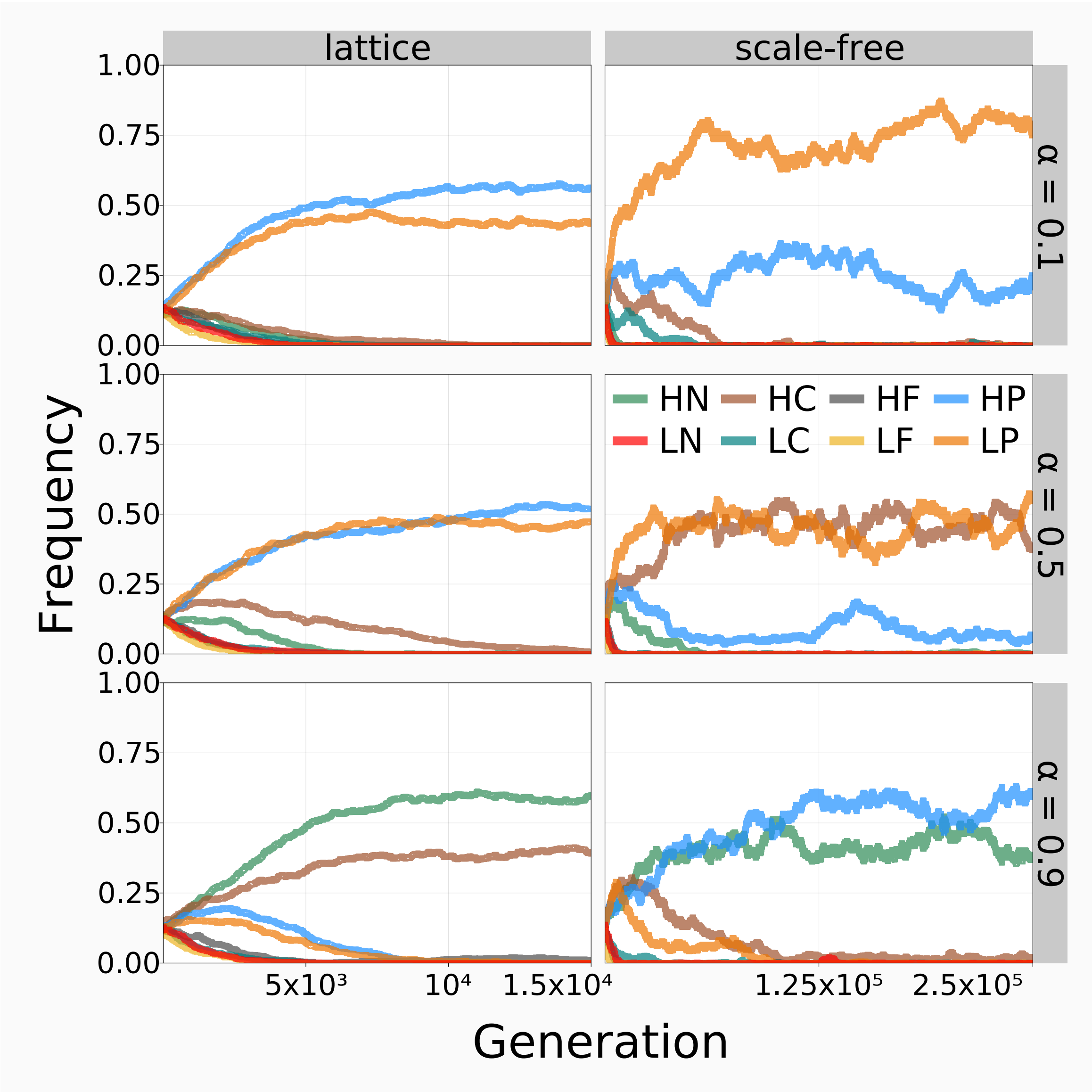

Fig. 5.4 **Time-evolution of frequencies of eight strategies (HP, LP HN, LN, HC, LC, LF, HF) in the presence of commitments**, for different levels of competitiveness: High ($\alpha = 0.1$), medium ($\alpha = 0.5$) and low ($\alpha = 0.9$).Other parameter values are the same as in Figure 5.3

shows the frequency of these strategies as a function of α in both lattice and SF networks. In general, the commitment proposing strategies HP and LP are more frequent in the population when the market competition is high (i.e. when α is small). When there is less competition in the market, HN and HC take over the population, leading to a monopolized market. This result is similar in lattice and SF networks. However, we note a small discrepancy between them, where commitment proposers have higher frequencies in SF network than in lattice, if α is sufficiently large. We also observe that the HN strategy has a higher frequency in lattice networks than in heterogeneous networks. For instance, when $\alpha = 1$, the fraction of HN strategists is 0.78 of the total in lattice networks, and 0.4 in SF networks.

Figure 5.5 studies the frequency of the strategies for varying the cost of arranging commitments, i.e. ε. For commitment proposers to engage in a commitment arrangement, the cost of arranging such a commitment needs to be sufficiently small. This observation is in line with previous works on pre-commitments in cooperation (Akdeniz and van Veelen, 2021; Han et al., 2013a, 2015c, 2017a; Sasaki et al., 2015b) and coordination (Ogbo et al., 2022) games, in the well-mixed population settings. That is, our analysis has again confirmed that prior commitments can provide a pathway for the evolution of coordination even in the presence of more complex networks of interaction.

In order to determine when commitments can lead to significant improvement (in terms of overall population payoff or welfare), in Figure 5.6 we compare the average population payoff when commitment is present and when it is absent, as a function of α (which is the competitiveness of the market, left panel) and ε (which is the cost of arranging a commitment, right panel). We observe here that commitments can lead to significant improvements when α and ε are sufficiently small. That is, arranging pre-commitments is highly beneficial whenever the market competitiveness level is high, and when it is not too costly to do so. We also observe that SF and lattice networks lead to similar population payoffs for all values of ε and α. One small difference is that SF leads to a slightly higher payoff when commitment is absent in highly competitive markets ($\alpha \lessapprox 0.2$), while this effect is reversed when commitments can be initiated. That is, the heterogeneity of SF networks might be slightly detrimental for population welfare when commitment is present. The main reason for this effect is that when the competitiveness level is low (i.e. large α), coordination is not as important as when the competitiveness level is high (a population of H players has a higher welfare when α increases, see Figure 6), and it is costly to arrange commitments. The evolution of commitment proposing strategies for large α (see Figures 3 and 4) leads to higher spending for arranging commitments in the population.

We also measure the effects of varying mutation rates in our work. In particular, we focus on how increasing mutation rates affect the coordination outcome in the population,

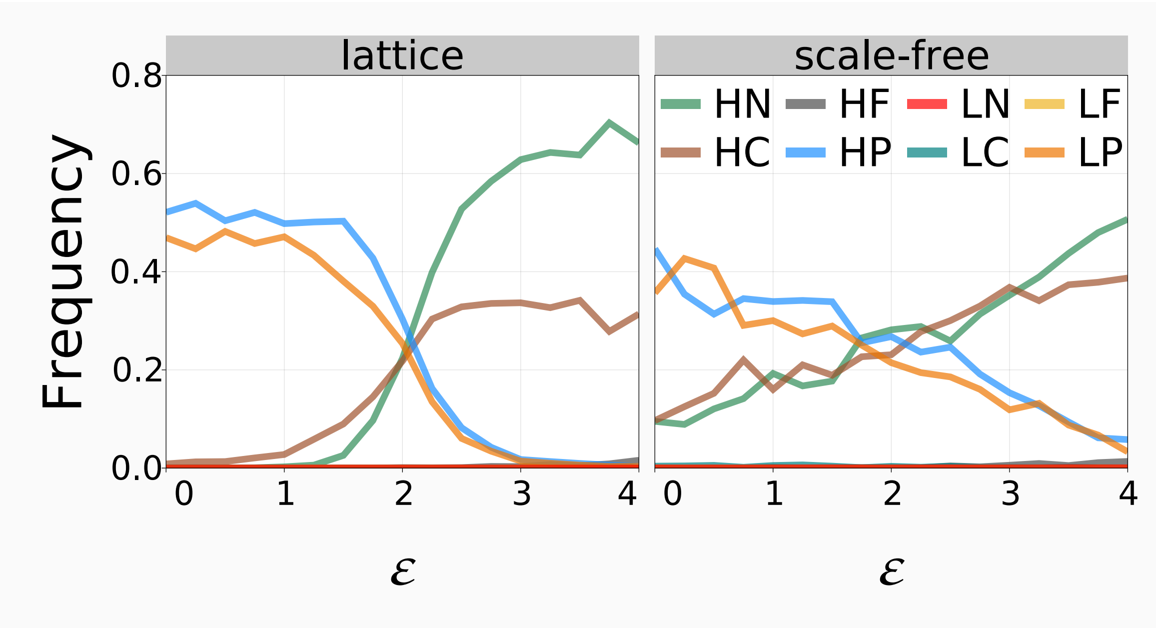

Fig. 5.5 **Frequencies for the eight strategies (HP, LP HN, LN, HC, LC, LF, HF) as a function of the cost of commitment ε for lattice (left panel) and scale-free (right panel) networks.** In general, we observe that for both lattice and SF networks, when the cost of arranging a commitment (ε) is sufficiently small (for lattice network when $\varepsilon = 2$ and for SF network when $\varepsilon = 1.8$, approximately), commitment strategies HP and LP are more abundant in the population. When ε exceeds these points, the non-proposing strategies HN and HC who do not pay for the cost of commitment deal dominate the population. Moreover, when ε is sufficiently large, commitment proposing strategies are more frequent in SF than in lattice. Parameters: in all panels $c_H = 1$, $c_L = 1$, $b_L = 2$, and $b_H = 6$, $\beta = 1$; $\mu = 0.001$; $\alpha = 0.5$; $\delta = 6$. Fair agreements are applied, where θ_1 and θ_2 are given by $\theta_1 = (b - c - \varepsilon)/2$ and $\theta_2 = (b - c + \varepsilon)/2$.

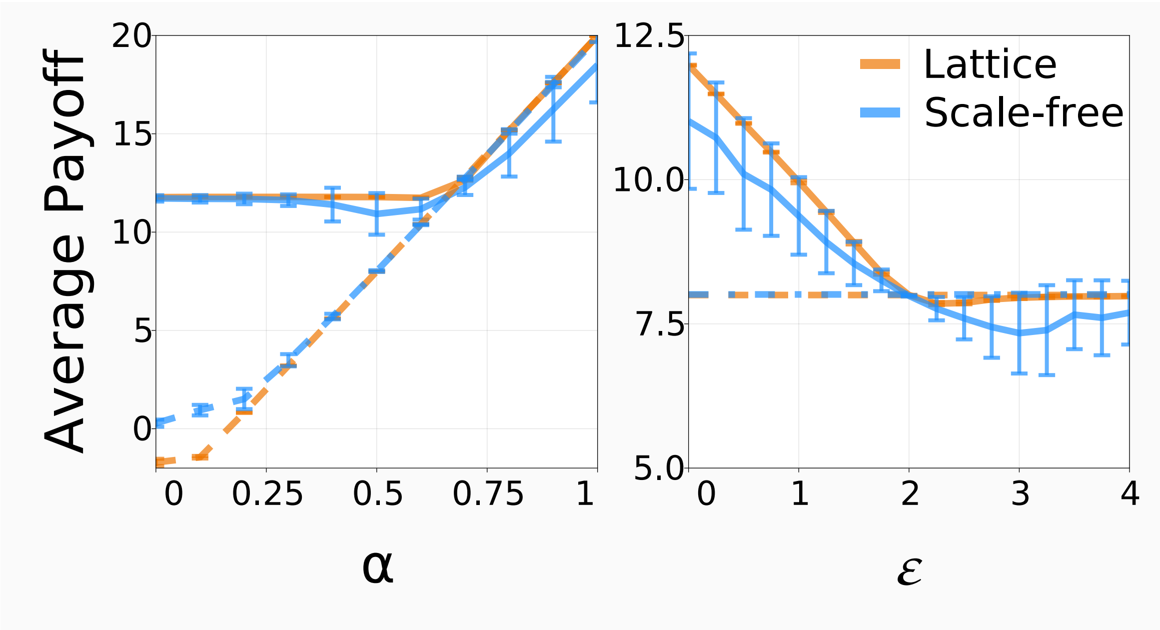

Fig. 5.6 **Average population payoff (welfare) as a function of α (left panel) and ε (right panel), in lattice and scale-free networks. We compare these payoffs when commitment is present (solid lines) vs when it is absent (dashed lines)**. We observe that arranging commitments leads to larger population payoffs than when it is not an option whenever α and ε are sufficiently small (up to around 0.7 and 2.0, respectively). That is, arranging pre-commitments is highly beneficial whenever the market competitiveness level is high, and when it is not too costly to do so. We also observe that, SF and lattice lead to similar population payoffs for all values of ε and α. SF leads to slightly higher payoff when commitment is absence when α is quite small (up to 0.2), while it is reversed when commitment is present. Other parameters in all: $\beta = 1$; $\mu = 0.001$; $\delta = 6$, $\theta_1 = (b-c-\varepsilon)/2$, $\theta_2 = (b-c+\varepsilon)/2$. Parameters in panel a; $\varepsilon = 0.1$, and panel b; $\alpha = 0.5$.

