ESSAYS ON ENVIRONMENTAL MANAGEMENT AND NETWORK ECONOMICS

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Dedication

To my parents and Chonthicha Chantarasap.

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Abstract

This dissertation, "Essays on Environmental Management and Network Economics", studies cooperation in common pooled resources. In the following three chapters, I develop a theoretical model and experiment to analyse different issues of cooperation in common pooled resource use and social network.

The first chapter examines dynamic resource management where the resource is dispersed across areas. By implementing a Two Part Punishment scheme, I characterize the condition under which cooperation is supportable as Subgame Perfect equilibrium. However that condition has limitations in the pattern of resource migration. I also characterize partial cooperation and side payment to facilitate cooperation.

The second chapter focuses on the effectiveness of partial communication where a majority of resource users jointly set up their own rule and apply for all users. The paper designs an experiment to compare three management regulatory scheme: external regulation, partial communication and full communication where all resource users jointly set up the rule and apply to all users. The most effective treatment to reduce the extraction is full communication, followed by partial communication and external regulation, respectively. The paper provides the explanation of the extraction difference among schemes is from group's commitment level and compliance behavior. For the commitment level, it is set higher under partial communication than social optimal level, whereas it is not different in full communicators. For compliance behavior, the most compliance regulatory scheme is full communication, followed by partial communication and external regulation. Finally, the paper focuses on the behavior of communicators and noncommunicators in partial cooperation. I find that

noncommunicators have less obedient than communicators.

The third chapter studies a model of network formation using the cost distance function, where an agent experiences benefit from their direct connection and costs from the distance of connections. I propose a double best response algorithm where the agent either offers or accepts the offer from his top choice, in the network formation model. The paper provides the configuration, which consists of independent components, for all possible cases. The size of the component is sensitive to the number of agents, and the magnitude of benefits range from direct connections.

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Chapter 1

Introduction

This dissertation, "Essays on Environmental Management and Network Economics", studies cooperation in common pooled resource. The relevance of my work lies in the fact that there is much evidence, especially in developing country, which shows that external authority has limitations to control the resource user's behavior. The primary motivation for my dissertation is fishing in Songkla Lake in Thailand. Fishermen use illegal fishing gear. However, local government has failed to enforce the sea and water law because they are confronted with strong protest. Fishing gear has been increasing since 1990 and now covers approximately 80% of the lake. Although there are many efforts to control fishing in the lake, those illegal harvest still exists.

By applying Game theory, this dissertation investigates managing the common pooled resource through self governance, rather than by an external authority. In addition, I account for the influence of social networks when people form the cooperation. In the following three chapters, I develop theoretical and experimental models to analyze different issues of cooperation in common pooled resource use and social networks.

Chapter 2 examines dynamic resource management in which the resource is dispersed across an area. The main contribution of this chapter is applying the Subgame Perfect equilibrium to spatial fishery management. The metapopulation model where fish larvae of one area disperses to many areas, allows me to capture the externality of fishing in one area to other areas. The model mimics the fishing situation in the Songkla Lake. By applying a Two Part punishment scheme, which allows all agents resume to cooperation after punishment period, I characterize the strategy by which fishing cooperation is supportable as Subgame Perfect equilibrium. However, this strategy is limited by the pattern of larvae dispersion. The pattern of dispersion is the key factor in creating a credible treat to enforce everyone cooperates. Therefore, Subgame Perfect equilibrium cannot be applied for all cases. Since that strategy has a limitation, I then investigate partial cooperation which is the second best solution. The intuition is straightforward; a player should form a coalition with one who benefits him and ignores the rest of the players. To complete the analysis, I consider a special case in which there exists an area where cooperation is redundant. In this case, side payment is required. By applying a Marginal Contribution principle, I finally provide the example of calculation the side payment.

Chapter 3 focuses on the comparison between self governing management and external regulation. The self governing management here means the situation in which resource users jointly create their own rule by communication and enforce the rule to all resource users. According to the literature, communication among subjects reduces resource extraction and increases subjects' earning. What one knows from literature is communication is more effective than external regulation. The communication commonly presents in the literature is full communication in which all subjects have a chance to communicate. However, this chapter focuses on the partial communication in which a majority of subjects can communicate. There are many reasons to consider the limitations of communication in the sense that not all participants can communicate to each other. For example, some resource users live far away from others or they probably use different language. I address three main questions (i) Does partial communication reduce subject's extraction? (ii) Comparing external regulation and self-governing institution which has partial communicaion, which policy is better in term of reducing extraction and constituting individual's cooperation behavior? (iii) Is there a statistical difference in extraction and cooperation behavior between partial and full communication? To answer those questions, I design the experiment under four treatments; external regulation, partial communication and full communication. The open access, no rule case, is treated as the benchmark. The result shows that the most effectiveness regulatory scheme to reduce extraction is full communication, followed by partial communication and external regulation, respectively. Moreover, I provide the explanation of this result by considering at group's commitment level and compliance behavior. The paper find that commitment level is set higher under partial communication than social optimal level. On the other hand, it is set not different from social optimum in full communication. For compliance behavior, the most compliance regulatory scheme is full communication, followed by partial communication and external regulation. Finally, the paper focuses on the behavior of communicators and noncommunicators in partial cooperation. I find the most compliance is subjects in full communication, followed by communicators, noncommunicators and subjects in external regulation, respectively.

Chapter 4 studies network formation, where agents experience benefits from their direct connection and costs from the distance of connections. Well known examples include an epidemic and financial contagion, where the disease spreads through the social network, and the latter, across other sectors, or countries. Since the probability is represented by the *decay* in distance. I model the cost function that captures the decay in distance and refer to it as the *cost distance function*. From the cost distant function, the configuration of network is sensitive to the number of agents and the magnitude of benefits range from direct connections. The paper provides the configuration, which consists of independent components, for all possible cases.

Chapter 2

Cooperation in Spatial Resource

2.1 Introduction

Since pioneer research conducted by Gordon (1954), economists have concluded when there is open access to common pool resources, overexploitation is inevitable; Hardin (1968) coined this as "tragedy of commons." Economists have been recommending government to use its authority to protect the overexploitation of such resources. One prominent tool is assigning property rights.

While there are many types of property rights, this paper focuses on Territorial User Right Fisheries (TURFs). TURFs are a type of property right which is distributed on a spatial basis. Although assigning TURFs solves the open access problem, it may not halt overexploitation. Many researches show TURFs cannot attain the first-best outcome when the resource migrates between areas (for example, Kaffine and Costello (2011) and Janmaat (2005)). A well-known example of a migratory resource is fish. The migration of fish creates an externality because it affects fish settlement of other resource production sites (patches) through dispersal. A production externality occurs as patch owners have no incentive to take into account others' fish stock. Therefore, the result of this externality is over harvesting.

I stress the overexploitation problem of TURFs not because it is theoretical exercise, but because it is a serious problem in reality. In local common pooled resources, local communities establish rules and enforce them completely. For example, fishermen around Songkhla Lake in Thailand allocate property right in the lake to harvest shrimp. They permanently set standing traps, a type of fishing gear (see Figure 2.1), in the lake and can perfectly monitor their trap. Legally, setting the trap permanently over the lake infringes marine legislation. However, local government officers fail to enforce the law because they are confronted with strong protest. Informally, fishermen control and enforce the area they set their traps and they treat traps and location as private goods. Although, initially property rights are allocated on a first-come fist-serve basis at zero cost, now that the traps are already in place, there is a price associated with taking over existing traps (and space) and this price varies across the lake. The price confirms that owners have property rights over area and standing traps and guarantees that there is no more free space for new entrant. Standing traps now cover approximately 80% of the lake (see Figure 2.2).

Figure 2.1: Standing Trap

Figure 2.2: Songkhla Lake

Likewise, previous research in marine highlight the consequence of overexploitation specifically decreasing biomass and the increasing number of standing traps. For example, using standing traps have been increasing from 900 units in 1983 (Sirimnataporn et al. (1983)) to $5,250$ units in 1993 (Mabuntham (2002)) and reached $29,604$ units in 2003 (ONEP (2004))-an overall increase of 168% annually. In 2005, the Songkhla Lake Basin Master Plan strongly recommended that the number of standing traps be decreased by 30%. Kongprom (2008) apply the Long-base Thomson and Bell Analysis to forecast the optimal level of standing trap. He estimated that the number of current standing traps exceeds the optimal sustainable level of approximately 40%. On the other hand, declining biomass is no different. The size of harvesting has beeen decreasing from 3.6 kg/day/trap in 1996 to 0.9 kg/day/trap in 2003 (ONEP (2004)) and 0.271 in kg/day/trap in 2011 (Sritakon et al. (2011)).