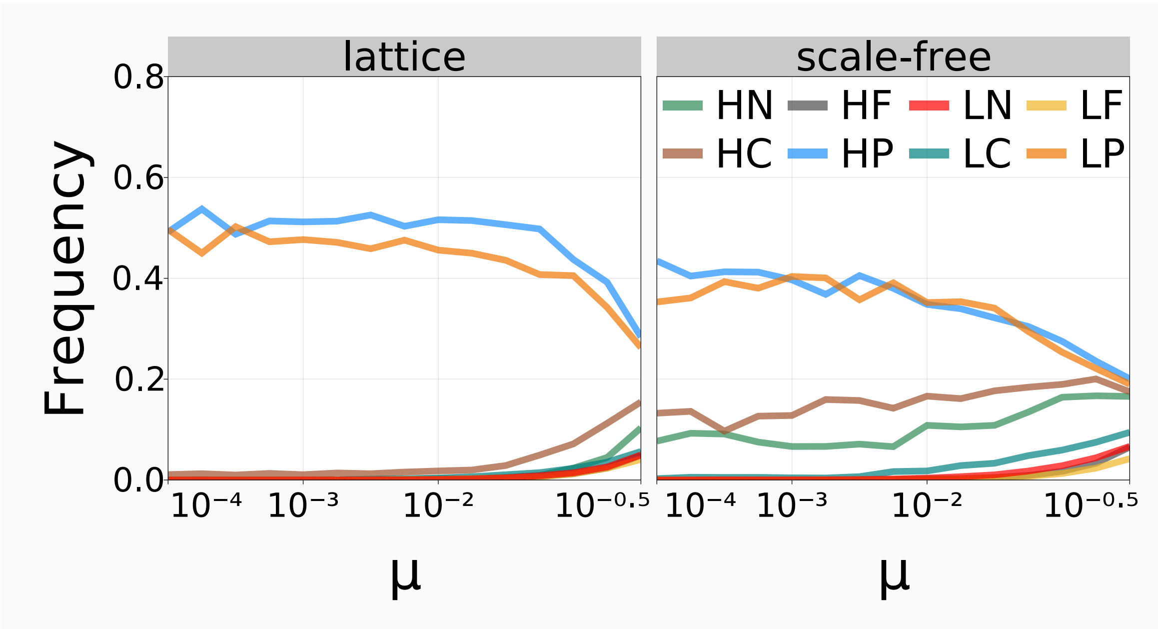

Fig. 5.7 **Frequencies for the eight strategies (HP, LP HN, LN, HC, LC, LF, HF) as a function of the mutation rate μ (ranging from a small $10^{-4} = 0.0001$ to a high $10^{-0.5} = 0.316$ values) for lattice (left panel) and scale-free (right panel) networks.** Larger mutation leads to greater levels of randomness in agents' behaviours, leading to strategies' frequencies being closer. Also, for the whole range of μ, SF leads to higher diversity in terms of strategic behaviours than in lattice. Parameters: in all panels $c_H = 1$, $c_L = 1$, $b_L = 2$, and $b_H = 6$. Other parameters: $\beta = 1$; $\varepsilon = 0.1$; $\alpha = 0.5$; $\delta = 6$. Fair agreements are applied, where θ_1 and θ_2 are given by $\theta_1 = (b - c - \varepsilon)/2$ and $\theta_2 = (b - c + \varepsilon)/2$.

differently from previous works which assume a small mutation limit (for convenience of theoretical and numerical analyses) (Han et al., 2013a; Ogbo et al., 2022). Indeed, Figure 5.7 shows the outcomes for varying mutation rates in both lattice and SF networks. We observe that a higher mutation leads to a more balanced state of the strategy frequencies in the population. This effect is more notable in SF networks than in lattice populations. Behavioural exploration aids in eliminating market monopolies.

Again, we have demonstrated using time evolution the interactions of players at different competitive level of the market when there is commitment Figure 5.4. Results show that when it is highly and moderately competitive, i.e $\alpha = 0.1, 0.5$, commitments thrive in the lattice networks. It is different for the scale-free networks when $\alpha = 0.5$. Here, the HC who accepts a commitment deal but never proposes have a higher frequency than the HP who proposes commitment deal. Furthermore, we see that when $\alpha = 0.9$ which indicates the market is less competitive, the commitment proposer (HP) in scale-free network still thrive in the population and also the HN strategy unlike in the lattice network where only the HN and HC (who do not propose a commitment deal) dominates the population. Overall, comparing lattice and SF networks, the commitment proposing strategies have higher frequency in SF than in lattice network, even when the market is less competitive.

5.4 Conclusions and Future Work

In this work, we have explored and quantified the effects of social diversity on the outcomes of technology adoption and coordination dynamics amongst firms, using two popular spatial structures. Specifically, we have studied the use of prior commitments to enhance coordination among agents making decisions to adopt competing technological solutions. We have discovered that prior commitments enhance coordination and social welfare in both lattice and scale-free networks, especially when the market is highly competitive or the cost of arranging commitments is sufficiently small. We have also observed that coordination is more achievable in the absence of commitments in the case of SF networks, compared to lattice networks. Correspondingly, the opposite is observed if the market is competitive and commitments are possible. Our results are in line with the analyses on well-mixed populations (in Chapter 3) (Ogbo et al., 2022). When commitment is present, the overall population welfare is similar in SF and lattice networks when the market competition level is high; it is however slightly lower in SF than lattice when this competition level is low. Ultimately, we find that commitments can improve population welfare and coordination in structured populations, and that these results are robust across a wide range of network structures, unlike the case when commitment is absent.

Overall, our analysis has provided further confirmation and theoretical evidence showing that arranging prior commitments can provide a flexible and efficient pathway to achieve high levels of collective behaviours (beyond social dilemmas settings) (Akdeniz and van Veelen, 2021; Frank, 1988; Han, 2013; Nesse, 2001a). In the future, we aim to expand this network analysis to study the effects of commitments in the multi-player version of the technology adoption game (Ogbo et al., 2022), where multiple firms participate in a technology market competition. Also as our results so far have shown that commitments can improve coordination in structured populations and it is not sensitive to changes in the network structure, further work will be carried out in future to determine if substantial changes may occur when there is structural (random) perturbations or noise on the network. For instance, a small mean degree (that is, the number of neighbors that a node has) of the network tends to induce cooperation (Allen et al., 2017; Nowak et al., 2006). Therefore, decreasing the weight of an edge or removing an edge is expected to enhance cooperation (Meng and Masuda, 2022). We aim to investigate this important issue in the future, to determine if random perturbations or noise on a network would affect the application of commitments to enhance coordination among players in a structured population.

Chapter 6

Conclusions and General Discussion

In this final chapter, we first summarise the findings and contributions presented throughout the thesis. We emphasise the possible transferability of our modelling research (on technology adoption) to other application domains. Through a critical review of our findings and recommendations, we also take advantage of the chance to discuss some of the shortcomings of our research. Finally, we propose different areas for future research.

6.1 Summary of Conclusions

In Chapters 1 and 2, we discussed and reviewed relevant issues on collective behaviour research. We observe that achieving collective behaviours among individuals with their own personal interest is an important and pressing social challenge in various societies (Ostrom, 1990a; Pitt et al., 2012; Sigmund, 2010). We reviewed the various mechanisms that can promote the emergence and stability of collective behaviours among such individuals, which have been proposed. They include kin and group selection, direct and indirect reciprocities, spatial networks, reward and punishment (Nowak, 2006b; Perc et al., 2017; Rand et al., 2013a). Moreover, we explored motivations for our main research questions and objectives, namely, how coordination issue can be resolved when there is asymmetric benefit among player; and, in particular, how other mechanisms like arranging a pre-commitment deal can be used to achieve high levels of coordination in a complex situation like our technology adoption game, as well as the potential impact of network structures on the evolutionary outcomes in such a game.

Chapters 3, 4 and 5 present our own findings and contributions. Resorting to the tool of evolutionary game theory, we provided a novel theoretical model to investigate on how firms can be coordinated to adopt different technologies where there are asymmetric benefits to be shared amongst them. We carried out our numerical and analytical analysis using various different parameter configurations to ensure accuracy and consistency of results. Our findings provide important insights that can be useful for policy and decision makers in various settings even though we have modelled our work in the technology innovation market setting (for clarity of presentation of the findings). Our analytical results and extensive computer simulations have shown that pre-commitments can be utilised for facilitating coordination amongst players. Below we summarize our main findings:

Our work has demonstrated that commitment is a viable tool for promoting the evolution of diverse collective behaviours among self-interested individuals, beyond the context of cooperation dilemmas where there is only one desirable collective outcome (Barrett et al., 2007; Han et al., 2013a, 2017a; Skyrms, 1996). It thus provides new insights into the complexity and beauty of behavioural evolution driven by humans' capacity for commitment (Frank, 1988; Nesse, 2001a).

Our analysis, both analytically and via numerical simulations, showed that whether pre-commitment would be a viable evolutionary mechanism for enhancing coordination and the overall population social welfare strongly depends on the collective benefit and severity of competition, and more importantly, how asymmetric benefits are resolved in a commitment deal. Moreover, in multiparty interactions, prior commitments prove to be crucial when a high level of group diversity is required for optimal coordination.

In both our pairwise and multiplayer interactions, we observed that the commitment proposing strategies dominate the population when the market competition is sufficiently high (leading to the need of efficient coordination among the competing players/firms to ensure high benefits) and the cost of arranging the commitment deal is low.

In the multi-player game setting, when the demand for high technology (H) in the group is small to intermediate (which describes the maximal number of players in the group that can adopt H without reducing their benefit due to competition), and the cost of arranging pre-commitment is also small, the commitment proposing strategies are dominant. This suggests that arranging pre-commitments might be more beneficial in such instances. These results also imply that μ is very essential in determining when commitment should be initiated. Apparently, the greater need for a group mixture or market diversity of technologies, indicating a more difficult coordination situation, the greater need for the utilization of commitment to enhance coordination among players is.

It is important to note that pre-commitments and agreements have been used extensively in the context of distributed and self-organizing multi-agent systems, for modelling and engineering a desirable collective behaviour, such as cooperation, coordination and fairness (Chopra and Singh, 2009; Singh, 1991; Winikoff, 2007). These works however do not consider the dynamical aspects of the systems nor under what conditions for instance regarding the relation between costs and benefits of coordination and those of arranging a reliable commitment, commitment proposing strategies can actually promote a high level of desirable system behaviour. Thus, our results provide important insights into the design of such distributed and self-organizing (adaptive) systems to ensure high levels of coordination, in both pairwise and multi-party interactions (Bonabeau et al., 1999; Pitt et al., 2012)

We observe that, similarly to previous well-mixed analyses, pre-commitments enhance coordination and the overall population payoff in structured populations, especially when the cost of commitment is justified against the benefit of coordination, and when the technology market is highly competitive. When commitments are absent, slightly higher levels of coordination and population welfare are obtained in scale-free than lattice network. In the presence of commitments and when the market is very competitive, the overall population welfare is similar in both lattice and heterogeneous networks; though it is slightly lower in scale-free when the market competition is low, while social welfare suffers in a monopolistic setting. Overall, from our findings we have demonstrated that commitments can improve coordination and population welfare in structured populations, but in its presence, the outcome of evolutionary dynamics is, interestingly, not sensitive to changes in the network structure.

6.2 Applicability

The main goal of this thesis has been to contribute to the literature of the dynamics and evolution of collective behaviours. Most specifically, we have gone beyond the conventional cooperation dilemma games, namely the Prisoner's Dilemma and the Public Goods Game (i.e. asymmetric games with a single desired collective outcome, which is mutual cooperation by all parties involved) and studied a more complex scenarios of multi-party coordination with asymmetric outcomes. Our findings are of significance and can be applicable to different sectors in the society. We summarise below some of the applicability of our work.

- **Digital transformation and Innovation**: Many social, political and economic situations require people to coordinate their behaviour with others in order to realize mutual gains. Even with the rapid digital transformation and innovation in recent times, it has become a need for governments and technology industries to determine how best to encourage collective behaviour amongst themselves for the overall goal of the society. Our commitment-based evolutionary game models can be applied to any technology adoption scenarios where coordination is required to achieve a common venture. For instance, for firms who need to make strategic decisions on which technology to adopt

(Zhu and Weyant, 2003), our approach can prove beneficial to achieving coordination amongst these firms.

- **AI Innovation Race:** With all the impact that AI promises, there is a risk that some adopters/developers will feel obliged to cut corners on safety precautions, or ignore societal consequences, in a race for technological supremacy. Prior commitment model can act as a key role in safety adoption within a race towards transformative AI. Han et al. (2022) investigated the potential of a regulatory mechanism that combines a voluntary commitment approach reminiscent of soft law, where technologists have the freedom of choice between independently pursuing their course of actions or establishing binding agreements to act safely, with either a peer or governmental sanctioning system of those that do not abide by what they pledged. Just like Han et al. (2022)'s voluntary commitment model, our model can also be applied in this context, which can help to coordinate players against unsafe technology adoption and even be utilised in government regulation of safe adoption of technology to ensure beneficial outcome to all parties involved and the society at large. These techniques can also be applied to other technologies and competitions, such as patent races or the development of biotechnology, pharmaceuticals, race for creating the first Covid-19 vaccines and even climate change mitigation technology, where institutions need to coordinate collective action for the larger goal of the society (Burrell and Kelly, 2021; Callaway, 2020; Campart and Pfister, 2014). People are more likely to invest in high-risk technology when there is sufficiently alluring potential gain (Andrews et al., 2018), which suggests that these insights are robust across numerous related fields where risk and innovation must constantly be balanced. With commitment models, agreements and regulations for safety and ethics can be enacted by involved parties so as to ensure their compliance to standards.

- **Health Decision-Making and Public Health Policy**: The COVID-19 pandemic represents a particularly notable case of a coordination dilemma (Ojea Quintana et al., 2021). Wherein, our commitment model can be applied to encourage global compliance with new social norms that the pandemic presents. In a highly interconnected world, efforts to mitigate the effects of COVID-19 needs to be coordinated, as an outbreak anywhere in the world puts all other countries at risk (Caparrós and Finus, 2020). For instance, if one country relaxes its control measures and provokes an outbreak, all other countries will be negatively affected. Countries can utilise commitment models to facilitate coordination amongst themselves to collectively contain and mitigate the spread of the pandemic. Our work would be of great interest in this area, applying commitment to encourage global compliance and governance between countries.

6.3 Future Work

Our future work will investigate how to further use pre-commitment mechanisms to provide a more adaptive and efficient approach for coordination enhancement in complex systems such as:

- **Multi-player versions**: A natural continuation of our research would be to expand our results from Chapter 5 which covers the impact of different population structures, including square lattice and scale-free networks, capturing homogeneous and heterogeneous network structures on the two-player technology adoption game with asymmetric benefit. We have shown that commitments can improve coordination and population welfare in structured populations, but in its presence, the outcome of evolutionary dynamics is, interestingly, not sensitive to changes in the network structure. More investigations will be needed here to consolidate our observations, thus, we could further expand this network analysis to study the effects of commitments in the multi-party version of our technology adoption model (Ogbo et al., 2022), where multiple firms participate in a technology market competition. This expansion can also be applied in a cross-sector coordination (Santos et al., 2016), where there might be a large number of desirable outcomes or equilibria, especially when the number of players in an interaction increases (Duong and Han, 2015; Gokhale and Traulsen, 2010).

- **Institutional Incentives**: It is in no doubt that the mechanisms we have proposed so far have advanced previous works on coordination, specifically on the use of pre-commitment to resolve coordination issue which involves asymmetric benefit. However, it would be also interesting to explore further on how institutional incentives can be used to promote commitment compliance (Han, 2022) in our technology adoption game. Han (2022) recently investigated how to distribute a per capita incentive budget effectively between enhancing the level of participation in a commitment and ensuring compliance with any adopted commitment, thereby optimising the overall level of cooperation. Previous works on institutional incentives (Chen et al., 2015; Cimpeanu et al., 2021; Sasaki et al., 2012; Sigmund et al., 2010; Wang et al., 2019) and prior commitment (Akdeniz and van Veelen, 2021; Han et al., 2013a, 2017a; Sasaki et al., 2015a) have not examined the interplay between different forms of incentive and commitment behaviours, including participation in and compliance with a prior commitment. Han (2022) points out the need for improving participation in a commitment before the interaction and because commitment usually involves a high cost and requires the involved parties to follow terms and conditions, participation in commitment might need to be encouraged which these research lacks. We can adapt (Han, 2022) mechanism in our future work, to ensure that commitment participation and compliance are promoted in our technology adoption game, resulting in enhanced coordination outcomes.

- **Cost-efficient institutional Regulation**: In future, we could look at having an external decision maker such as the government/institution as a player in our coordination model, to encourage adoption in a cost-efficient way and to enable large scale-cooperation (Duong and Han, 2021a). Most modern societies implement certain forms of institutions for governing and promoting collective behaviours, including cooperation, coordination and technology innovation (Ostrom, 1990b; Scotchmer, 2004; Wu et al., 2014). Collective action often requires determining both the best thing to do and how to get everyone to do the same thing. In our current work, the evolution of desired collective behaviour in achieving technology adoption is typically shaped by the combined actions of individuals within the system. We can now begin to explore other mechanisms like how an external interference, where the advocating of certain desired collective behaviour is carried out by an external decision maker, who does not belong to the system (e.g. external decision makers such as the United Nations and the European Union) that has a budget to interfere in the population to achieve a desirable outcome (Cimpeanu et al., 2019a; Duong and Han, 2021b; Han et al., 2015d; Wang et al., 2019). We plan to incorporate these mechanisms to our technology adoption model in future work, exploring how an external decision maker can influence technology adoption amongst multiple interacting agents in a cost efficient way.

- **Climate Change Coordination and Mitigation**: Our commitment-based approach can be applied to research on collective risk dilemma problems such as the interactions in climate change negotiation, which is needed to prevent the hazardous consequences of climate change (Barrett et al., 2007; Milinski et al., 2008; Santos et al., 2020). Reducing greenhouse gas emissions stands as a costly action that, if done by a sufficient number of countries, allows preventing catastrophic outcomes and benefits everyone (Santos et al., 2020). Our approach could prove useful to deal with this problem, investigating how the players here can be coordinated to achieve a collective goal, therefore identifying solutions that are robust across a wider range of social dilemmas.

- **Punishment**: In both pairwise and multi-player coordination settings, our analysis has shown that the cost of arranging agreement must be sufficiently small, to be justified for the cost and benefit of coordination. This is in line with previous works in the context of PD and PGG (Han et al., 2013a, 2015c, 2017a). It is due to the fact that those who refuse to commit can escape sanction or compensation. Solutions to this problem have been proposed in the context of PD and PGG, namely, to combine commitment with peer punishment, intention recognition, apology or social exclusion to address non-committers (Han and Lenaerts, 2016a; Han et al., 2015a,c; Martinez-Vaquero et al., 2017; Quillien, 2020) or to delegate the costly process of arranging commitment to an external party (Cherry and McEvoy, 2013; Cherry et al., 2017). Our future work will investigate how to combine pre-commitments with such mechanisms to provide a more adaptive and efficient approach for coordination enhancement in complex systems.

- **Wealth Inequality**: Another area of interest to explore further in our research is the coordination outcome of when there is wealth inequality amongst firms adopting technology. A recent effort in this direction by Ngai (2004), suggests relevant barriers to adopting more productive technologies as an explanation for cross-country income differences. There are studies that also suggest that inequalities in initial income distributions have a bearing on the issue of technology adoption. For example, in the work of Horii et al. (2005), credit market imperfections, in conjunction with inequality prevent the adoption of more capital intensive technologies.

- **Data-driven Approaches and Machine Learning**: The models and analyses we have explored and proposed in this thesis have not considered the use of data-driven approaches to resolve the issue of coordinating technology adoption as a social dilemma problem. In the future, it would be worth investigating how data-driven approaches like machine learning techniques can be applied to our work. The difficulty involved in its design, calibrating its parameters, and interpretation of results are some of the major features of Agent based modelling (ABM). However, machine learning algorithms can complement ABM, given the greater availability of data, computational resources, and learning algorithms (Lamperti et al., 2018; Platas-Lopez et al., 2023). Using machine learning techniques, we can explore existing real data to calibrate our model components (e.g. the cost and benefits of investment in a technology adoption, the market demand for a certain technology, the network structure in a given market, and even the intensity of selection). We can also investigate on applying machine learning techniques to the data produced by the model, either to calibrate the parameters towards a state of validation of the results or to analyse the results by identifying which inputs produce which outputs and so develop a hypothesis of the simulation behaviour.

References

Gautam Ahuja. Collaboration networks, structural holes, and innovation: A longitudinal study. *Administrative science quarterly*, 45(3):425–455, 2000.

Aslıhan Akdeniz and Matthijs van Veelen. The evolution of morality and the role of commitment. *Evolutionary Human Sciences*, pages 1–53, 2021.

Benjamin Allen, Gabor Lippner, Yu-Ting Chen, Babak Fotouhi, Naghmeh Momeni, Shing-Tung Yau, and Martin A. Nowak. Evolutionary dynamics on any population structure. *Nature (London)*, 544(7649):227–230, 2017.

Luca Anderlini. Communication, computability, and common interest games. *Games and Economic Behavior*, 27(1):1–37, 1999. ISSN 0899-8256. doi: https://doi.org/10.1006/game.1998.0652. URL https://www.sciencedirect.com/science/article/pii/S0899825698906522.

Christopher M. Anderson and Louis Putterman. Do non-strategic sanctions obey the law of demand? the demand for punishment in the voluntary contribution mechanism. *Games and Economic Behavior*, 54(1):1–24, January 2006.

Peter Andras, Lukas Esterle, Michael Guckert, The Anh Han, Peter R Lewis, Kristina Milanovic, Terry Payne, Cedric Perret, Jeremy Pitt, Simon T Powers, et al. Trusting intelligent machines: Deepening trust within socio-technical systems. *IEEE Technology and Society Magazine*, 37(4):76–83, 2018.

Talbot M. Andrews, Andrew W. Delton, and Reuben Kline. High-risk high-reward investments to mitigate climate change. *Nature Climate Change*, 8(10):890–894, October 2018. doi: 10.1038/s41558-018-0266-y. URL https://ideas.repec.org/a/nat/natcli/v8y2018i10d10.1038_s41558-018-0266-y.html.

I. Artico, I. Smolyarenko, V. Vinciotti, and E. C. Wit. How rare are power-law networks really? *Proceedings of the Royal Society. A, Mathematical, physical, and engineering sciences*, 476(2241):20190742–20190742, 2020.

Alexios Arvanitis, Marietta Papadatou-Pastou, and Alexandra Hantzi. Agreement in the ultimatum game: An analysis of interpersonal and intergroup context on the basis of the consensualistic approach to negotiation. *New ideas in psychology*, 54:15–26, 2019.

Robert J Aumann and Sylvain Sorin. Cooperation and bounded recall. *Games and Economic Behavior*, 1(1):5–39, 1989. ISSN 0899-8256. doi: https://doi.org/10.1016/0899-8256(89)90003-1. URL https://www.sciencedirect.com/science/article/pii/0899825689900031.

Robert Axelrod. *The Evolution of Cooperation*. Basic Books, ISBN 0-465-02122-2, 1984.

Robert Axelrod. On six advances in cooperation theory. *Analyse & Kritik*, 22(1):130–151, 2000. doi: doi:10.1515/auk-2000-0107. URL https://doi.org/10.1515/auk-2000-0107.

Robert Axelrod and W.D. Hamilton. The evolution of cooperation. *Science*, 211:1390–1396, 1981.

Istvan Back and Aneas Flache. The adaptive rationality of interpersonal commitment. *Rationality and society*, 20(1):65–83, 2008.

Daniel Balliet, Laetitia B. Mulder, and Paul A. M Van Lange. Reward, punishment, and cooperation: A meta-analysis. *Psychological bulletin*, 137(4):594–615, 2011.

AL Barabasi and R. Albert. Emergence of scaling in random networks. *Science (American Association for the Advancement of Science)*, 286(5439):509–512, 1999.

Albert-Laszlo Barabasi. *Linked-how Everything is Connected to Everything Else and what it Means F*. Perseus Books Group, 2014.

Albert-László Barabási and Réka Albert. Emergence of scaling in random networks. *science*, 286(5439):509–512, 1999.

Indranil Bardhan, Ryan Sougstad, and Ryan Sougstad. Prioritizing a portfolio of information technology investment projects. *Journal of Management Information Systems*, 21(2): 33–60, 2004.

Scott Barrett. Coordination vs. voluntarism and enforcement in sustaining international environmental cooperation. *Proceedings of the National Academy of Sciences*, 113(51): 14515–14522, 2016.

Scott Barrett et al. *Why cooperate?: the incentive to supply global public goods*. Oxford University Press on Demand, 2007.

Kaushik Basu. The traveler's dilemma: Paradoxes of rationality in game theory. *The American economic review*, 84(2):391–395, 1994.

Péter Bayer, Robert A. Gatenby, Patricia H. McDonald, Derek R. Duckett, K. Staňková, and Joel S. Brown. Coordination games in cancer. *PloS one*, 17(1 January):e0261578–e0261578, 2022.

Ogbo Ndidi Bianca and The Anh Han. Emergence of coordination with asymmetric benefits via prior commitment. In *Artificial Life Conference Proceedings*, pages 163–170. MIT Press, 2019.

E. Bonabeau, M. Dorigo, and G. Theraulaz. *Swarm Intelligence: From Natural to Artificial Systems*. Oxford University Press, USA, 1999.

Robert Boyd and Peter J. Richerson. The evolution of reciprocity in sizable groups. *Journal of Theoretical Biology*, 132(3):337–356, 1988. ISSN 0022-5193. doi: https://doi.org/10.1016/S0022-5193(88)80219-4. URL https://www.sciencedirect.com/science/article/pii/S0022519388802194.

Robert Boyd, Herbert Gintis, Samuel Bowles, and Peter J. Richerson. The evolution of altruistic punishment. *Proceedings of the National Academy of Sciences - PNAS*, 100(6): 3531–3535, 2003.

Robert Boyd, Herbert Gintis, and Samuel Bowles. Coordinated punishment of defectors sustains cooperation and can proliferate when rare. *Science*, 328(5978):617–620, 2010. doi: 10.1126/science.1183665.

Anna D. Broido and Aaron Clauset. Scale-free networks are rare. *Nature communications*, 10(1):1017–1017, 2019.

M. Broom, C. Cannings, and G. T. Vickers. Multi-player matrix games. *Bulletin of mathematical biology*, 59(5):931–952, 1997.

Anuraag Bukkuri and Joel S. Brown. Evolutionary game theory: Darwinian dynamics and the g function approach. *Games*, 12(4):72, 2021.

Robert Burrell and Catherine Kelly. The covid-19 pandemic and the challenge for innovation policy. *Northern Ireland legal quarterly*, 72(S1):212–219, 2021.

Ewen Callaway. The race for coronavirus vaccines: a graphical guide. *Nature (London)*, 580 (7805):576–577, 2020.

Sandy Campart and Etienne Pfister. Technological races and stock market value: evidence from the pharmaceutical industry. *Economics of innovation and new technology*, 23(3): 215–238, 2014.

Alejandro Caparrós and Michael Finus. The Corona-Pandemic: A Game-theoretic Perspective on Regional and Global Governance. (2020-10), June 2020. URL https://ideas.repec.org/p/grz/wpaper/2020-10.html.

Valerio Capraro. A model of human cooperation in social dilemmas. pages 1–6. PLOS ONE, 2013.

Jeffrey P. Carpenter. The demand for punishment. *Journal of Economic Behavior & Organization*, 62(4):522 – 542, 2007. ISSN 0167-2681. doi: 10.1016/j.jebo.2005.05.004. URL http://www.sciencedirect.com/science/article/pii/S0167268106000175.

GUILLERMO CARUANA and LIRAN EINAV. A theory of endogenous commitment. *The Review of economic studies*, 75(1):99–116, 2008.

Xiao-Ping Chen and Samuel S Komorita. The effects of communication and commitment in a public goods social dilemma. *Organizational Behavior and Human Decision Processes*, 60(3):367–386, 1994.

Xiaojie Chen, Attila Szolnoki, and Matjaž Perc. Probabilistic sharing solves the problem of costly punishment. *New Journal of Physics*, 16(8):083016, 2014.

Xiaojie Chen, Tatsuya Sasaki, Åke Brännström, and Ulf Dieckmann. First carrot, then stick: how the adaptive hybridization of incentives promotes cooperation. *Journal of The Royal Society Interface*, 12(102):20140935, 2015.

Todd L Cherry and David M McEvoy. Enforcing compliance with environmental agreements in the absence of strong institutions: An experimental analysis. *Environmental and Resource Economics*, 54(1):63–77, 2013.

Todd L Cherry, David M McEvoy, et al. Refundable deposits as enforcement mechanisms in cooperative agreements: Experimental evidence with uncertainty and non-deterrent sanctions. *Strategic Behavior and the Environment*, 7(1–2):9–39, 2017.

Benoît Chevalier-Roignant, Christoph M Flath, Arnd Huchzermeier, and Lenos Trigeorgis. Strategic investment under uncertainty: A synthesis. *European Journal of Operational Research*, 215(3):639–650, 2011.

Amit K. Chopra and Munindar P. Singh. Multiagent commitment alignment. In *AAMAS'2009*, pages 937–944, 2009.

Theodor Cimpeanu, The A. Han, and Francisco C. Santos. Exogenous rewards for promoting cooperation in scale-free networks. 2019a.

Theodor Cimpeanu, The Anh Han, and Francisco C Santos. Exogenous rewards for promoting cooperation in scale-free networks. In *Artificial Life Conference Proceedings*, pages 316–323. MIT Press, 2019b.

Theodor Cimpeanu, Cedric Perret, and The Anh Han. Cost-efficient interventions for promoting fairness in the ultimatum game. *Knowledge-Based Systems*, page 107545, 2021.

Theodor Cimpeanu, Francisco C Santos, Luís Moniz Pereira, Tom Lenaerts, and The Anh Han. Artificial intelligence development races in heterogeneous settings. *Scientific Reports*, 12(1):1–12, 2022.

Eric Clemons. Evaluation of strategic investments in information technology. *Communications of the ACM*, 34(1):22–36, 1991.

P. R. Cohen and H. J. Levesque. Intention is Choice with Commitment. *Artificial Intelligence*, 42(2-3):213–261, 1990.

Andrew M. Colman. Cooperation, psychological game theory, and limitations of rationality in social interaction. *The Behavioral and brain sciences*, 26(2):139–153, 2003.