In order to eliminate standing traps from the lake, the government by Fishery department offered standing trap owners the option to exchange it with purse net, a type of fishing gear allowed by law. Unfortunately, the program was not successful. Only a handful of fishermen signed up for this program. Recently, the government created a program to purchase standing traps back from fishermen but the program has not been implemented until now.

Since law enforcement has proven ineffective, the current paper seeks to investigate the incentive scheme to reduce standing traps in the lake. In particular, the purpose of this paper is to study cooperation among fishermen. I ask the question : what is the strategy to constitute cooperation Subgame Perfect Nash Equilibrium?, If full cooperation is impossible, is there room for partial cooperation? If so, what is such condition?. Furthermore, I apply a Marginal Contribution principle to calculate the side payment when some players do not have bargaining power.

To achieve those answers, I develop a dynamic model of resource management includeing spatial connectivity between patches through larvae dispersal. Current harvesting in one patch affects the next period of fish stock of other patches. The disperse of larvae between patches allow the creation of a non-credible threat among players. Based on this assumption, I define the strategy σ^*, which supports cooperation as Subgame Perfect equilibrium. The strategy here adopts the optimal penal code from Abreu (1988). To prove the Subgame Perfect equilibrium, I design punishment from harvesting by lemma 2. Proposition 1 is the main proposition formally stating that strategy σ^* supports Subgame Perfect equilibrium. In addition, proposition 2 applies the folk theorem to guarantee the existence of σ^*.

Proposition 3 and corollary 4 show that strategy σ^*, which is full cooperation, supports

Subgame Perfect equilibrium only in a special case. In particular, it depends on pattern of fishing dispersal. However, for some players cooperating is still the best response; this is the key reason to form a coalition and partial cooperation.

This paper has contributions to the literature. As far as I know, there is very little research in cooperation and spatial resource. The closest paper is Kaffine and Costello (2011). However, they do not focus on the punishment scheme to punish cheater. This paper focuses in the scheme which constitute cooperation among fishermen. Moreover, the paper propose the room for cooperation in the situation there are some players do not have bargaining power to create credible treat to other players.

In the following section, I review the literature. In section 3, I combine the dynamic game and Bioeconomic model, and the results are shown in section 4. Finally, the conclusion is in section 5.

2.2 Literature review

This paper links dynamic game theory and spatial fishery management. I start by applying the dynamic game theory to common pool resources. Polasky et al. (2006) apply the dynamic game to fishing. In particular, they introduce the optimal penal code proposed by Abreu (1988) to the problem of overharvesting. The strategy allows all players to resume cooperation after someone cheats. Tarui et al. (2008) apply the optimal code to overharvesting fishing but players cannot observe others' actions. Rather than focusing in strategy, Hannesson (1997) considers cooperation through the grim strategy. He focuses on the relation between cooperation and number of players. The number of agents supporting cooperation is limited and it depends on heterogeneity in the cost function of agents.

The model applied here called *"Metapopulation"* was first proposed by Brown and Roughgarden (1997). Brown and Roughgarden (1997) embed the natural characteristics of marine resources to the economic model by assuming two states of fish life, larvae and adult. However, the dispersal pattern is uni-directional in which there is only one pool to source larvae to other patches. Sanchirico and Wilen (1999) use the same model but in discrete time to characterize equilibrium pattern in each patch. Rather than uni-directional in dispersal, they apply five standard marine biology dispersal patterns to the model and find that Bioeconomic conditions both within patches and across patches play a key role to determining the behavior of effort in each patch.

Although a metapopulation model supports dynamic optimization, optimal harvesting (or escapement) is not analyzed intensively until Costello and Polasky (2008). They consider the optimal harvest in both interior and corner solutions and also the effect of uncertainty equilibrium. Based on the corner solution, they examine the effect of closed patch on open patch. Their contribution lies in establishing a new area of research- the effect of marine reserve areas. In addition, Sanchirico and Wilen (2005) analyze the optimal harvest in each patch but only consider the interior solution in open access regulation. They find that the regulator can choose a spatially heterogeneous landing and effort tax to achieve the first best solution.

The paper most closely resembles that of Kaffine and Costello (2011). They apply the unitization concept in the mining industry to study cooperation in fishery. Each member must contribute rent and receives a dividend from the unitization. In this set up, cooperation occurs because the maximum dividend attains when all agents follow joint rent maximization.

Although Kaffine and Costello (2011) also study in cooperation among fishermen, the key concept is different. In this paper, success of cooperation is based on credible threat and punishment, while Kaffine and Costello (2011) focus on contribution and profit sharing rule. Consequently, the pattern of fish dispersal is more important in this paper since it determines the bargaining power and credible threat of each player.

2.3 The Model

The model here is a metapopulation model in the style of Costello and Polasky (2008).[1] In young stage, larvae disperse across patches. I assume they become an adult after one period. Adult fish reproduce young fish and are caught by fisherman. Unlike the young stage, adult fish settle in a particular area.

Let I be a set of player: $I = \{1, 2, \ldots, N\}$. Each agent has his own patch and he can perfectly enforce property right over his patch. I assume that the property right remains permanent throughout the model horizon. The model is discrete in time $t = \{0, 1, 2, \ldots\}$. Let s_{it} be the fish stock at the beginning of period t of patch i and e_{it} be the stock at the end of period t of patch i. The identity between s_{it} and e_{it} is $h_{it} \equiv s_{it} - e_{it}$, where h_{it} is harvest during period t of patch i. For simplicity, I assume that $s_{i0} = s_0$ and $K_i = K, \forall i$, where K represents the carrying capacity.

In the young stage, the larvae are reproduced by

$$l_{it} = g_i(e_{it})$$

where l_{it} is the larvae of patch i in period t. $g_i(e_{it})$ is the reproduction function of offspring in patch i. Assume that $g_i'(.) \geq 0$ and $g_i''(.) < 0$, for all i.

I capture the dispersal of larvae across patches by D_{ij}. D_{ij} denotes the proportion of juveniles originated in patch j and settle in patch i. D_{ij} can be either stochastic or deterministic. It can be stochastic if it is interpreted to be the current, weather, wind etc. However, Sanchirico and Wilen (1999) examined five patterns of fish migration and treat D_{ij} as deterministic.[2] I assume $D_{ii} > 0$ and $\sum_{i \in I} D_{ij} = 1$ for all $i \neq j$.

[1] Costello and Polasky (2008) assume there is only one sole owner who has many patches. They focus on how to optimize harvest among patches. However, in this paper, there are many owners who only have one patch.

[2] Although the stochastic migration is more realistic, Sanchirico and Wilen (1999) claim that the five migration patterns are enough to capture the reality.

The transition of fish stock is

$$s_{it+1} = e_{it} + \sum_{j=1}^{N} g_j(e_{jt}) D_{ij} \tag{2.1}$$

The (adult) fish stock at the beginning of period $t+1$ in patch i is equal to old adult fish which survive from catch in period t and new adult fish which disperse from other patches, including young fish originated in their own patch i but not move to other places.