Andrew M. Colman and Natalie Gold. Team reasoning: Solving the puzzle of coordination. *Psychonomic bulletin & review*, 25(5):1770–1783, 2017;2018.

Russell Cooper, Douglas V. DeJong, Robert Forsythe, and Thomas W. Ross. Communication in coordination games. *The Quarterly journal of economics*, 107(2):739–771, 1992.

Miguel A. Costa-Gomes. A suggested interpretation of some experimental results on preplay communication. *Journal of economic theory*, 104(1):104–136, 2002.

Luca Dall'Asta, Andrea Baronchelli, Alain Barrat, and Vittorio Loreto. Nonequilibrium dynamics of language games on complex networks. *Physical Review E*, 74(3):036105, 2006.

RM Dawes. Social dilemmas. *Annual review of psychology*, 31(1):169–193, 1980.

Robyn M. Dawes and David M. Messick. Social dilemmas. *International journal of psychology*, 35(2):111–116, 2000.

Henk de Vos, Rita Smaniotto, and Donald A. Elsas. Reciprocal altruism under conditions of partner selection. *Rationality and society*, 13(2):139–183, 2001.

Douglas V. DeJong, Russell Cooper, Thomas W. Ross, and Robert Forsythe. Communication in the battle of the sexes game: Some experimental results. *The Rand journal of economics*, 20(4):568–587, 1989.

F. Dercole, F. Della Rossa, and C. Piccardi. Direct reciprocity and model-predictive rationality explain network reciprocity over social ties. *Scientific reports*, 9(1):5367, 2019.

Alessandro Di Stefano, Marialisa Scatà, Aurelio La Corte, Pietro Liò, Emanuele Catania, Ermanno Guardo, and Salvatore Pagano. Quantifying the role of homophily in human cooperation using multiplex evolutionary game theory. *PloS one*, 10(10):e0140646, 2015.

Alessandro Di Stefano, Marialisa Scatà, Barbara Attanasio, Aurelio La Corte, Pietro Liò, and Sajal K Das. A novel methodology for designing policies in mobile crowdsensing systems. *Pervasive and Mobile Computing*, 67:101230, 2020.

Mary-Ann Dimand and Robert W. Dimand. *The History Of Game Theory, Volume 1: From the Beginnings to 1945*. Routledge, London, 1 edition, 1996. ISBN 0415072573;9780415072571;9780203416471;0203416473;.

S Dorogovtsev. *Complex networks*. Oxford: Oxford University Press, 2010.

Manh H. Duong and The A. Han. Cost efficiency of institutional incentives for promoting cooperation in finite populations. *Proceedings of the Royal Society. B, Biological sciences*, 477(2254), 2021a.

Manh Hong Duong and The Anh Han. On the expected number of equilibria in a multi-player multi-strategy evolutionary game. *Dynamic Games and Applications*, pages 1–23, 2015.

Manh Hong Duong and The Anh Han. Analysis of the expected density of internal equilibria in random evolutionary multi-player multi-strategy games. *Journal of Mathematical Biology*, pages 1–34, 2016. doi: 10.1007/s00285-016-1010-8. URL http://dx.doi.org/10.1007/s00285-016-1010-8. In Press.

Manh Hong Duong and The Anh Han. Cost efficiency of institutional incentives for promoting cooperation in finite populations. *Proceedings of the Royal Society A*, 477(2254):20210568, 2021b.

Martijn Egas and Arno Riedl. The economics of altruistic punishment and the maintenance of cooperation. *Proceedings of the Royal Society B: Biological Sciences*, 275(1637):871–878, 2008. URL http://dx.doi.org/10.1098/rspb.2007.1558.

E. Fehr and S. Gachter. Cooperation and punishment in public goods experiments. *The American economic review*, 90(4):980–994, 2000.

Ernst Fehr and Simon Gachter. Altruistic punishment in humans. *Nature*, 415:137–140, 2002.

Ruud T. Frambach and Niels Schillewaert. Organizational innovation adoption: a multi-level framework of determinants and opportunities for future research. *Journal of business research*, 55(2):163–176, 2002.

Robert H. Frank. *Passions Within Reason: The Strategic Role of the Emotions*. Norton and Company, 1988.

Drew Fudenberg and David K. Levine. Whither game theory?: Towards a theory of learning in games. *The Journal of economic perspectives*, 30(4):151–169, 2016.

H. Gintis. Beyond selfishness in modeling human behavior. In Randolf M. Nesse, editor, *Evolution and the capacity for commitment*. New York: Russell Sage, 2001.

Chaitanya S. Gokhale and Arne Traulsen. Evolutionary games in the multiverse. *Proc. Natl. Acad. Sci. U.S.A.*, 107(12):5500–5504, March 2010. doi: 10.1073/pnas.0912214107.

Carlos Gracia-Lázaro, José A Cuesta, Angel Sánchez, and Yamir Moreno. Human behavior in prisoner's dilemma experiments suppresses network reciprocity. *Scientific reports*, 2(1): 1–4, 2012a.

Carlos Gracia-Lázaro, Alfredo Ferrer, Gonzalo Ruiz, Alfonso Tarancón, José A Cuesta, Angel Sánchez, and Yamir Moreno. Heterogeneous networks do not promote cooperation when humans play a prisoner's dilemma. *Proceedings of the National Academy of Sciences*, 109(32):12922–12926, 2012b.

Jelena Grujić and Tom Lenaerts. Do people imitate when making decisions? evidence from a spatial prisoner?s dilemma experiment. *Royal Society open science*, 7(7):200618, 2020.

Francesco Guala. Reciprocity: Weak or strong? what punishment experiments do (and do not) demonstrate. *Behavioral and Brain Sciences*, 35(1):1–15, 2012. doi: 10.1017/S0140525X11000069.

António R. Góis, Fernando P. Santos, Jorge M. Pacheco, and Francisco C. Santos. Reward and punishment in climate change dilemmas. *Scientific reports*, 9(1):16193–9, 2019.

W.D. Hamilton. The genetical evolution of social behaviour. i. *Journal of Theoretical Biology*, 7(1):1 – 16, 1964. ISSN 0022-5193. doi: 10.1016/0022-5193(64)90038-4. URL http://www.sciencedirect.com/science/article/pii/0022519364900384.

T. A. Han and Tom Lenaerts. A synergy of costly punishment and commitment in cooperation dilemmas. *Adaptive Behavior*, 24(4):237–248, 2016a.

T. A. Han, L. M. Pereira, and F. C. Santos. The emergence of commitments and cooperation. In *AAMAS'2012*, pages 559–566, 2012a.

T. A. Han, A. Traulsen, and C. S. Gokhale. On equilibrium properties of evolutionary multiplayer games with random payoff matrices. *Theoretical Population Biology*, 81(4): 264–272, June 2012b.

T. A. Han, L. M. Pereira, F. C. Santos, and T. Lenaerts. Good agreements make good friends. *Scientific reports*, 3(2695), 2013a.

T. A. Han, L. M. Pereira, F. C. Santos, and T. Lenaerts. Why Is It So Hard to Say Sorry: The Evolution of Apology with Commitments in the Iterated Prisoner's Dilemma. In *IJCAI'2013*, pages 177–183. AAAI Press, 2013b.

T. A. Han, F. C. Santos, T. Lenaerts, and L. M. Pereira. Synergy between intention recognition and commitments in cooperation dilemmas. *Scientific reports*, 5(9312), 2015a.

T. A. Han, F. C. Santos, T. Lenaerts, and L. M. Pereira. Synergy between intention recognition and commitments in cooperation dilemmas. *Scientific reports*, 5(9312), 2015b.

The A. Han and Tom Lenaerts. A synergy of costly punishment and commitment in cooperation dilemmas. 2016b.

The A. Han, Luís M. Pereira, and Francisco C. Santos. Corpus-based intention recognition in cooperation dilemmas. 2012c.

The A. Han, Luís M. Pereira, and Tom Lenaerts. Evolution of commitment and level of participation in public goods games. 2016.

The Anh Han. *Intention Recognition, Commitments and Their Roles in the Evolution of Cooperation: From Artificial Intelligence Techniques to Evolutionary Game Theory Models*, volume 9. Springer SAPERE series, 2013. ISBN 978-3-642-37511-8.

The Anh Han. Emergence of social punishment and cooperation through prior commitments. In *AAAI'2016*, pages 2494–2500, Phoenix, Arizona, USA, 2016.

The Anh Han. Institutional incentives for the evolution of committed cooperation: Ensuring participation is as important as enhancing compliance. *Journal of the Royal Society Interface*, 19(188):20220036, 2022. doi: 10.1098/rsif.2022.0036.

The Anh Han and Luís Moniz Pereira. Context-dependent incremental decision making scrutinizing the intentions of others via bayesian network model construction. *Intelligent Decision Technologies*, 7(4):293–317, 2013.

The Anh Han, Luís Moniz Pereira, and Tom Lenaerts. Avoiding or Restricting Defectors in Public Goods Games? *J. Royal Soc Interface*, 12(103):20141203, 2015c. doi: 10.1098/rsif.2014.1203.

The Anh Han, Long Tran-Thanh, Nicholas R Jennings, et al. The cost of interference in evolving multiagent systems. In *AAMAS'2015*, pages 1719–1720, 2015d.

The Anh Han, Luís Moniz Pereira, and Tom Lenaerts. Evolution of commitment and level of participation in public goods games. *Autonomous Agents and Multi-Agent Systems*, 31(3):561–583, 2017a. ISSN 1573-7454. doi: 10.1007/s10458-016-9338-4. URL http://dx.doi.org/10.1007/s10458-016-9338-4.

The Anh Han, Luís Moniz Pereira, and Tom Lenaerts. Evolution of commitment and level of participation in public goods games. *Autonomous Agents and Multi-Agent Systems*, 31(3):561–583, 2017b. ISSN 1573-7454. doi: 10.1007/s10458-016-9338-4. URL http://dx.doi.org/10.1007/s10458-016-9338-4.

The Anh Han, Luís Moniz Pereira, and Tom Lenaerts. Modelling and Influencing the AI Bidding War: A Research Agenda. In *AAAI/ACM conference AI, Ethics and Society*, 2019.

The Anh Han, Cedric Perret, and Simon T Powers. When to (or not to) trust intelligent machines: Insights from an evolutionary game theory analysis of trust in repeated games. *Cognitive Systems Research*, 68:111–124, 2021.

The Anh Han, Tom Lenaerts, Francisco C Santos, and Luís Moniz Pereira. Voluntary safety commitments provide an escape from over-regulation in ai development. *Technology in Society*, 68:101843, 2022.

G. Hardin. The tragedy of the commons. the population problem has no technical solution; it requires a fundamental extension in morality. *Science (American Association for the Advancement of Science)*, 162(3859):1243–1248, 1968.

Jonh C. Harsanyi and Reinhard Selten. A general theory of equilibrium selection in games. *Discrete Applied Mathematics*, 26(1):126–127, 1990.

Mohammad Rashedul Hasan and Anita Raja. Emergence of cooperation using commitments and complex network dynamics. In *IEEE/WIC/ACM Intl Joint Conferences on Web Intelligence and Intelligent Agent Technologies*, pages 345–352, 2013.

C. Hauert, A. Traulsen, H. Brandt, M. A. Nowak, and K. Sigmund. Via freedom to coercion: The emergence of costly punishment. *Science*, 316:1905–1907, 2007.

Thomas Hobbes. *Leviathan: The Matter, Forme, and Power of a Common-Wealth Ecclesiastical and Civill*. Floating Press, The, Auckland, 2009. ISBN 9781775415336;1775415333;.

Geoffrey M. Hodgson and Kainan Huang. Evolutionary game theory and evolutionary economics: are they different species? *Journal of evolutionary economics*, 22(2):345–366, 2012.

J. Hofbauer and K. Sigmund. *Evolutionary Games and Population Dynamics*. Cambridge University Press, 1998.

Ryo Horii, Ryoji Ohdoi, and Kazuhiro Yamamoto. Finance, technology and inequality in economic development. *SSRN Electronic Journal*, 05 2005. doi: 10.2139/ssrn.702884.

Feng Huang, Xiaojie Chen, and Long Wang. Evolution of cooperation in a hierarchical society with corruption control. *Journal of theoretical biology*, 449:60–72, 2018.

Feng Huang, Xiaojie Chen, and Long Wang. Evolutionary dynamics of networked multi-person games: mixing opponent-aware and opponent-independent strategy decisions. *New journal of physics*, 21(6):63013, 2019.

Feng Huang, Ming Cao, and Long Wang. Learning enables adaptation in cooperation for multi-player stochastic games. *Journal of the Royal Society interface*, 17(172):20200639–20200639, 2020.

Robert Huggins and Hiro Izushi. 1Competition, competitive advantage, and clusters: the ideas of Michael Porter. 02 2011. doi: 10.1093/acprof:oso/9780199578030.003.0001. URL https://doi.org/10.1093/acprof:oso/9780199578030.003.0001.

L. A. Imhof, D. Fudenberg, and Martin A. Nowak. Evolutionary cycles of cooperation and defection. *Proc. Natl. Acad. Sci. U.S.A.*, 102:10797–10800, 2005.

Xin Jin, Min Dan, Nan Zhang, Wei Yu, Xinwen Fu, and Sajal K. Das. Chapter 2 - game theory for infrastructure security: The power of intent-based adversary models11part of the results included in this chapter was presented in [1], [2]. In Sajal K. Das, Krishna Kant, and Nan Zhang, editors, *Handbook on Securing Cyber-Physical Critical Infrastructure*, pages 31–53. Morgan Kaufmann, Boston, 2012. ISBN 978-0-12-415815-3. doi: https://doi.org/10.1016/B978-0-12-415815-3.00002-9. URL https://www.sciencedirect.com/science/article/pii/B9780124158153000029.

Matthew I. Jones, Scott D. Pauls, and Feng Fu. The dual problems of coordination and anti-coordination on random bipartite graphs. *New journal of physics*, 23(11):113018, 2021.

Marcus Krellner and The Anh Han. Putting oneself in everybody's shoes - Pleasing enables indirect reciprocity under private assessments. ALIFE 2020: The 2020 Conference on Artificial Life:402–410, 2020. doi: 10.1162/isal_a_00292. URL https://doi.org/10.1162/isal_a_00292.

Aanjaneya Kumar, Valerio Capraro, and Matjaž Perc. The evolution of trust and trustworthiness. *Journal of The Royal Society Interface*, 17(169):20200491, Aug 2020. ISSN 1742-5662. doi: 10.1098/rsif.2020.0491. URL http://dx.doi.org/10.1098/rsif.2020.0491.

Robert Kurzban, Kevin McCabe, Vernon L Smith, and Bart J Wilson. Incremental commitment and reciprocity in a real-time public goods game. *Personality and Social Psychology Bulletin*, 27(12):1662–1673, 2001.

Amrei Lahno and Bernd Lahno. Team reasoning as a guide to coordination. *Revue d'économie politique*, 128(3):393–422, 2018.

Robert A. Laird. Sequential interactions—in which one player plays first and another responds—promote cooperation in evolutionary-dynamical simulations of single-shot prisoner's dilemma and snowdrift games. *Journal of theoretical biology*, 452:69–80, 2018.

Francesco Lamperti, Andrea Roventini, and Amir Sani. Agent-based model calibration using machine learning surrogates. *Journal of economic dynamics control*, 90:366–389, 2018.

John O. Ledyard. Public goods: A survey of experimental research. 1994. URL https://ideas.repec.org/p/wpa/wuwppe/9405003.html.

Frederic Legendre and Fabien L. Condamine. When darwin's special difficulty promotes diversification in insects. *Systematic biology*, 67(5):873–887, 2018.

J-S. Lerat, T. A. Han, and T. Lenaerts. Evolution of Common-Pool Resources and Social Welfare in Structured Populations. In *Proceedings of the 23nd international joint conference on Artificial intelligence (IJCAI'2013)*. AAAI Press, 2013.

Erez Lieberman, Christoph Hauert, and Martin A. Nowak. Evolutionary dynamics on graphs. *Nature*, 433(7023):312–316, 2005.

M. W. Macy and A. Flache. Learning dynamics in social dilemmas. *Proceedings of the National Academy of Sciences of the United States of America*, 99:7229–7236, 2002.

Hannu Makkonen, Wesley J. Johnston, and Rajshekhar (. G. Javalgi. A behavioral approach to organizational innovation adoption. *Journal of business research*, 69(7):2480–2489, 2016.

Luis A Martinez-Vaquero, The Anh Han, Luís Moniz Pereira, and Tom Lenaerts. Apology and forgiveness evolve to resolve failures in cooperative agreements. *Scientific reports*, 5 (10639), 2015.

Luis A Martinez-Vaquero, The Anh Han, Luis Moniz Pereira, and Tom Lenaerts. When agreement-accepting free-riders are a necessary evil for the evolution of cooperation. *Scientific reports*, 7(1):1–9, 2017.

J. Maynard-Smith. *Evolution and the Theory of Games*. Cambridge University Press, Cambridge, 1982.

John Maynard Smith, Eors Szathmary, E?rs Szathm?ry, and E. R. Szathm Ry. *The Major Transitions in Evolution*. Oxford University Press, Oxford, 1998. ISBN 9780198502944;019850294X;.

Roger A. McCain and Richard Hamilton. Coordination games, anti-coordination games, and imitative learning. *The Behavioral and brain sciences*, 37(1):90–91, 2014.

Lingqi Meng and Naoki Masuda. Perturbation theory for evolution of cooperation on networks. Technical report, Cornell University Library, arXiv.org, 2022.

Paul Milgrom and John Roberts. Predation, reputation, and entry deterrence. *Journal of Economic Theory*, 27(2):280–312, 1982. ISSN 0022-0531. doi: https://doi.org/10.1016/0022-0531(82)90031-X. URL https://www.sciencedirect.com/science/article/pii/002205318290031X.

Manfred Milinski, Ralf D. Sommerfeld, Hans-Jürgen Krambeck, Floyd A. Reed, and Jochem Marotzke. collective-risk social dilemma and the prevention of simulated dangerous climate change. *Proceedings of the National Academy of Sciences - PNAS*, 105(7):2291–2294, 2008.

Carey D. Nadell, Kevin R. Foster, and João B. Xavier. Emergence of spatial structure in cell groups and the evolution of cooperation. *PLoS computational biology*, 6(3):e1000716–e1000716, 2010.

R. M. Nesse. *Evolution and the capacity for commitment*. Foundation series on trust. Russell Sage, 2001a. ISBN 9780871546227.

Randolf M. Nesse. *Natural selection and the capacity for subjective commitment*. New York: Russell Sage, 2001b.

Randolf M. Nesse. Natural selection and the capacity for subjective commitment. In Randolf M. Nesse, editor, *Evolution and the capacity for commitment*, pages 1–44. 2001c.

Mark EJ Newman. The structure and function of complex networks. *SIAM review*, 45(2): 167–256, 2003.

Mark EJ Newman. Coauthorship networks and patterns of scientific collaboration. *Proceedings of the national academy of sciences*, 101(suppl 1):5200–5205, 2004.

L. R. Ngai. Barriers and the transition to modern growth. *Journal of monetary economics*, 51 (7):1353–1383, 2004.

Nikos Nikiforakis and Hans-Theo Normann. A comparative statics analysis of punishment in public-good experiments. *Experimental Economics*, 11(4):358–369, 2008. doi: 10.1007/s10683-007-9171-3. URL http://dx.doi.org/10.1007/s10683-007-9171-3.

M. A. Nowak. *Evolutionary Dynamics: Exploring the Equations of Life*. Harvard University Press, Cambridge, MA, 2006a.

M. A. Nowak and K. Sigmund. Tit for tat in heterogeneous populations. *Nature*, 355: 250–253, 1992.

M. A. Nowak and K. Sigmund. Evolution of indirect reciprocity. *Nature*, 437(1291-1298), 2005.

M. A. Nowak, A. Sasaki, C. Taylor, and D. Fudenberg. Emergence of cooperation and evolutionary stability in finite populations. *Nature*, 428:646–650, 2004.

Martin A. Nowak. Five rules for the evolution of cooperation. *Science*, 314(5805):1560, 2006b.

Martin A. Nowak and Robert M. May. Evolutionary games and spatial chaos. *Nature (London)*, 359(6398):826–829, 1992.

Martin A Nowak and Robert M May. The spatial dilemmas of evolution. *International Journal of bifurcation and chaos*, 3(01):35–78, 1993.

Martin A. Nowak and Karl Sigmund. Evolution of indirect reciprocity1998. *Nature (London)*, 393(6685):573–577, 1998.

Martin A. Nowak, Hisashi Ohtsuki, Christoph Hauert, and Erez Lieberman. A simple rule for the evolution of cooperation on graphs and social networks. *Nature*, 441(7092):502–505, 2006.

Martin A. Nowak, Corina E. Tarnita, and Tibor Antal. Evolutionary dynamics in structured populations. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 365 (1537):19–30, 2010.

Ndidi Bianca Ogbo, Aiman Elragig, and The Anh Han. Evolution of coordination in pairwise and multi-player interactions via prior commitments. *Adaptive Behavior*, 30(3):257–277, 2022. doi: 10.1177/1059712321993166.

Hisashi Ohtsuki. Evolutionary dynamics of coordinated cooperation. *Frontiers in Ecology and Evolution*, 6:62, 2018.

Hisashi Ohtsuki and Yoh Iwasa. The leading eight: Social norms that can maintain cooperation by indirect reciprocity. *Journal of theoretical biology*, 239(4):435–444, 2006.

Hisashi Ohtsuki and Martin A. Nowak. The replicator equation on graphs. *Journal of Theoretical Biology*, 243(1):86–97, 2006. ISSN 0022-5193. doi: https://doi.org/10.1016/j.jtbi.2006.06.004. URL https://www.sciencedirect.com/science/article/pii/S0022519306002426.

Hisashi Ohtsuki, Christoph Hauert, Erez Lieberman, and Martin A Nowak. A simple rule for the evolution of cooperation on graphs and social networks. *Nature*, 441(7092):502–505, 2006.

Hisashi Ohtsuki, Martin A Nowak, and Jorge M Pacheco. Breaking the symmetry between interaction and replacement in evolutionary dynamics on graphs. *Physical review letters*, 98(10):108106, 2007.

Ignacio Ojea Quintana, Sarita Rosenstock, and Colin Klein. The coordination dilemma for epidemiological modelers. *Biology and amp; Philosophy*, 36(6), 2021. doi: 10.1007/s10539-021-09828-9.

Isamu Okada. A review of theoretical studies on indirect reciprocity. *Games*, 11(3):27, 2020.

Elinor Ostrom. *Governing the commons: The evolution of institutions for collective action*. Cambridge university press, 1990a.

Elinor Ostrom. *Governing the Commons: The Evolution of Institutions for Collective Action*. Political Economy of Institutions and Decisions. Cambridge University Press, 1990b. doi: 10.1017/CBO9780511807763.

Hiroki Ozono, Nobuhito Jin, Motoki Watabe, and Kazumi Shimizu. Solving the second-order free rider problem in a public goods game: An experiment using a leader support system. *Scientific reports*, 6(1):38349–38349, 2016.

Hiroki Ozono, Yoshio Kamijo, and Kazumi Shimizu. Punishing second-order free riders before first-order free riders: The effect of pool punishment priority on cooperation. *Scientific reports*, 7(1):14379–9, 2017.

Jorge M. Pacheco, Francisco C. Santos, Max O. Souza, and Brian Skyrms. Evolutionary dynamics of collective action in n-person stag hunt dilemmas. *Proc. R. Soc. B*, 276: 315–321, 2009.

Karen M Page, Martin A Nowak, and Karl Sigmund. The spatial ultimatum game. *Proceedings of the Royal Society of London. Series B: Biological Sciences*, 267(1458):2177–2182, 2000.

Ana Paiva, Fernando Santos, and Francisco Santos. Engineering pro-sociality with autonomous agents. *Proceedings of the AAAI Conference on Artificial Intelligence*, 32(1), 2018.

Karthik Panchanathan and Robert Boyd. Indirect reciprocity can stabilize cooperation without the second-order free rider problem. *Nature*, 432(7016):499–502, 2004.

Gregory L. Parsons. Information technology: A new competitive weapon. *Sloan management review*, 25(1):3, 1983.

Jorge Pena, Henri Volken, Enea Pestelacci, and Marco Tomassini. Conformity hinders the evolution of cooperation on scale-free networks. *Physical Review E*, 80(1):016110, 2009.

Matjaž Perc and Attila Szolnoki. Coevolutionary games—a mini review. *BioSystems*, 99(2): 109–125, 2010.

Matjaž Perc, Jesús Gómez-Gardeñes, Attila Szolnoki, Luis M Floría, and Yamir Moreno. Evolutionary dynamics of group interactions on structured populations: a review. *Journal of The Royal Society Interface*, 10(80):20120997, 2013a.

Matjaž Perc, Jillian J Jordan, David G Rand, Zhen Wang, Stefano Boccaletti, and Attila Szolnoki. Statistical physics of human cooperation. *Physics Reports*, 687:1–51, 2017.

Matjaž Perc. Phase transitions in models of human cooperation. *Physics letters. A*, 380(36): 2803–2808, 2016.

Matjaž Perc, Jesús Gómez-Gardeñes, Attila Szolnoki, Luis M. Floría, and Yamir Moreno. Evolutionary dynamics of group interactions on structured populations: a review. *Journal of the Royal Society interface*, 10(80):20120997–20120997, 2013b.

Jorge Peña, Bin Wu, and Arne Traulsen. Ordering structured populations in multiplayer cooperation games. *Journal of the Royal Society interface*, 13(114):20150881–20150881, 2016.

Flavio L Pinheiro, Francisco C Santos, and Jorge M Pacheco. How selection pressure changes the nature of social dilemmas in structured populations. *New Journal of Physics*, 14(7): 073035, 2012.

Jeremy Pitt, Julia Schaumeier, and Alexander Artikis. Axiomatization of socio-economic principles for self-organizing institutions: Concepts, experiments and challenges. *ACM Transactions on Autonomous and Adaptive Systems (TAAS)*, 7(4):39, 2012.

Alejandro Platas-Lopez, Alejandro Guerra-Hernandez, Marcela Quiroz-Castellanos, and Nicandro Cruz-Ramirez. Agent-based models assisted by supervised learning: A proposal for model specification. *Electronics (Basel)*, 12(3):495, 2023.

Jan L. Pletzer, Daniel Balliet, Jeff Joireman, D. M. Kuhlman, Sven C. Voelpel, and Paul A. M. Van Lange. Social value orientation, expectations, and cooperation in social dilemmas: A meta-analysis. *European journal of personality*, 32(1):62–83, 2018.

Julia Poncela, Jesús Gómez-Gardenes, LM Floría, and Yamir Moreno. Robustness of cooperation in the evolutionary prisoner's dilemma on complex networks. *New Journal of Physics*, 9(6):184, 2007.

Simon T Powers, Daniel J Taylor, and Joanna J Bryson. Punishment can promote defection in group-structured populations. *Journal of theoretical biology*, 311:107–116, 2012.

Tadeg Quillien. Evolution of conditional and unconditional commitment. *Journal of Theoretical Biology*, 492:110204, 2020.

Matthew Rabin. A model of pre-game communication. *Journal of Economic Theory*, 63 (2):370–391, 1994. ISSN 0022-0531. doi: https://doi.org/10.1006/jeth.1994.1047. URL https://www.sciencedirect.com/science/article/pii/S0022053184710477.

Tomasz Raducha and Maxi San Miguel. Coordination and equilibrium selection in games: the role of local effects. *Scientific reports*, 12(1):3373–3373, 2022.

David G Rand, Drew Fudenberg, and Anna Dreber. It's the thought that counts: The role of intentions in reciprocal altruism. *Available at SSRN 2259407*, 2013a.

David G. Rand, Corina E. Tarnita, Hisashi Ohtsuki, and Martin A. Nowak. Evolution of fairness in the one-shot anonymous ultimatum game. *Proc. Natl. Acad. Sci. USA*, 110: 2581–2586, 2013b.

L. Rendell, R. Boyd, D. Cownden, M. Enquist, K. Eriksson, M. W. Feldman, L. Fogarty, S. Ghirlanda, T. Lillicrap, and K. N. Laland. Why copy others? insights from the social learning strategies tournament. *Science*, 328(5975):208–213, 2010. doi: 10.1126/science.1184719. URL http://www.sciencemag.org/content/328/5975/208.abstract.

Ruby Roberts, Rhona Flin, David Millar, and Luca Corradi. Psychological factors influencing technology adoption: A case study from the oil and gas industry. *Technovation*, 102: 102219, 2021.

Goldman Sachs. B2b: 2b or not 2b. 2000.

F. C. Santos and J. M. Pacheco. Scale-free networks provide a unifying framework for the emergence of cooperation. *Phys. Rev. Lett.*, 95:098104, 2005. ISSN 0031-9007.

F. C. Santos, J. M. Pacheco, and T. Lenaerts. Evolutionary dynamics of social dilemmas in structured heterogeneous populations. *Proceedings of the National Academy of Sciences of the United States of America*, 103:3490–3494, 2006a.