Price is constant in this model-a standard assumption applied in local common pooled resource. Changing the quantity of fish supply in the local area does not affect the price. The cost function is heterogeneous across patches. In particular, the cost of each fisherman represents the distance between the patch and dock in the sense that the farther away the patch is located, the higher cost incurred by the fishermen. $c_i(s_i)$ is the unit cost of harvest where $c_i'(s_i) < 0$ and $c_i''(s_i) > 0, \forall i$. The patch owner is not allowed to drive fish stock to extinction level by assuming $\int_0^{s_i} c_i(\omega)d\omega = \infty, \forall i$. By this assumption and monotonicity of the cost function, there exists a break even level of fish stock which is $p - c_i(\underline{s}_i) = 0, \forall i$. In other words, the revenue function can be written as

$$R_i = \begin{cases} \int_{e_i}^{s_i} [p - c_i(\omega)]d\omega & \text{if } e_i \in (0, s_i] \\ -\infty & \text{if } e_i = 0 \end{cases}$$

2.3.1 Cooperation

The harvest in patch i creates an externality to fish stock of patch j by D_{ji}. For a cooperative outcome, all patch owners' problem are treated as a rent manager's problem. The joint rent maximization is the maximization of all players i.

$$\underset{\{e_{it}\}_{t=0}^{\infty}}{\text{maximize}} \quad \sum_{t=0}^{\infty} \beta^t \sum_{i=1}^{N} \int_{e_{it}}^{s_{it}} [p - c_i(\omega)] d\omega$$

$$\text{subject to} \quad s_{it+1} = e_{it} + \sum_{j=1}^{N} g_j(e_{jt}) D_{ij} \qquad , \forall i$$

The Bellman equation is

$$V(s_t) = \max_{0 \le e_{it} \le s_{it}} \sum_{i=1}^{N} \int_{e_{it}}^{s_{it}} [p - c_i(\omega)] d\omega + \beta V(s_{t+1}),$$

The necessary condition for all periods when the harvest is positive or when $s_{it} > e^*_{it}$ is

$$-[p - c_i(e^*_{it})] + \beta \sum_{j=1}^{N} \frac{\partial V(s_{t+1})}{\partial s_{jt+1}} \frac{\partial s_{jt+1}}{\partial e_{it}} = 0 \qquad , \forall i \tag{2.2}$$

The escapement (or harvest) in one patch affects future of fish stock in all patches by $\sum_{j=1}^{N} \frac{\partial V(s_{t+1})}{\partial s_{jt+1}} \frac{\partial f_j(e^*_{jt}, e^*_{it})}{\partial e_{it}}$, where $f_j(e^*_{jt}, e^*_{it}) = e^*_{jt} + \sum_{i=1}^{N} g_i(e^*_{it}) D_{ji}$. The constraint equations can be substituted to the necessary condition as

$$-[p - c_i(e^*_{it})] + \beta\{[p - c_i(f_i(e^*_{it}, e^*_{jt}))] + \sum_{j=1}^{N} \{[p - c_j(f_j(e^*_{jt}, e^*_{it}))] g'_i(e^*_{it}) D_{ji}\}\} = 0 \quad , \forall i \tag{2.3}$$

Since s_{it} is determined by e_{it} and e_{jt}, the optimal e^*_{it} is solved simultaneously from the system of equation 2.3 for all patches. The optimal e^*_{it} is determined by the trade-off between current and future rent. The first term is the value of rent that fishermen give up in current period by increasing escapement, $-[p - c_i(e^*_{it})]$. It is equal to the discounted value of rent in next period. The increasing number of old adult fish raise market value of patch i by$[p - c_i(f_i(e^*_{it}, e^*_{jt}))]$. In addition, old adult fish of patch i delivers new adult fish to other patches in period $t + 1$. It is measured in term of market value by $\sum_{j=1}^{N} \{[p - c_j(f_j(e^*_{jt}, e^*_{it}))] g'_i(e_{it}) D_{ji}\}$. The discount rate is β.

To guarantee the existence of e^*_{it}, the function $V(s_t)$ must be concave in escapement for all i. The following assumption guarantee concavity.

Assumption 1

$$c'_i(e^*_{it})-\beta c'_i(f_i(e^*_{it},e^*_{jt}))+\beta\sum_{j=1}^{N}\{[p-c^*_j(f_j(e^*_{jt},e^*_{it})]g''_i(e^*_{it})D_{ji}-(g'_i(e^*_{it})D_{ji})^2c'_j(f_j(e^*jt,e^*_{it}))\}<0$$

for all i and j.

This assumption is derived from the second order derivative of $V(s_t)$. In the interior solution, I know that $e^*_{it} \leq f_i(e^*_{it}, e^*_{jt})$. Then, $c'_i(e^*_{it})-\beta c'_i(f_i(e^*_{it},e^*_{jt}))<0$. Since $g''(.)<0$ and $c'(.)<0$, the first term in the summation bracket must be larger than the second term. In other words, assumption 1 states that the (absolute value of) concavity in $g(.)$ has to be larger than $c'(.)$ for all patches.

However, the optimal path for the case $s_{it} \leq e^*_{it}$ is zero harvest. Therefore, the optimal harvest is

$$h^*_i = \begin{cases} s_i - e^*_i & \text{if } s_i \geq e^*_i \\ 0 & \text{otherwise} \end{cases} \tag{2.4}$$

2.3.2 Non-Cooperation

In this case, the problem is similar to the Cournot model in game theory literature. The main characteristics of optimal escapement path are: 1) it is independent from other agents' escapement and 2) it is independent history from any escapement. The individual fisherman's problem is

$$\begin{aligned} &\underset{\{e_{it}\}_{t=0}^{\infty}}{\text{maximize}} && \sum_{t=0}^{\infty}\beta^t\int_{e_{it}}^{s_{it}}[p-c_i(\omega)]d\omega \\ &\text{subject to} && s_{it+1}=e_{it}+\sum_{j=1}^{N}g_j(e_{j,t})D_{ij} \end{aligned}$$

The necessary condition is

$$-[p - c_i(\hat{e}_{it})] + \beta \sum_{j=1}^{N} \frac{\partial V(s_{t+1})}{\partial s_{jt+1}} \frac{\partial s_{jt+1}}{\partial \hat{e}_{it}} = 0$$

which is the same as equation 2.2. However, since agents do not take into account other agent's action, the escapement of agent i is independent with others. The necessary condition can then rewritten as

$$-[p - c_i(\hat{e}_{it})] + \beta\{p - c_i(s_{it+1}) + [p - c_i(s_{it+1})]g_i'(\hat{e}_{it})D_{ii}\} = 0 \tag{2.5}$$

The brace bracket in this equation is a part of the brace bracket of equation 2.3. Since $c'(.) < 0$, it implies that $e^*_{it} > \hat{e}_{it}$. This result is straightforward because the individual agent i does not take into account his effect on other patches. I provide the case that $e^*_{it} > \hat{e}_{it}$ when $c'(.) = 0$ in Appendix.

Since $V(s^*_t) = \max\{\sum_{i=1}^{N} \int_{e_{it}}^{s_{it}} [p - c_i(\omega) d\omega] + \beta V(s_{t+1})\}$, it implies that $V(s^*_t) \geq \sum_{i \in N} V(\hat{s}_{it})$, where s^* and $\hat{s}$ correspond to e^* and $\hat{e}$ respectively. In the rest of paper, I consider the strategy supporting the cooperation case.

2.4 Results

2.4.1 The Two-Part Punishment Scheme

The two-part punishment scheme is composed of a punishment and recovery state. Although the two part punishment scheme here is not so common as the grim strategy, it is reasonable in our environment. The grim strategy requires all agents play non cooperation (Nash best response) forever. Theoretically, the punishment scheme has the same result in the sense that punishment is off equilibrium. However, the two part punishment scheme is easier to implement because it allows all agents enjoy the benefit of cooperation after punishment period.

The equilibrium I apply here is *worst perfect equilibrium*, proposed by Abreu (1988), It is called the worst because it drives the cheater's payoff to the minimum. In particular, punishment will make the (present value of) payoff equals to the worst. In this context, the minimum payoff is equal to zero and it happens when agent sets zero harvest. Since the critical part of punishment scheme is punishment, I need the assumption that everyone has capability to be punished.

Assumption 2 *Given any $e_i \in [0, s_i]$,*

$$e_i + g_i(e_i)D_{ii} + \sum_{i \neq j} g_j(\underline{s}_j)D_{ij} \leq \underline{s}_i$$

for all i and j.

Assumption 2 states that the stock of patch i intensely depends on dispersal from other patches. The rest of agents can punish agent i by driving their stock to $\underline{s}_j$. This assumption implies the rent of agent i is negative if other agents choose $\underline{s}_j$. The next lemma formally states this point.

Lemma 1 *For any $e_i \in [0, s_i]$, there exists e_{-i} such that makes $p - c_i(s_i) \leq 0$, $\forall i$.*

For simplicity, I assume that all patches are fully connected, $\min\{D_{ij}, D_{ji}\} > 0$ for all $i, j \in N$. This assumption is relaxed in the next section. The following definition states the characteristic of biological system

Definition 1 *The **fully connected** system is the patch such that min$\{D_{ij}, D_{ji}\} > 0$ for all $i, j \in N$. The **partially connected** system is the patch such that min$\{D_{ij}, D_{ji}\} = 0$ for some $i, j \in N$.*

In words, the fully connected system is the set of patch that delivers larvae to others and receives them from others as well. The partial connected system is otherwise. Next the strategy supporting Subgame Perfect equilibrium, when all patches are fully connected, is stated formally.