F. C. Santos, J. M. Pacheco, and T. Lenaerts. Evolutionary dynamics of social dilemmas in structured heterogeneous populations. *Proceedings of the National Academy of Sciences*, 103(9):3490–3494, 2006b.

F. C. Santos, J. M. Pacheco, and T. Lenaerts. Evolutionary dynamics of social dilemmas in structured heterogeneous populations. *Proceedings of the National Academy of Sciences of the United States of America*, 103:3490–3494, 2006c. ISSN 0027-8424.

F. C. Santos, M. D. Santos, and J. M. Pacheco. Social diversity promotes the emergence of cooperation in public goods games. *Nature*, 454:214–216, 2008.

F. C. Santos, J. M. Pacheco, and B. Skyrms. Co-evolution of pre-play signaling and cooperation. *Journal of Theoretical Biology*, 274(1):30–35, 2011.

Fernando P Santos, Sara Encarnação, Francisco C Santos, Juval Portugali, and Jorge M Pacheco. An evolutionary game theoretic approach to multi-sector coordination and self-organization. *Entropy*, 18(4):152, 2016.

Fernando P Santos, Jorge M Pacheco, Ana Paiva, and Francisco C Santos. Structural power and the evolution of collective fairness in social networks. *PLoS one*, 12(4):e0175687, 2017.

Fernando P Santos, Samuel Mascarenhas, Francisco C Santos, Filipa Correia, Samuel Gomes, and Ana Paiva. Picky losers and carefree winners prevail in collective risk dilemmas with partner selection. *Autonomous Agents and Multi-Agent Systems*, 34:1–29, 2020.

Francisco C. Santos and Jorge M. Pacheco. Risk of collective failure provides an escape from the tragedy of the commons. *Proceedings of the National Academy of Sciences of the United States of America*, 108(26):10421–10425, 2011.

Sumit Sarkar. Out-think!: How to use game theory to outsmart your competition, 2016. URL http://ezproxy.tees.ac.uk/other-sources/out-think-how-use-game-theory-outsmart-your/docview/1786821379/se-2. Copyright - Copyright Ringgold Inc May 4, 2016; Last updated - 2016-05-05.

Tatsuya Sasaki, Åke Brännström, Ulf Dieckmann, and Karl Sigmund. The take-it-or-leave-it option allows small penalties to overcome social dilemmas. *Proceedings of the National Academy of Sciences - PNAS*, 109(4):1165–1169, 2012.

Tatsuya Sasaki, Isamu Okada, Satoshi Uchida, and Xiaojie Chen. Commitment to cooperation and peer punishment: Its evolution. *Games*, 6(4):574–587, 2015a.

Tatsuya Sasaki, Isamu Okada, Satoshi Uchida, and Xiaojie Chen. Commitment to cooperation and peer punishment: Its evolution. *Games*, 6(4):574–587, 2015b.

T. C. Schelling. *The strategy of conflict*. London: Oxford University Press, 1990.

Melissa A Schilling and Corey C Phelps. Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. *Management science*, 53(7):1113–1126, 2007.

Suzanne Scotchmer. *Innovation and incentives / Suzanne Scotchmer.* MIT Press, Cambridge, Mass. ; London, 2004. ISBN 0262195151.

Matteo Serafino, Giulio Cimini, Amos Maritan, Andrea Rinaldo, Samir Suweis, Jayanth R. Banavar, and Guido Caldarelli. True scale-free networks hidden by finite size effects. *Proceedings of the National Academy of Sciences - PNAS*, 118(2):1, 2021.

Andrew Shipilov and Annabelle Gawer. Integrating research on interorganizational networks and ecosystems. *Academy of Management Annals*, 14(1):92–121, 2020.

Panpan Shu, Lei Gao, Pengcheng Zhao, Wei Wang, and H. E. Stanley. Social contagions on interdependent lattice networks. *Scientific reports*, 7(1):44669–44669, 2017.

K Sigmund, C Hauert, and M Nowak. Reward and punishment. *P Natl Acad Sci USA*, 98 (19):10757–10762, 2001a.

K. Sigmund, H. De Silva, A. Traulsen, and C. Hauert. Social learning promotes institutions for governing the commons. *Nature*, 466:7308, 2010.

Karl Sigmund. *The Calculus of Selfishness*. Princeton University Press, 2010.

Karl Sigmund and Martin A. Nowak. Evolution of indirect reciprocity. *Nature*, 437(7063): 1291–1298, 2005.

Karl Sigmund, Christoph Hauert, and Martin A. Nowak. Reward and punishment. *Proceedings of the National Academy of Sciences*, 98(19):10757–10762, 2001b. doi: 10.1073/pnas.161155698. URL https://www.pnas.org/doi/abs/10.1073/pnas.161155698.

Roberta Sinatra, Jaime Iranzo, Jesus Gomez-Gardenes, Luis M Floria, Vito Latora, and Yamir Moreno. The ultimatum game in complex networks. *Journal of Statistical Mechanics: Theory and Experiment*, 2009(09):P09012, 2009.

Munindar P. Singh. Intentions, commitments and rationality. In *In 13th Annual Conference of the Cognitive Science Society*, pages 493–498, 1991.

Brian Skyrms. *Evolution of the Social Contract*. Cambridge University Press, 1996.

Brian Skyrms. *The Stag Hunt and the Evolution of Social Structure*. Cambridge University Press, 2003.

Brian Skyrms. *Signals: Evolution, Learning, and Information*. Oxford University Press, 2010.

J. Maynard Smith and GEORGE R. Price. The logic of animal conflict. *Nature*, 246:15–18, 1973. doi: https://doi.org/10.1038/246015a0.

Joel Sobel. A note on pre-play communication. *Games and Economic Behavior*, 102: 477–486, 2017. ISSN 0899-8256. doi: https://doi.org/10.1016/j.geb.2017.02.008. URL https://www.sciencedirect.com/science/article/pii/S0899825617300349.

Qi Su, Alex McAvoy, Long Wang, and Martin A. Nowak. Evolutionary dynamics with game transitions. *Proceedings of the National Academy of Sciences*, 116(51):25398–25404, 2019. doi: 10.1073/pnas.1908936116. URL https://www.pnas.org/content/116/51/25398.

Shinsuke Suzuki and Eizo Akiyama. Reputation and the evolution of cooperation in sizable groups. *Proceedings of the Royal Society. B, Biological sciences*, 272(1570):1373–1377, 2005.

G. Szabó and G. Fáth. Evolutionary games on graphs. *Phys Rep*, 97-216(4-6), 2007.

Eörs Szathmáry and John Maynard Smith. *The major transitions in evolution*. WH Freeman Spektrum Oxford, UK:, 1995.

Attila Szolnoki and Matjaž Perc. Evolutionary advantages of adaptive rewarding. *New Journal of Physics*, 14(9):093016, 2012.

Attila Szolnoki, Matjaž Perc, and György Szabó. Defense mechanisms of empathetic players in the spatial ultimatum game. *Physical review letters*, 109(7):078701, 2012.

Jun Tanimoto. How does resolution of strategy affect network reciprocity in spatial prisoner's dilemma games? *Applied mathematics and computation*, 301:36–42, 2017.

Corina E. Tarnita, Tibor Antal, Hisashi Ohtsuki, and Martin A. Nowak. Evolutionary dynamics in set structured populations. *Proceedings of the National Academy of Sciences - PNAS*, 106(21):8601–8604, 2009.

Corina E. Tarnita, Nicholas Wage, and Martin A. Nowak. Multiple strategies in structured populations. *Proceedings of the National Academy of Sciences - PNAS*, 108(6):2334–2337, 2011.

Kyle A. Thomas, Peter DeScioli, Omar S. Haque, and Steven Pinker. The psychology of coordination and common knowledge. *Journal of personality and social psychology*, 107 (4):657–676, 2014.

A. Traulsen and M. A. Nowak. Evolution of cooperation by multilevel selection. *Proceedings of the National Academy of Sciences of the United States of America*, 103(29):10952, 2006.

A. Traulsen, M. A. Nowak, and J. M. Pacheco. Stochastic dynamics of invasion and fixation. *Phys. Rev. E*, 74:11909, 2006.

R. L. Trivers. The evolution of reciprocal altruism. *Quaterly Review of Biology*, 46:35–57, 1971.

Paul A. M. Van Lange, Jeff Joireman, Craig D. Parks, and Eric Van Dijk. The psychology of social dilemmas: A review. *Organizational behavior and human decision processes*, 120 (2):125–141, 2013.

Paul A. M. Van Lange, Jeff Joireman, and Manfred Milinski. Climate change: What psychology can offer in terms of insights and solutions. *Current directions in psychological science : a journal of the American Psychological Society*, 27(4):269–274, 2018.

Vandana R. Venkateswaran and Chaitanya S. Gokhale. Evolutionary dynamics of complex multiple games. *Proceedings of the Royal Society. B, Biological sciences*, 286(1905): 20190900–20190900, 2019.

John Von Neumann and Oskar Morgenstern. *Theory of games and economic behavior*. Princeton University Press, Princeton, NJ, 1994.

Shengxian Wang, Xiaojie Chen, and Attila Szolnoki. Exploring optimal institutional incentives for public cooperation. *Communications in Nonlinear Science and Numerical Simulation*, 79:104914, 2019.

S.A. West, A.A. Griffin, and A. Gardner. Evolutionary explanations for cooperation. *Current Biology*, 17:R661–R672, 2007.

Stuart A. West, Ido Pen, and Ashleigh S. Griffin. Cooperation and Competition Between Relatives. *Science*, 296(5565):72–75, 2002.

Sera Whitelaw, Mamas A. Mamas, Eric Topol, and Harriette G C Van Spall. Applications of digital technology in covid-19 pandemic planning and response. *The Lancet. Digital health*, 2(8):e435–e440, 2020.

Michael Winikoff. Implementing commitment-based interactions. AAMAS '07, pages 868–875, 2007.

Bin Wu, Arne Traulsen, and Chaitanya Gokhale. Dynamic properties of evolutionary multiplayer games in finite populations. *Games*, 4(2):182–199, 2013a.

J. J. Wu, B. Y. Zhang, Z. X. Zhou, Q. Q. He, X. D. Zheng, R. Cressman, and Y. Tao. Costly punishment does not always increase cooperation. *Proc Natl Acad Sci U S A.*, 106(41): 17448–51, 2009.

Jia-Jia Wu, Cong Li, Bo-Yu Zhang, Ross Cressman, and Yi Tao. The role of institutional incentives and the exemplar in promoting cooperation. *Scientific reports*, 4(1):6421–6421, 2014.

Te Wu, Feng Fu, Yanling Zhang, and Long Wang. Adaptive role switching promotes fairness in networked ultimatum game. *Scientific reports*, 3:1550, 2013b.

Linjun Zhang, Michael Small, and Kevin Judd. Exactly scale-free scale-free networks. *Physica A*, 433:182–197, 2015.

Kevin Zhu and John P Weyant. Strategic decisions of new technology adoption under asymmetric information: a game-theoretic model. *Decision sciences*, 34(4):643–675, 2003.

Ioannis Zisis, Sibilla Di Guida, The Anh Han, Georg Kirchsteiger, and Tom Lenaerts. Generosity motivated by acceptance - evolutionary analysis of an anticipation games. *Scientific reports*, 5(18076), 2015.

Appendix A

Additional Results for Chapter 3

Results for different values of θ_1 and θ_2

In the main text, we assume that a fair agreement is always arranged. We consider here what would happen if HP and LP can personalise the commitment deal they want to propose, i.e. any θ_1 and θ_2 can be proposed (instead of always being fair). Namely, Figure A.1 shows the average population payoff varying these parameters, for different values of α. We observe that when α is small, the highest average payoff is achieved when θ_1 is sufficiently small and θ_2 is sufficiently large, while for large α, it is reverse for the two parameters. That is, in a highly competitive market (i.e. small α), commitment proposers should be strict (HP keeps sufficient benefit while LP requests sufficient payment, from their commitment partners), while when the market is less competitive (i.e. large α), commitment proposers should be more generous (HP proposes to give a larger benefit while LP requests a smaller payment, from their commitment partners). Our results confirm that this observation is robust for different values of ε, δ and β.

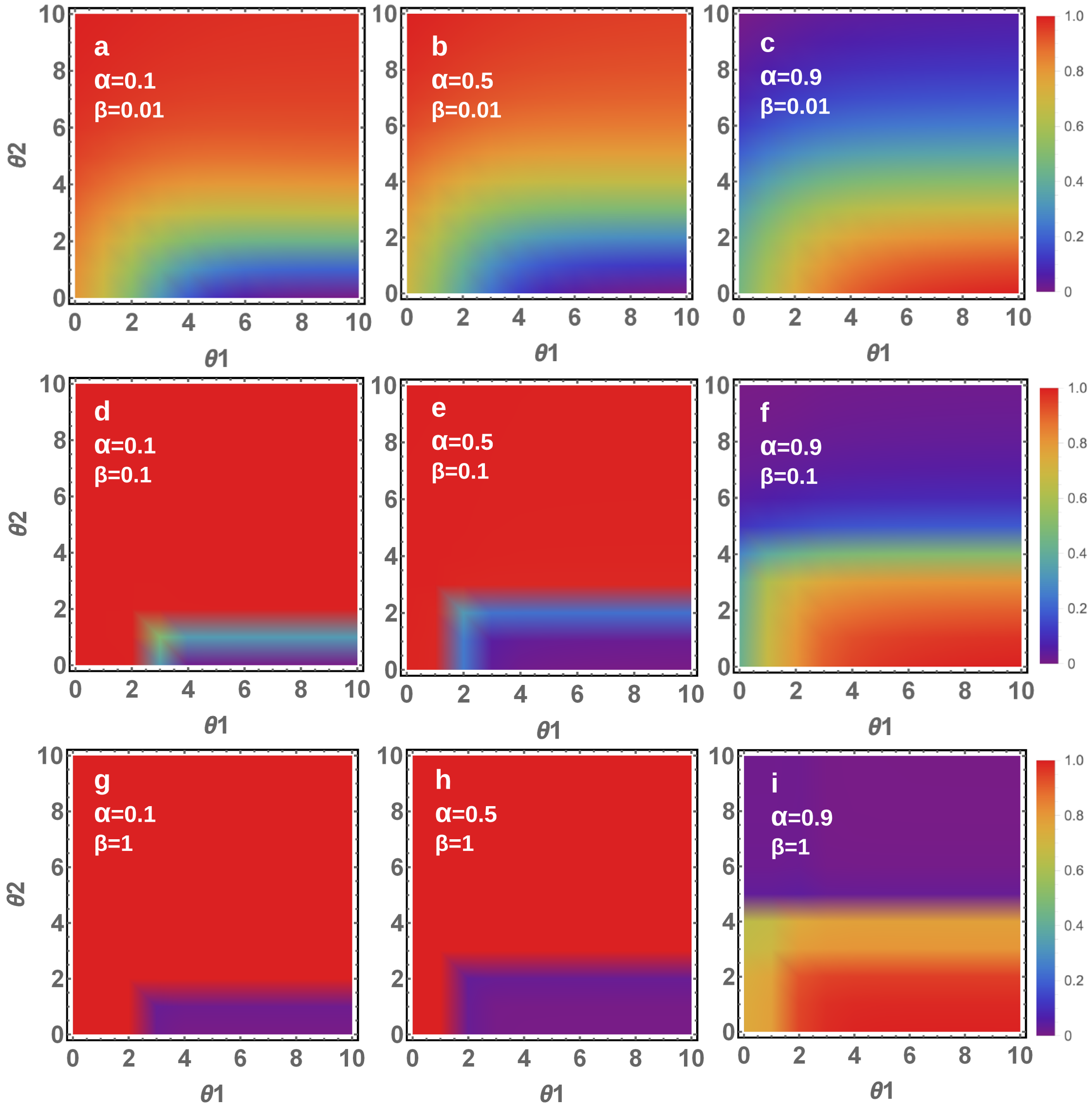

Fig. A.1 **Average population payoff as a function of θ_1 and θ_2**, for different values of α and β (for pairwise TD games). When α is small (panels a and b), the highest average payoff is achieved when θ_1 is sufficiently small and θ_2 is sufficiently large, while for large α (panel c), it is the case when θ_1 is sufficiently large and θ_2 is sufficiently small. Figure 4 also shows that for a small value of β, the highest average payoff is achieved when α is very minimal compared to other panels with higher value of β (compare panel a, d and g). Parameters: in all panels $c_H = 1$, $c_L = 1$, $b_L = 2$ (i.e. $c = 1$), and $b_H = 6$ (i.e. $b = 5$). Other parameters: $\delta = 4,\ \varepsilon = 1$; $\beta = 0.01,\ 0.1$ and 1; population size $Z = 100$.