Strategy σ^*

<u>*Phase I.*</u> For $t \geq 0$, all players play cooperation $h_i^* = s_i - e_i^*$ as long as $e_i \geq e_i^*$ until one player deviate from h^* by choosing $h^d > h^*$. If there is any agent $k \in I$ that deviates in period t_0, move to Phase $II(k)$.

<u>*Phase $II(k)$.*</u> At period $t_0 + 1$, for agents $j \neq k$, they punish k by playing

$$h_j^p = \begin{cases} 0 & \text{if } s_j < \underline{s}_j \\ s_j - \underline{s}_j & \text{otherwise} \end{cases}$$

For an agent k, he plays h_k^p which is defined below. The next phase starts at $s_k^p = f_k(e_k^p, e_j^p)$ where $e_k^p = s_k^d - h_k^p$ and $s_j^p = f_j(e_j^p, e_k^p)$, where $e_j^p = \underline{s}_j$. Otherwise, start $PhaseII(k)$ again.

<u>*Phase $III(k)$.*</u> From period $t_0 + 2$, all players set $h_i = 0$, until $s_i = s_i^*$, for all i where $s_i^* = e_i^* + \sum_{j=1}^{N} g_j(e_j^*) D_{ij}$. Let τ_i be minimum periods that the stock grows from $t_0 + 2$ to periods at which $s_i = s_i^*$. Define $\tau = max\{\tau_1, \ldots, \tau_N\}$. If an agent $r \in I$ deviates during $[t_0 + 2, t_0 + 2 + \tau]$, go to phase $II(r)$. Otherwise, go to phase I.

In *Phase I*, everyone plays cooperation until period t_0 in which agent k deviates from h_k^* by playing h_k^d, where $h_k^d > h_k^*$. The rest of the agents observe at the end of period and start the punishment phase. In *Phase* $II(k)$, period $t_0 + 1$, they retaliate agent k by driving their stock to $\underline{s}_j$ by choosing h_j^p. By assumption 2, agent k loses because $s_k < \underline{s}_k$. The key point of the two part punishment scheme is that the cheater is willing to receive a negative return because it is his best response. In *Phase* $III(k)$, after period $t_0 + 2$, all agents will not harvest (or set escapement level equals to their stock) during recovery period, τ. The idea of two part punishment is simplified in Figure 2.3. The summation of (the present value of) punishment and cooperation represented in area $\Pi_{II(k)}$ and $\Pi_{III(k)}$ is equal to zero which is the lowest payoff in our model.

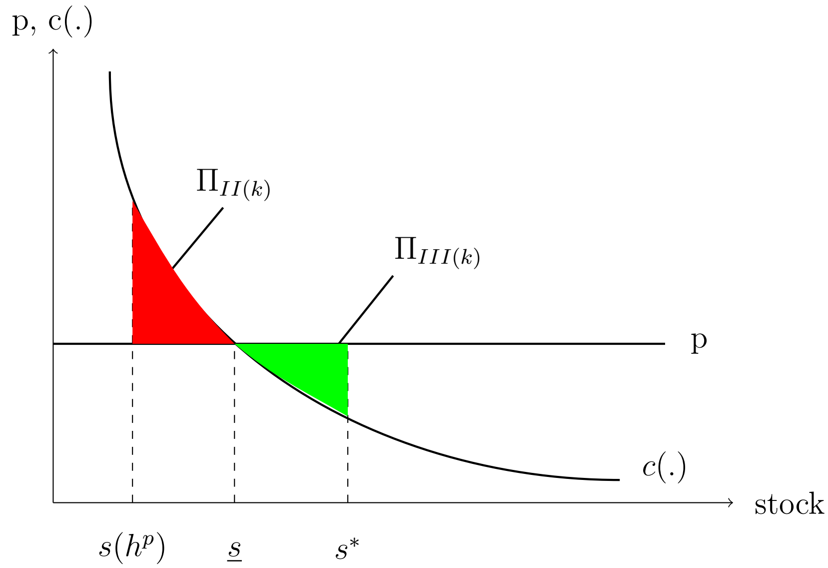


Figure 2.3: Two Part Punishment

There are many strategies of two part punishment scheme supporting Subgame Perfect equilibrium. Let T_0 and T_1 be the length of punishment and recovery period. All pairs (h_k^p, T_0+T_1) which are consistent with $\Pi_{II(k)}+\Pi_{III(k)} = 0$ are Subgame Perfect equilibrium.[3] The difficulty of designing the optimal strategy is how to choose the best pair of (h_k^p, T_0+T_1). Since $T_0 + T_1$ is the length of time that fish stock deviates from s_i^* and there is no harvest, the optimal pair (T_0, T_1) is solved from

$$\begin{aligned} &\underset{T_0,T_1\geq 0}{\text{minimize}} \quad T_0 + T_1 \\ &\text{subject to} \quad \Pi_{II(k)}(T_0) + \Pi_{III(k)}(T_1) = 0 \end{aligned} \tag{2.6}$$

Obviously, $T_0 = 1$ and $T_1 = \tau$ in strategy σ^* are the solution of program 2.6. Furthermore, the solution of program 2.6 is consistent with the most rapid approach path (bang-bang condition) which is the optimal condition of joint rent maximization problem.

[3]Generally, the worst perfect equilibrium requires $\Pi_{II(k)} + \Pi_{III(k)} = \gamma$, where γ is the lowest payoff. In our model, the worst payoff happens when agents stop harvesting. Hence, $\gamma = 0$.

Next I consider the optimal h_k^p. The punishment phase will start after all agents but k observe e_k^d at the end of period t_0, where $e_k^d = s_k - h_k^d$. According to the strategy σ^*, the length of punishment phase is only one period. The desired variable, h_k^p, will wipe out agent k's payoff from the begining of punishment period. In other words, the h_k^p is consistent with $\Pi_{II(k)} + \Pi_{III(k)} = 0$ discounted back to the beginning of punishment period. That means

$$\int_{s_k^d - h_k^p}^{s_k^d} [p - c(\omega)]d\omega + \beta^{\tau+1} v_k(s_k^*) = 0 \tag{2.7}$$

where s_k^d is fish stock in patch k after agent k cheats in period t_0, $h_k^p = s_k^d - e_k^p$ and $v_k(s_k)$ is value function of agent k starting from s_k. The first term is the negative payoff in punishment period, $t_0 + 1$. The second term is the value function of cooperation when all agents resume to play cooperation and $\beta^{\tau+1}$ is the discounted value dating back from period $t_0 + 2 + \tau$ to $t_0 + 1$. Since the second term is positive, the sufficient condition to satisfy equation 2.7 is $s_k^d \leq \underline{s}_k$. Note h_k^p is well defined because $\int_0^s c(\omega)d\omega = \infty$,

Given s_k and h_j^* where $j \neq k$, the maximum amount payoff of agent k receive from cheating is

$$\int_{s_k - (h_k^d)^*}^{s_k} [p - c_k(\omega)]d\omega \tag{2.8}$$

Note this equation has only one term because h_k^p cancels out with the payoff after cheating. The next lemma will state formally optimal h_k^d.

Lemma 2 *Given other agents choose e_i^*, the optimal deviation action for player k is*

$$(h_k^d)^* = \begin{cases} s_k - \underline{s}_k & \textit{if } s_k > \underline{s}_k \\ 0 & \textit{otherwise} \end{cases}$$

Proof. The maximum rent that agent k receives from cheating is

$$\underset{\underline{s}_k \le h_k \le K}{\text{maximize}} \quad \int_{s_k - h_k}^{s_k} [p - c_k(\omega) d\omega]$$

The first order condition is

$$p - c(s_k - (h_k^d)^*) = 0$$

The necessary condition implies that $(h_k^d)^* = s_k - \underline{s}_k$, if $s_k > \underline{s}_k$, ■

Lemma 2 reveals that the optimal strategy for the cheater is to drive his stock to $\underline{s}_k$, which is the maximum he can extract. This condition is different from a single patch sharing with many owners. For instance, Tarui et al. (2008) allow the cheating player to harvest until $s < \underline{s}$. In that case, it occurs because although total return decreases, the cheater's share increase. It is optimal in the sense that if other agents are harvesting, the cheater will drive stock until $s < \underline{s}$.

Showing that strategy σ^* supports Subgame Perfect equilibrium which requires the condition that guarantees the payoff of one shot deviation is less than the present value of payoff of cooperation.

Condition 3 *Given* $s_i \in [\underline{s}_i, s_i^*]$

$$\frac{1 - \beta^{\tau+2}}{1 - \beta} \int_{e_i^*}^{s_i} [p - c_i(\omega)] d\omega \ge \int_{\underline{s}_i}^{s_i} [p - c_i(\omega)] d\omega$$

for all i.

Condition 3 of cooperation during punishment and recovery period dating back to t_0 is greater than the payoff of one shot cheating. The payoff in cooperation periods is irrelevant because it will be the same in both cooperation and deviation cases. This condition will guarantee no players have the incentive to deviate.

Proposition 1 *Given a fully connected system, assumption 2 and condition 3, σ^* supports Subgame Perfect equilibrium for all $s_i \in [0, s_i^*]$.*

Proof. The strategy σ^* is Subgame Perfect Equilibrium if and only if (i) given player k's extraction, following σ^* is the best respond for all players N/k and (ii) given player N/k's extraction, following σ^* is the best respond for player k.

Consequently, it is enough to show that no player deviates in each part of the strategy σ^*. The proof compose of 4 parts : 1) for any s_0, all agents have no incentive to deviate from cooperation in $PhaseI$. 2) agents $j \in N\backslash k$ have no incentive to deviate from $PhaseII(k)$. 3) agent k has no incentive to deviate from $phaseII(k)$ and 4) all agents have no incentive to deviate from $phaseIII(k)$

1. *Show that for any $s_i \leq s_i^*$, all agents have no incentive to deviate from cooperation in $PhaseI$.*

All players play cooperation from $t \geq 0$ until there is one player that deviates. Suppose agent k deviates from h_k^* by playing $h_k^d > h_k^*$ in period t_0 and s_k^d is result. Since h_k^p suport $\Pi_{II(k)} + \Pi_{III(k)} = 0$. Agent k receives $\int_{s_k - h_d^*}^{s_k} [p - c(\omega)]d\omega$. On the other hand, agent k receives $\frac{\beta^{\tau+2}}{1-\beta} \int_{e_i^*}^{s} [p - c(\omega)]d\omega$ during punishment and recovery periods, if he choose to cooperate. Then, by condition 3

$$\frac{\beta^{\tau+2}}{1-\beta} \int_{e_i^*}^{s} [p - c_k(h_k^*)]d\omega \geq \int_{\underline{s}_k}^{s_k} [p - c_k(\omega)]d\omega \geq \int_{s_k - h_d^k}^{s} [p - c_k(\omega)]d\omega$$

There is no incentive for agent k to deviate from σ^* in phase $PhaseI$. For the case there is s_i such that $s_i < e_i^*$, go to part 4.

2. *Show that agents $j \in N\backslash k$ have no incentive to deviate from $phaseII(k)$.*

Following σ^*, agents $j \in N\backslash k$ drive $s_j = \underline{s}_j$ and rewards $\int_{\underline{s}_j}^{s_j} [p - c(\omega)]d\omega$. Suppose $j \in N\backslash k$ does not follow σ^*, given other agents do. In the case that $s_j \leq \underline{s}_j$, he gains at most 0. In the case that $s_j > \underline{s}_j$, his payoff is (upper) bounded by $\int_{\underline{s}_j}^{s_j} [p - c(\omega)d\omega]$. The maximum payoff he gains is $max\{0, \int_{\underline{s}_j}^{s_j} [p - c(\omega)d\omega]\}$. In addition, cheating leads to start

$PhaseII(j)$ and agent j gains negative payoff because the rest players will set $s_i = \underline{s_i}$ for all $i \neq j$. Therefore, following σ^* is the best respond strategy for agent $j \in N \backslash k$.

3. *Show that agent k has no incentive to deviate from $phaseII(k)$.*

According to severe punishment of σ^*, agent k plays h_k^p. The (present value) payoff of agent k is 0 because h_k^p is designed to be consistent with $\Pi_{PhaseII(k)} + \Pi_{PhaseIII(k)} = 0$. Suppose agent k deviates from σ^*. Given agent $j \in N \backslash k$ follows σ^*, agent k's return is negative regardless how much he harvests because everyone plays $s_j = \underline{s}_j$ for all $j \in N \backslash k$ and $s_k \leq \underline{s}_k$ (by assumption 2). Furthermore, the deviation will lead to start $PhaseII(k)$ again. He will play h_k^p finally and receives 0 payoff. Therefore, deviation from σ^* returns negative payoff, while following σ^* attains 0. The best response for agent k is following σ^*.

4. *Show that all agents have no incentive to deviate from $phaseIII(k)$*

Suppose agent i deviates in period τ_i, where $\tau_i < \tau$. He rewards only one shot because all players will go back to $PhaseII(i)$ again. In the case that $s_i \leq \underline{s}_i$, he gains at most 0. In the case that $s_i > \underline{s}_i$, he is rewarded at most $\int_{\underline{s}_i}^{s_i} [p - c(\omega) d\omega]$. He gains $\max\{0, \int_{\underline{s}_i}^{s_i} [p - c(\omega) d\omega]\}$ which is exactly the same as what deviator receives in $phaseI$. The condition 3 will guarantee that no one has incentive to deviate from strategy σ^* in $phaseIII(k)$.

The proof is done. ■

Next I illustrate folk theorem in order to guarantee that if agents are patient enough σ^* can support subgame perfect equilibrium. The dynamic game here is different from repeated game. In repeated game, payoff in every state is independent from each other. However, the fish stock depends on the escapement level in predecessor period, which is determined by how much agent patient. Consequently, $e_i^* = e_i^*(\beta_i)$ in the sense that agent will set escapement higher, if he is more patient.

Since agent can set $h_i = 0$ or $(e_i = s_i)$ for all t, the worst payoff agent i gains is zero. In other words,

$$0 = \min_{h_{-i}} [\max_{h_i} V_i(s_i)]$$

The lowest payoff agent i can hold is zero (given he plays the best response), although opponents choose any h_{-i} to hurt him (other players do not play their best response). Another piece to prove the folk theorem is the convex hull of payoff. Let Δ_i be the set of feasible and individually rational payoff of agent i for long run.

$$\Delta_i = [0, \max_{e_i} \sum_{t=0}^{\infty} \int_{e_{it}}^{s_{it}} [p - c_i(\omega)] d\omega]$$

Then $\Delta = \Delta_1 \times \cdots \times \Delta_N$ is the set of feasible payoff for all players. Clearly, the payoff from following σ^* is feasible and individually rational. The following proposition is the classical folk theorem of Fudenberg and Maskin (1986).[4]

Proposition 2 *Given a fully connected system and condition 3, for every positive payoff in Δ, there exists $\tilde{\beta}$ such that σ^* is Subgame Perfect equilibrium where each player i achieves $\int_{e_i^*(\tilde{\beta})}^{s_i} [p - c(\omega(\tilde{\beta}))] d\omega(\tilde{\beta})$.*

Proof. By condition 3, for any $\tilde{s}_i \in [\underline{s_i}, K]$ the condition

$$\frac{1 - \tilde{\beta}^{\tau+2}}{1 - \tilde{\beta}} \int_{e_i^*(\tilde{\beta}_i)}^{s_i} [p - c_i(\omega(\tilde{\beta}_i))] d\omega(\tilde{\beta}_i) \geq \int_{\underline{s}_i}^{s_i} [p - c_i(\omega)] d\omega$$

must be hold for some $\tilde{\beta}$ and for all $s_i \in [\underline{s_i}, \tilde{s}_i]$. Now I set $\tilde{s}_i = s_i^*$ for all i. Therefore, $\tilde{\beta}$ constitutes σ^* and each player achieves $\int_{e_i^*(\tilde{\beta})}^{s_i} [p - c(\omega(\tilde{\beta}))] d\omega(\tilde{\beta})$. Note the above argument is hold for all positive payoff in Δ. ■

Generally, the condition 3 is not monotonic in β. However, Dutta (1995) shows that the cooperation condition (condition 3) will be monotonic when the worst perfect equilibrium payoff is independent from state variable (fish stock). In our context, the worst equilibrium payoff is zero, which is independent from state variable. Therefore, the condition 3 is monotonic in β in this model.