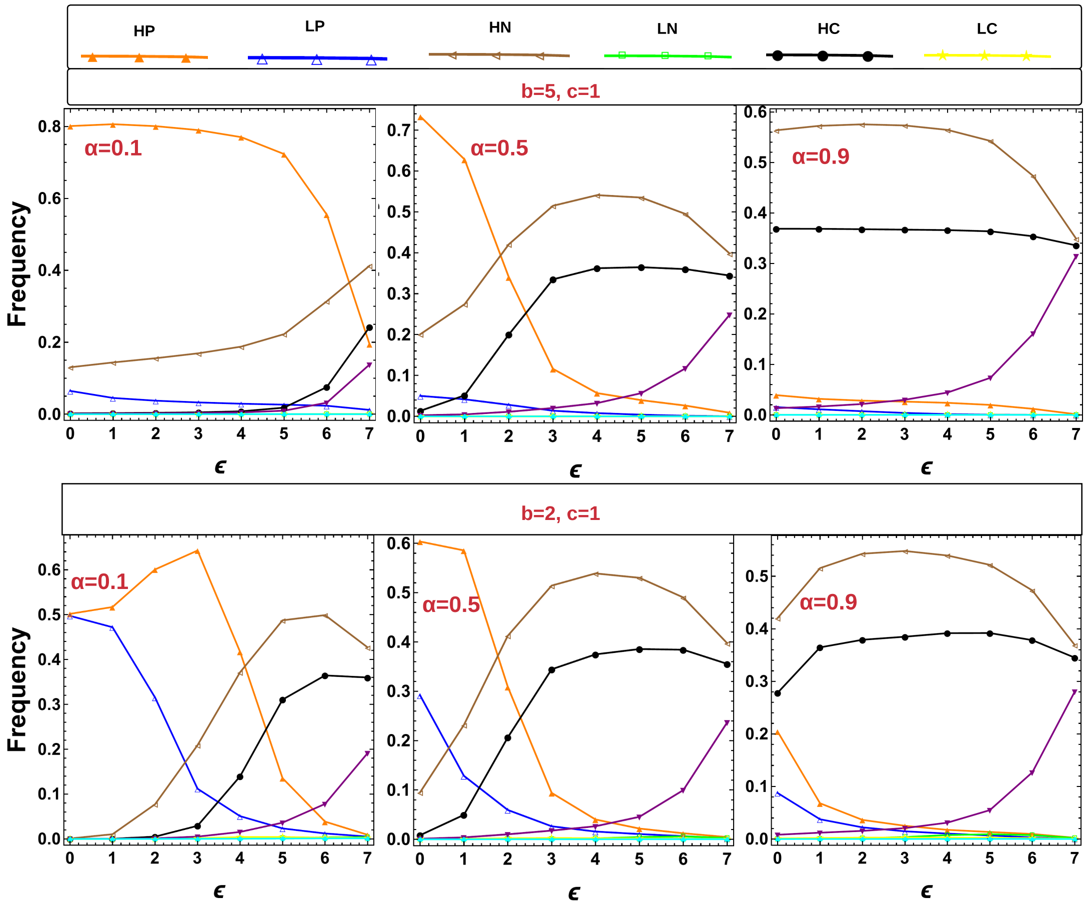

Fig. A.2 **Frequency of six strategies, HP, LP, HN, LN, HC and LC, as a function of ε, for different values of α and game configurations.** From observation, when $\alpha = 0.1 and 0.5$ and ε is sufficiently small, the commitment proposing strategies have a high frequency. It is better for the population to engage in commitment. However, when $\alpha = 0.9$, the non-proposing strategies have a higher frequency. This means that there is no competition and commitment will not be needed. Parameters: in all panels $c_H = 1$, $c_L = 1$, $b_L = 2$ (i.e. $c = 1$); Top row) $b_H = 6$ (i.e. $b = 5$) and bottom row) $b_H = 3$ (i.e. $b = 2$); Other parameters: $\delta = 6$; $\beta = 0.1$; population size $N = 100$; Fair agreements are used, where θ_1 and θ_2 are given by $\theta_1 = (b - c - \varepsilon)/2$ and $\theta_2 = (b - c + \varepsilon)/2$.

Appendix B

Additional Results for Chapter 4

Numerical confirmation of risk-dominant conditions in the N-player game

See Figure 4.1 for numerical results confirming the risk-dominant conditions in the N-player game in the main text.

Results for other intensities of selection in the N-player game

Figure B.1 confirms similar observations for other values of intensity of selection (β) in the N-player TD game, as compared to Figure 4.3 in the main text.

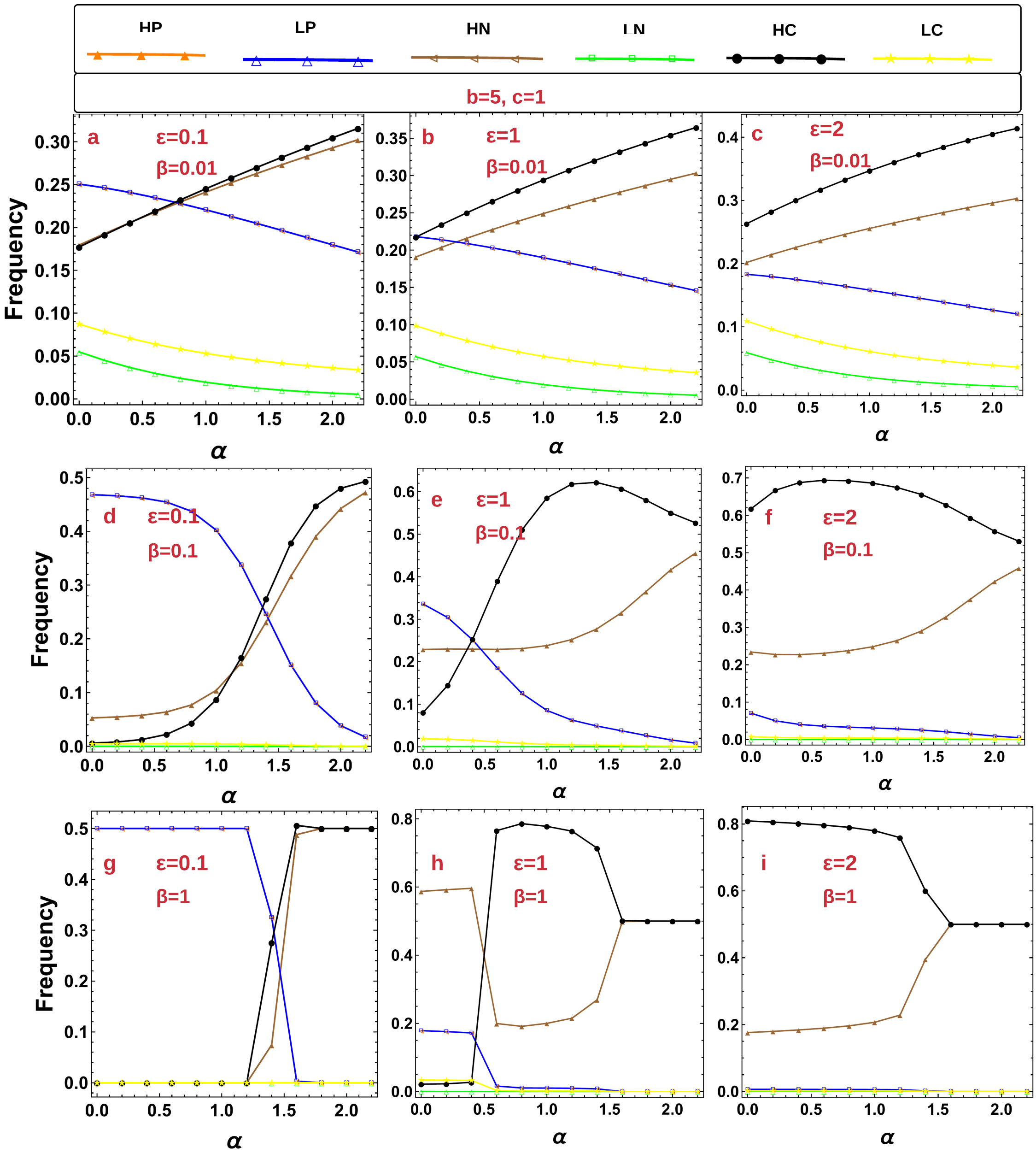

Fig. B.1 **Frequency of six strategies HP, LP, HN, LN, HC and LC, as a function of α and for different values of ε and β.** The commitment proposing strategies HP and LP dominate the population when the values of α and ε are sufficiently small, in all cases of β. Furthermore, as the value of ε increases, the non-proposing strategies dominate the population. Parameters: in all panels $c_H = 1$, $c_L = 1$, $b_L = 2$ (i.e. $c = 1$), $b_H = 6$ (i.e. $b = 5$); Other parameters: $N = 5$, $\varepsilon = 0.1,\ 1,\ 2$; $\beta = 0.01,\ 0.1,\ 1$.

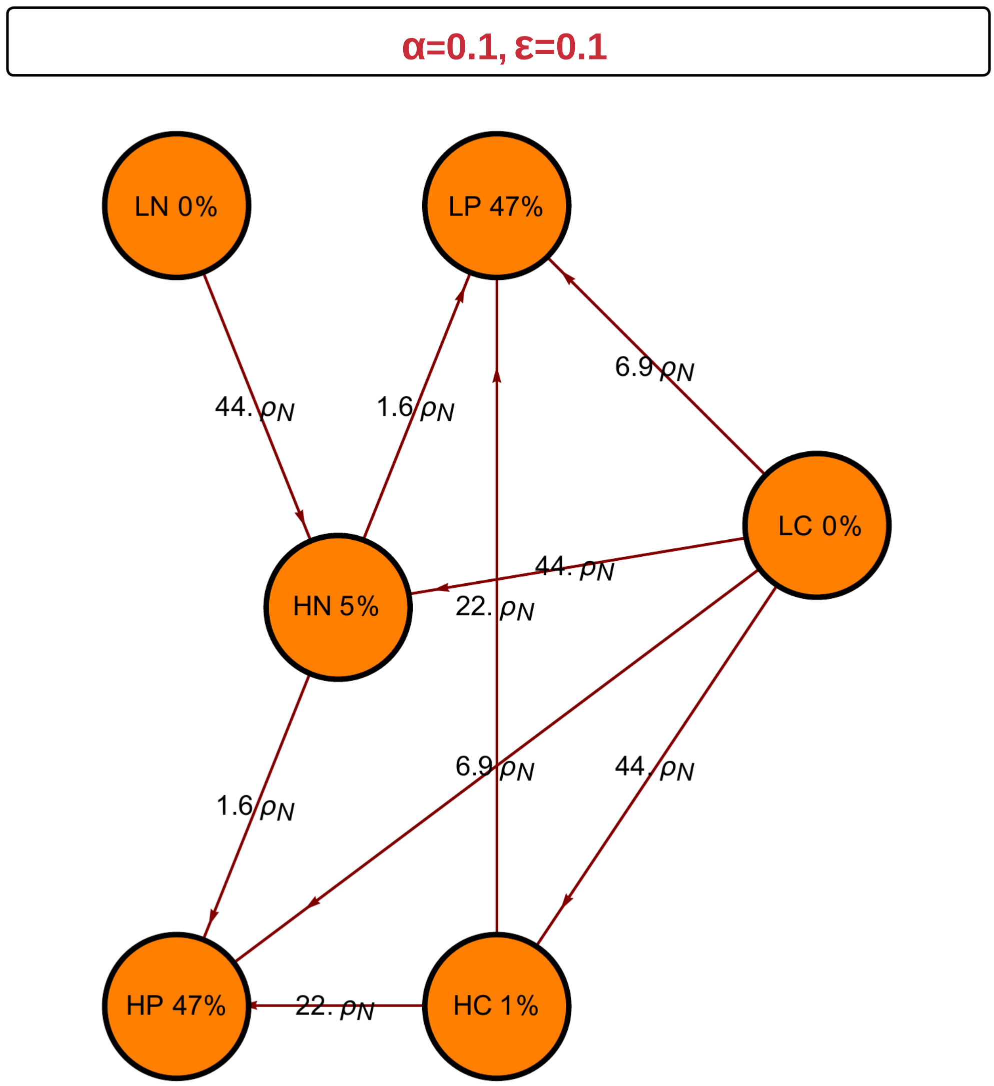

Fig. B.2 **Stationary distribution and transitions directions among the eight strategies. The arrows displayed show the direction where the transition probability is stronger for the indicated values of α and ε.** We see here the transition from one strategy to another. When α is sufficiently small, indicating how strongly competitive the market is, players should utilise pre-commitment to enhance coordination. Our result shows the transition, with the HF and LP strategies at 47%, the HN at 5% and HC at 1%/ Parameters: $\alpha = 0.1$, $\varepsilon = 0.1$, $\mu = 2$, $\theta_1 = 0.45$, $\theta_2 = 0.55$, $c_H = 1$, $c_L = 1$, $b_L = 2$ (i.e. $c = 1$), and $b_H = 6$ (i.e. $b = 5$). Other parameters: $\beta = 0.1$; population size $N = 100$.