[4]There are many versions of folk theorem. See chapter 5 in Fudenberg and Tirole (1991).

2.4.2 Partial Cooperation

From part 4.1, proposition 1 holds in the case fully connected system, $\min\{D_{ij}, D_{ji}\} > 0$ for all $i, j \in N$. This part will show that if all patches are not fully connected to each other, the strategy σ^* is not subgame perfect equilibrium. In other words, strategy σ^* is not the best response in a partially connected system.

Now I consider the case that $\min\{D_{ij}, D_{ji}\} = 0$ for some $i, j \in N$. There are some uni-directional patches which either only feed to or only receive from others. In this case, it is impossible to make a credible threat against those owners. For instance, patch i only feeds to patch j but not receives larvae back, $D_{ji} > 0$ but $D_{ij} = 0$. Agent j cannot over harvest against agent i when agent i violates an agreement.

Proposition 3 *Suppose that min*$\{D_{ij}, D_{ji}\} = 0$ *for some* $i, j \in N$*, the strategy* σ^* *is not Subgame Perfect equilibrium.*

Proof. In the case that $D_{ij} = D_{ji} = 0$ for all $i, j \in N$, it is clear that the best response of all players is non cooperation. Consider $\min\{D_{ij}, D_{ji}\} = 0$. Let K be a number of agents who have $\min\{D_{ij}, D_{ji}\} > 0$ for some $i, j \in N$.

Suppose that $D_{ji} > 0$ but $D_{ij} = 0$, for some $i \in K$, $j \in N \backslash K$. In this case, fish stock in K is not affected by the outside patch. Since agent j knows that all agents in K will not take into account his harvest, he has no incentive to play cooperation. In other words, if agent j over harvests, the best response for agents $i \in K$ is still playing h_i^* because patch j feeds noting to patch i. Hence, the best response for all agents $i \in K$ is to form a coalition and cooperate with other agents who are in K. For agents $j \in N \backslash K$, the best response is non-cooperation.

Suppose $D_{ji} = 0$ but $D_{ij} > 0$, for some $i \in K$, $j \in N \backslash K$. In this case, the fish stock among K is affected from agent's j harvesting. Since the fish stock of agent $j \in N \backslash K$ is independent from others' harvest, there is no incentive for him to cooperate. Therefore, j's best response is non-cooperation. ■

In the proof, I show that the strategy σ^* is not Subgame Perfect equilibrium in the sense that cooperation is not the best response for some player. In the case of partially connected system, the assumption 2 can be restated as

Assumption $2'$ Given any $e_i \in [0, s_i]$,

$$e_i + g_i(e_i)D_{ii} + \sum_{i \neq j} g_j(\underline{s}_j)D_{ij} \leq \underline{s}_i$$

for i and j, which $\min\{D_{ij}, D_{ji}\} > 0$

If the assumption $2'$ holds, the strategy σ^* can be applied for i and j who have patches connect to each other. Therefore, It is rational for agents in the coalition because they cannot control the harvesting of outside agents. The only thing they can do is play their best response which is cooperation with whom they can control through credible threat. This point is clearly stated in the next corollary.

Corollary 4 *Given min$\{D_{ij}, D_{ji}\} = 0$ for some $i, j \in N$ and assumption $2'$, there exists partial cooperation in the sense that all agents who have min$\{D_{ij}, D_{ji}\} > 0$ form a coalition and play cooperation to each other.*

Example 1 *Consider the case of 3 patches. Assume that patch i and m are fully connected but patch j is partial connected with patch i, $D_{mi} = D_{im} > 0$ and $D_{ji} > 0$ but $D_{ij} = 0$. From figure 2.4, patch j does not feed to patch i and m. In this case, patch m and i feed fish together; then, the best respond for them is playing cooperation together. In addition, that cooperation does not require action from j. On the other hand, there is no reason for agent j to play cooperation. In this example, agent m and i form the coalition while agent j plays non cooperation.*

Example 2 *Assume that $D_{mi} = D_{im} > 0$ and $D_{ij} > 0$ but $D_{ji} = 0$. The patch j is source of patch i and j. For agent i, he cannot make any credible threat against agent j. The best*

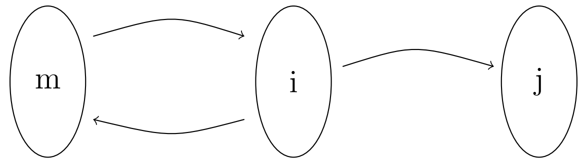


Figure 2.4: Dispersal : $D_{mi} = D_{im} > 0$ and $D_{ji} > 0$ but $D_{ij} = 0$

strategy for agent i and m are playing cooperation together, given fish stock feeding from patch j. On the other hand, agent j does not have an incentive to play cooperation with others.

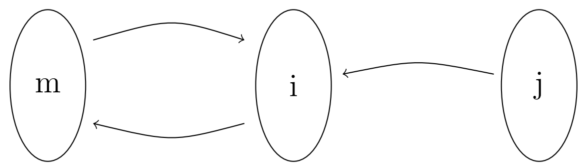


Figure 2.5: Dispersal : $D_{mi} = D_{im} > 0$ and $D_{ij} > 0$ but $D_{ji} = 0$

It is worthwile to remark that the strategy σ^* can apply to the case that all patches are not fully connected. In particular, full cooperation is supportable as a Subgame Perfect equilibrium, although there is no fully connected among all patches. The following example illustrates that the strategy σ^* is still the best response in the case $\min\{D_{ij}, D_{ji}\} > 0$ for some $i, j \in N$.

Example 3 *Assume that $D_{mi} = D_{im} > 0$, $D_{ij} = D_{ji} > 0$ but $D_{mj} = D_{jm} = 0$. From Figure 2.6 patch i links patches m and j together. Suppose agent m overharvests. Agent i set h_i^p so that $s_i = \underline{s}_i$. In response to behavior's agent i, agent j will set h_j^p and drive $s_j = \underline{s}_j$. For the deviator, the best response is following the strategy σ^*. Thus cooperation is the best response for all players.*

According to Sanchirico and Wilen (1999) and Carr and Reed (1993), there are five general patterns of larvae dispersal in biological system: fully integrated, closed patches, sink source,

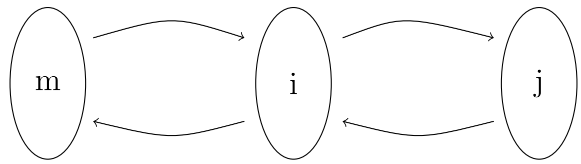


Figure 2.6: Dispersal : $D_{mi} = D_{im} > 0$ and $D_{ij} = D_{ji} = 0$ but $D_{mj} = D_{jm} > 0$

multiple source and spatially linear (see pp.134 in Sanchirico and Wilen (1999)). The results in full and partial cooperation here can apply to all five patterns and show that cooperation has potential to be the outcome of all patterns.

2.4.3 Side Payment

So far, this paper focuses on the role of strategy to support cooperation in Non-Cooperative game. In this part, I examine the amount of compensation to agents who do not have incentive to play cooperation; for instance, agent j in figure 2.5.

The objective of this part is to apply the Marginal Contribution principle to calculate an amount of payment to compensate agents. To create side payment, payoff is treated as unit of utility. In the game theory terminology, this game is called *Transferable Utility (TU)* game. The TU game is defined by (N, v). Let $N = \{1, \ldots, n\}$ be the set of finite players. For each coalition $s \subset N$, $v_i(s) : s \to \mathbb{R}$ is agent i's payoff if he is a member of coalition s and $v(s)$ is a $(v_i(s), \ldots, v_n(s))$. If $s = N$, it is a grand coalition. $v_i(s)$ is a characteristic function. Let $x = (x_1, \ldots, x_n)$ be an allocation of side payment.

Definition 2 *An allocation of side payment is* ***Efficient****, if* $\sum_{i=1}^{n} x_i = \sum_{i=1}^{n} v_i(N)$. *The* ***Marginal Contribution (MC)*** *of agent i is* $\sum_{j \neq i}^{n} v_j(N) - \sum_{j \neq i}^{n} v_j(N \backslash i)$.

The efficient collection means that the value of grand coalition can be divided among all agents. The MC_i is calculated from incremental payoff if agent i is not in grand coalition. In this context, it means that agent i plays non cooperation against other agents who play cooperation.

Proposition 4 *A collection of payoff is efficient, if* $x_i \leq MC_i$ *for all* $i \in N$.

Proof. Let i be a member of grand coalition N. Suppose that there is an agent i such that $x_i > MC_i$. It implies that the value captured by the rest agent in coalition is less than $\sum_{j\neq i}^{n} v_j(N\backslash i)$ which is the actual value that all agents but i created jointly. In other words, $\sum_{j\neq i} x_j < \sum_{j\neq i}^{n} v_j(N\backslash i)$. For agents $N\backslash i$, it is better to form coalition without i. A contradiction. ■

Proposition 4 implies that the maximum amount of side payment agent i receive is his contribution. To calculate the marginal contribution, I first specify the grand coalition's payoff and $N\backslash i$ coalition's payoff that agent i plays non cooperation.

For simplicity, I limit my consideration to the the case $N = \{1, 2, 3\}$. The individual rent function is transformed from

$$p(s_{it} - e_{it}) - \int_{e_{it}}^{s_{it}} c_i(\omega)d\omega$$

to $Q_i(s_{it}) - Q_i(e_{it})$, where $Q_i(s_{it}) = p(s_{it} - \underline{s}_{it}) - \int_{\underline{s}_{it}}^{s_{it}} c_i(\omega)d\omega$. By this transformation, the problem of joint rent maximization is

$$\begin{aligned} V(s_t) = & \max_{\{e_{1t},e_{2t},e_{3t}\}} \quad \sum_{j=1}^{3}[Q_j(s_{it}) - Q_j(e_{it})] + \beta V(s_{t+1}) \\ \text{subject to} \quad & s_{jt+1} = f(e_{jt}) \\ & f(e_{jt}) = e_{jt} + \sum_{i=1}^{3} g_i(e_{it})D_{ij} \quad ,\forall i = 1, 2, 3 \end{aligned}$$

The first order condition is

$$-Q_i'(e_{it}^{*c}) + \beta\{Q_i'(f(e_{it}^{*c})) + \sum_{j=1}^{3} Q_j'(f(e_{jt}^{*c}))g_i'(e_{it}^{*c})D_{ji}]\} = 0 \qquad ,\forall i = 1, 2, 3 \tag{2.9}$$

The main characteristic of this equation is it is independent from the current fish stock, s_t. Costello and Polasky (2008) state this property as "*state independent control*".

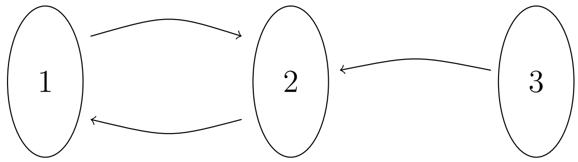


Figure 2.7: Dispersal : $D_{12}, D_{21} > 0$ and $D_{23} > 0$ but $D_{32} = 0$

Now I turn to consider the case where agent 3 plays non cooperation against agent 1 and 2. The dispersal pattern is above in Figure 2.7. The non cooperation maximization problem for agent 3 is

$$\begin{aligned}
&\max_{\{e_{3,t}\}} && Q_3(s_{3t}) - Q_3(e_{3t}) + \beta V(s_{3t+1}) \\
&\text{subject to} && s_{3t+1} = e_{3t} + \sum_{i=1}^{3} g_3(e_{3t}) D_{3j}
\end{aligned}$$

Since agent 3 does not export larvae to other patches, the first order condition is

$$-Q_3'(\hat{e}_{3t}) + \beta\{Q_3'(f(\hat{e}_{3t})) + Q_3'(f(\hat{e}_{3t}))g_i'(\hat{e}_{3,t})D_{33}\} = 0 \tag{2.10}$$

Since the bracketed term captures only the future valuation of patch 3 which is a part of the bracketed term of equation 2.9, I have $Q_3'(\hat{e}_{3t}) < Q_3'(e^*_{3t})$ and $e^*_{3t} > \hat{e}_{3t}$.[5] Applying this result to equation 2.9 yields e^{*n} for agent 1 and 2.

$$\begin{aligned}
-Q_i'(e^{*n}_{it}) + \beta\{Q_i'(f(e^{*n}_{it})) + \sum_{j=1}^{2} Q_j'(f(e^{*n}_{jt}))) g_i'(e^{*n}_{it}) D_{ji} \\
+ Q_3'(f(\hat{e}_{3t})) g_i'(e^{*n}_{it}) D_{3i}\} < 0 \qquad , \forall i = 1, 2
\end{aligned} \tag{2.11}$$

The inequality is due to the fact that $Q_3'(f(\hat{e}_{3t})) < Q_3'(f(e^*_{3t}))$. Since V is concave in escapement (by assumption 1), $e^{*n}_{it} > e^{*c}_{it}$ (or $h^{*n}_{it} < h^{*c}_{it}$), $\forall i = 1, 2$. Therefore, the marginal

[5]By transformation, we know that $Q_i(e_{it}) = p(e_{it} - \underline{s}_i) - \int_{\underline{s}_i}^{e_{it}} c_i(\omega)d\omega$. Hence, $Q_i'(e_{it}) = p - [c_i(e_{it}) - c_i(\underline{s}_i)] > 0$ and $Q_i''(e_{it}) = -c_i'(e_{it}) > 0$.

contribution to agent 3 is

$$\begin{aligned} MC_3 &= \sum_{i=1}^{2}\{[ph_i^{*c} - c_i(h^{*c})] - [ph_i^{*n} - c_i(h^{*n})]\} \\ &= \sum_{i=1}^{2}\{[p(h^{*c} - h^{*n}] - [c_i(h^{*c}) - c_i(h^{*n})]\} \end{aligned} \tag{2.12}$$

By propostion 4, the maximum amount side payment that agent 1 and 2 is willing to pay for agent 3 to play cooperation is equation 2.12.

2.5 Conclusion

This paper applies a two part punishment scheme, punishment and resume to cooperation, to Bioeconomic model. I study the cooperation in a dynamic game taking into account the effect of resource dispersal between patches. The environment of this paper is different from the standard common pooled resource in the sense that agents have property rights over their patch but the resource disperses across patches. By applying a worst perfect equilibrium, I state the strategy that cooperation is supportable as Subgame Perfect equilibrium. An agent who deviates from cooperation will be severely punished and drive the payoff to the minimum. Moreover, I find that level of cooperation depends on the pattern of fishing dispersal. The main reason is that the bargaining power among agents depends on the pattern of dispersal (i.e. which patch the fish migrates to or from). In particular, the patch which only receive fish migration from others does not have bargaining power. That patch owner cannot make a punishment. In this scenario, Subgame Perfect equilibrium is not supported and a side payment mechanism to sustain cooperation is needed. I also propose the side payment mechanism, marginal contribution scheme, and show how to calculate the amount of payment.

Looking back to the fishing situation in Songkhla lake, local government officers have a conflict with fishermen. Although the standing trap is illegal, the question based on the current situation is if we cannot remove all traps, which one should be removed first? The finding of this paper might be the answer of this question and open the room of negotiation between fishermen and officers. My results show that in the case of partially connected system, especially in the pattern of Figure 2.7, the traps which is in the patches that are the source of larvae should be removed first. The reason is other patch owners attain the benefit from the removing and they do not loose the fish because the fishes do not migrate back to the source owner. In term of increasing the number of fish, removing the source patch have more benefit than other patches. In reality, since the larvae flows along the water course, the source patch might be the patches which are located on the course. In term of negotiation, the local government or other patch owners can apply the side payment proposed in this paper as the benchmark to set the real compensation to patch owners who remove the traps.

The paper has presented cooperation among patch owners when they can observe action of other agents. However, it does not consider the non observable action case. This issue might change the result or it requires other punishment schemes to constitute Subgame Perfect equilibrium. In addition, this paper does not focus on the characteristic of side payment mechanism. There is room to investigate how side payments support Subgame Perfect equilibrium or how to relate side payment to folk theorem. To answer those questions, one might need to add voluntary participation constraint to the model. Also, there are many issues in empirical work. For example, since I show the importance of fishery dispersal pattern, how can we estimate it in reality.