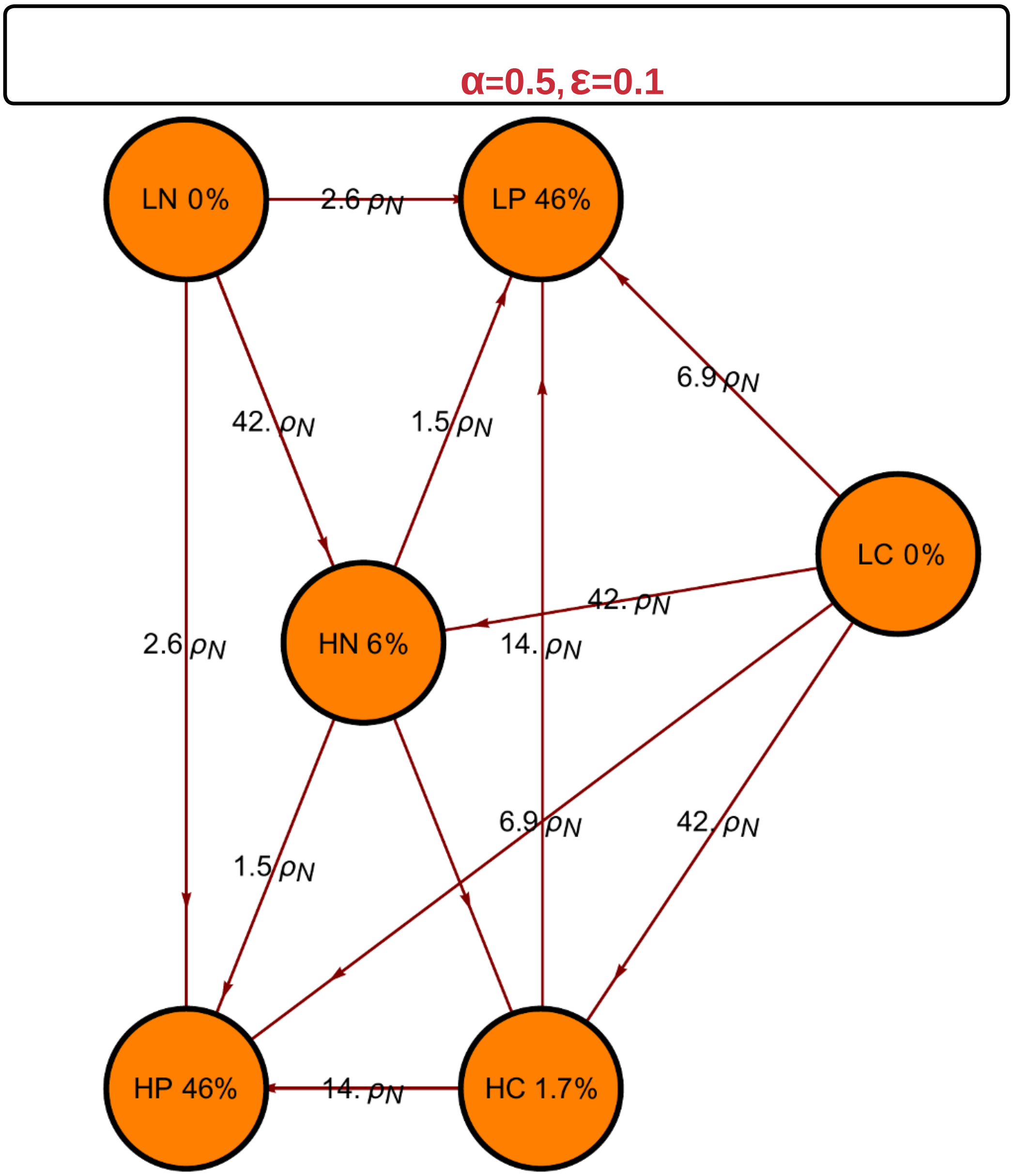

Fig. B.3 **Stationary distribution and transitions directions among the eight strategies. The arrows displayed show the direction where the transition probability is stronger for the indicated values of α and ε.** In general, when the value of α is at intermediate and the value of ε is small, there is a high transition from the other strategies to the commitment proposing strategies (HP and LP). This means that in a competitive market and with a very small cost of arranging a commitment deal, the commitment proposing strategies would dominate the population. It is more beneficial for players to go into an agreement/commitment deal in this case. Parameters: $\alpha = 0.1$, $\varepsilon = 0.1$, $\mu = 2$, $\theta_1 = 0.45$, $\theta_2 = 0.55$, $c_H = 1$, $c_L = 1$, $b_L = 2$ (i.e. $c = 1$), and $b_H = 6$ (i.e. $b = 5$). Other parameters: $\beta = 0.1$; population size $N = 100$.

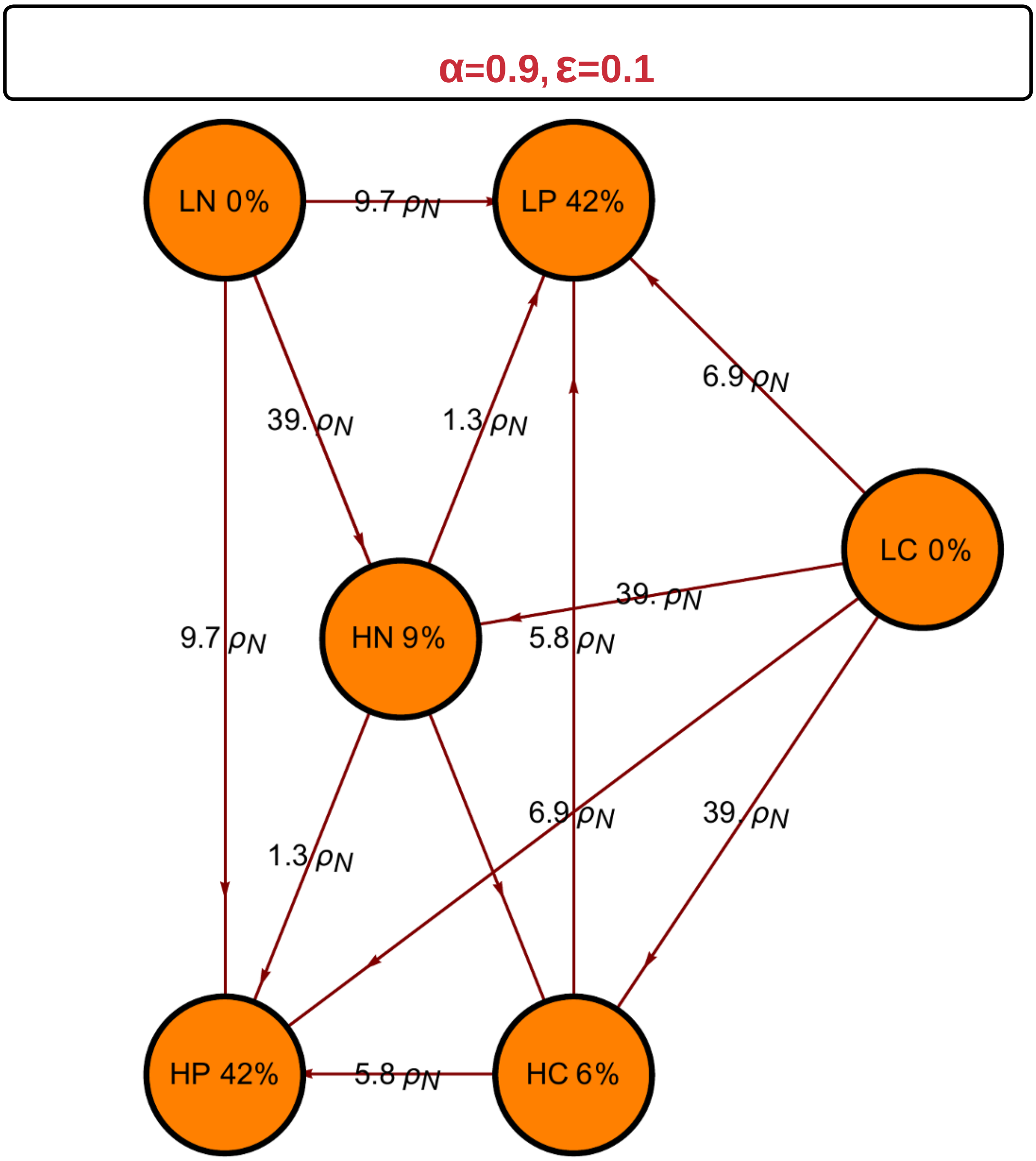

Fig. B.4 **Stationary distribution and transitions directions among the eight strategies. The arrows displayed show the direction where the transition probability is stronger for the indicated values of α and ε.** In general, we observed here that even when the value of α is sufficiently large and ε is small, there is still a high transition from other strategies to the HP and LP strategy. Parameters: $\alpha = 0.9$, $\varepsilon = 0.1$, $\mu = 2$, $\theta_1 = 0.45$, $\theta_2 = 0.55$, $c_H = 1$, $c_L = 1$, $b_L = 2$ (i.e. $c = 1$), and $b_H = 6$ (i.e. $b = 5$). Other parameters: $\beta = 0.1$; population size $N = 100$.

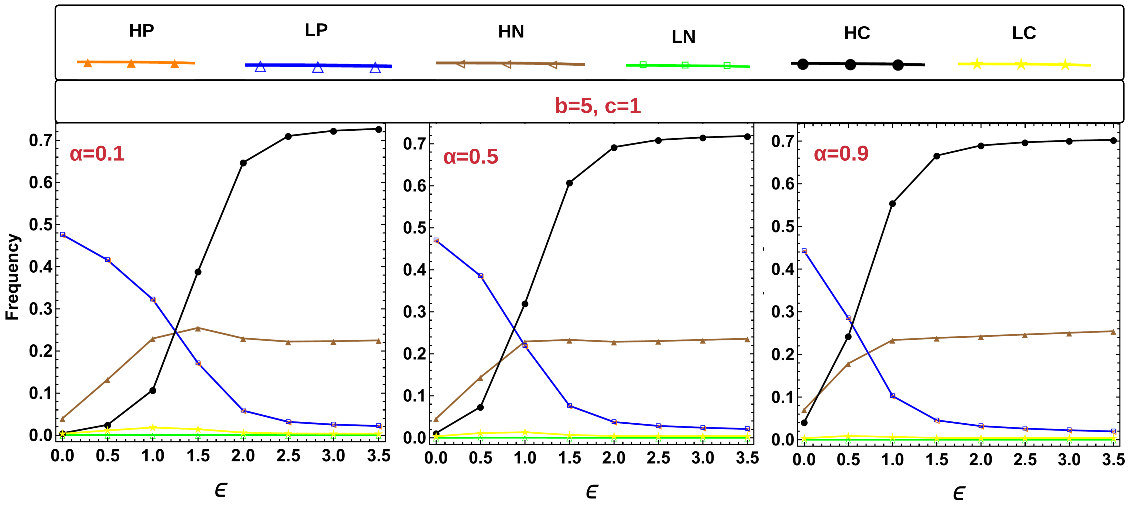

Fig. B.5 **Frequency of six strategies HP, LP, HN, LN, HC and LC, as a function of ε and for different values of α.** In general, our result shows that when the competitive level is very fierce, intermediate and none competitive, in addition to a sufficiently small value of ε, the population spends more time in the commitment proposing strategies. As the value of ε increases, the HC and HN strategies dominate the population. Parameters: in all panels $c_H = 1$, $c_L = 1$, $b_H = 6$ (i.e. $b = 5$); Other parameters: $N = 5$, $\beta = 0.1$, $\mu = 2$, population size $N = 100$.

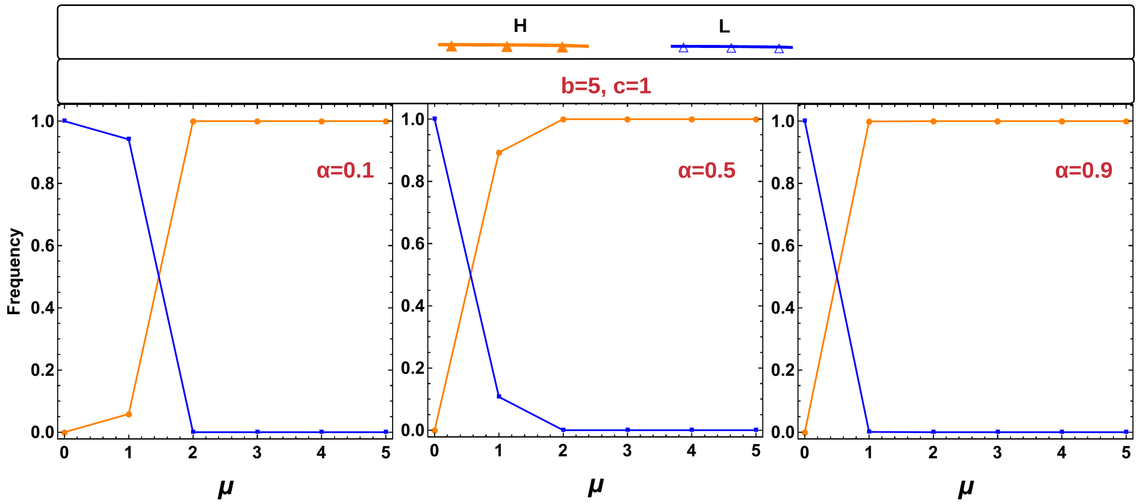

Fig. B.6 **Frequency of μ with different values of α, showing when commitment is not present.** We compare results for different values of α. We observe that when the value of μ is high (μ indicates the demand for high technology (H) in the group), the H strategy will dominate the population regardless of the market competitive level ($\alpha = 0, 0.5 and 0.9$). In this case, we see here the need for players to be coordinated to achieve a group mixture of technology adoption, arranging pre-commitment may be more beneficial in enhancing coordination among the players. Parameters: $b_H = 6$ (i.e. $b = 5$), $c_H = 1$, $c_L = 1$, $b_L = 2$ Other parameters: $N = 5$, $\beta = 0.1$, population size $N = 100$.