Chapter 3

Cooperation under Partial Communication and External Regulation

3.1 Introduction

Since Gordon (1954) proposed "tragedy of the commons", there has been debated about the control of the collective action in common pooled resource (CPR). Because everyone can access the CPR without regulation, one of the solutions to the CPR problem is to assign property rights. To assign the appropriate property right, all stakeholders have to design jointly with the institution.[1] Ostrom (1990) points out the failure of an institution designed by external authority. The reason is

"CPR institutions that use this principle are better able to tailor their rules to local circumstances because the individuals who directly interact with one another and with the physical world can modify the rules over time so as to better fit them to the specific characteristics of their setting, Ostrom (1990) pp. 93"

[1]Libecap (1993) defines property rights as the social institution which defines or restricts the privilege of an individual over specific resources such as land, water

In addition, she proposes eight desirable principles for a successful self-governing institution. One of those principles is that "most individuals affected by the operational rules can participate in modifying the operational rules." This paper will focus on the effectiveness of self-governance when not all participants create their own rule. In particular, I focus on the situation when some participants have limited communication with others.

The fundamental of self governing institution is communication among resource users. Communication without a binding agreement is more crucial than one thought. Ostrom and Walker (1991) show that communication challenges noncooperative game theory. Without credible commitment, the theory predicts that Nash equilibrium will be a result. The well-known example is the prisoner's dilemma game. However, Ostrom and Walker (1991) find that communication without a binding commitment improve efficiency. In particular, the result is close to the social optimal outcome. The explanation is non-binding communication forms the expectation toward other players' strategy. Consequently, the cooperation outcome can be sustainable, regardless of players' type. Ostrom (1990) establishes the sufficiency condition to attain the social optimal outcome: the players must agree on (i) the target of a group (ii) the rule to divide the benefit from cooperation and (iii) the punishment scheme against the cheater.

Rather than a self governing institution, the classical approach to control resource users is command and control policy. This approach relies on the principle that the external authority internalizes the externality to resource user's decision through policy such as taxes, quota etc. There are many articles which compare the effectiveness of exogeneous policy and self governing institution such as Cardenas et al. (2000), Cardenas (2004), del Pilar Moreno-Sánchez et al. (2008) and Abatayo and Lynham (2016). They find that endogeneous rule created through communication is more effective than external regulation. With communication, agents reduce the level of extraction and keep resources at a high level.

However, in the previous literature, all participants can participate and create their own rule. It is reasonable to propose the question; what if all members of the group cannot communicate with each other? There are many reasons to consider the limitations of communication in the sense that not all resource users communicate to each other. For example, some resource users live far away from others or they probably use different language.

In reality, there is evidence of partial communication. In particular, a majority of resource users jointly establish their own rule and force that rule upon all users. For example, inshore community fishermen of Pattani province in Thailand establishes their own rule on the size of the net. The rule applies to all fishermen who harvest in the area. Since the color of net is different, they know what size net fishermen use. The community has a potential to sanction people who are not in compliance. Another example comes from the same community, who announce that harvest will stop in spawning season. The rule is applied for both member and non member of the community.

There is limited research analyzing partial communication, where not all participants can communicate. Schmitt et al. (2000) tests the robustness of cooperation by limiting a number of subjects participating in a self governing group. Unsurprisingly, the result in extraction and social efficiency of full communication is better.

According to the literature, self governing institutions that use (fully) face-to-face communication dominates the external regulation. As far as I know, there is no research that compares the effectiveness of external regulation and partial communication. This issue is critical for the policymaker. Should government push resource users to form the self governing institutions, if they cannot fully communicate?

Specifically, I address three main questions (i) Does partial communication reduce subject's extraction? (ii) Comparing external regulation and self-governing institutions which have partial communicaion, which policy is better in terms of reducing extraction and constituting individual's cooperation behavior? (iii) Is there a statistical difference in extraction and cooperation behavior between partial and full communication?

The organization of the paper is following. The next section is literature review. Section 3 provides the theoretical prediction. The experimental design is in section 4. Section 5 reports the results. The conclusion is in section 6.

3.2 Literature Review

Ostrom (1990) has collected examples of the self-governing institutions around the world. She observes the common factor and establishes the eight principles that are key of successful self-governing institution. All of them involve agreement in resource use and penalty to noncompliers. Ostrom et al. (1992) show that communication and sanctions reduce subject's extraction and significantly increase rent dissipation, especially when subjects have an opportunity to select a fee-fine scheme. In addition, the efficiency of the communication and fee-fine self selection treatment is approximately 90% of the social optimal level. Casari and Plott (2003) study the role of sanctions but in another mechanism in which monitoring subjects pay a fee to a monitored subjects, and monitored subjects pay a fine to a monitoring subject if he does not follow an agreement. This mechanism is called "Carte di Reloga" which was applied to a village in the Italian Alps at the beginning of 13^{th} century. The result confirms that communication and sanction improve the efficiency of resource use. However, the more interesting result is subjects' behavior in the fee and fine scheme. They find that the fee and fine scheme is consistent with other-regarding utility function.[2]

The behavior of agents which is consistent with other-regarding utility functions is also found in the public goods literature. The excellent survey in this area is Ledyard (1997) and Chaudhuri (2011).

Although Ostrom's principle emphasizes the communication and sanction mechanism, there is literature showing that communication only can improve resource extraction behavior. Ostrom et al. (1994) show that subjects who have an opportunity to communicate can keep extraction close to the social optimum and enjoy high rent. Although communication

[2]The other-regarding utility function is the utility function that weights between own monetary income and others' monetary income. The literature calls altruism agent if his utility increase when others' income increase while his monetary income is constant. It is called spiteful agent, if his utility decrease when others' income increase while his monetary income is constant.

is just a non binding agreement among subjects, it changes the outcome of the game from noncooperation to cooperation behavior. The reason is communication creates trust among agents, but not all communication can create trust. Rocco and Warglien (1996) compares the behavior of subjects in two treatments, face-to-face communication and a computer chatting program. They find that the effectiveness of communication significantly drops when subjects communicate by the chatting program. The cooperation is fragile when a subject does not know whom he is talking to.

Rather than a laboratory experiment, Cardenas et al. (2000) apply communication to rural villages in Columbia, where subjects extract CPR in daily life. The result is consistent with laboratory experiment in the sense that face-to-face communication (without sanction) improves the efficiency of resource use. It is more efficient than external regulation which applies a fine to noncomplier subjects who are caught randomly. This result is robust. Cardenas (2004) varies the amount of the fine from weak to strong punishment, but communication is still more efficient.

Cardenas et al. (2000) and Cardenas (2004) interpret the ineffectiveness of external regulation that the other-regarding behavior of subjects might be deteriorated by a fine scheme, especially when the sanction mechanism is not a part of an agreement. The result shows that when an external fine scheme is imposed, subjects lose public spirit and the loss overwhelms the fine. They call it the "crowding out effect". This effect is not only observed in the CPR game. Frolich and Oppenheimer (1998) observe this behavior in voluntary contribution public goods game. Oakley et al. (1997) show that people are more willing to freely donate blood than when they are compensated with some amount of money.

Abatayo and Lynham (2016) compare the efficiency when the agreement is from exogeneous and endogeneous rules. Exogeneous and endogeneous rules are not different when communication is not allowed. However, the resource is statistically higher when subjects can communicate with each other. Also, they find the crowding out effect in external regulation treatment.

Schmitt et al. (2000) examine the communication when only a subset of subjects can communicate. They do not have the monitoring and sanction mechanism. Communicators and non communicators are perfectly separated. In this situation, cooperation among subjects is low because subjects inside the communication group have a “scapegoat”. They always blame high extraction on outside subjects, but they actually infringe on the commitment extraction level.

This paper is different from Schmitt et al. (2000) in three ways. First, this paper compares partial communication to external regulation. Second, subjects in the communication group and outside subjects are not perfectly separated. All subjects know the game. In particular, the outside subjects know the agreement of communication group and communicators know that the outside subjects know their agreement. With this setup, the information is symmetric and the outside subjects can follow commitment extraction if they want to play cooperation. Finally, I introduce the monitoring and sanction system to both communicators and outside subjects.

3.3 Theoretical prediction

3.3.1 The common pooled resource game

The framework applied here is standard in the CPR experiment. It is proposed by Ostrom et al. (1994). There are n resource users who can access the common pooled resource (CPR). Assume that n is fixed (no entry and exist). Each individual is endowed with e unit of resource. The economy is composed of two markets. For market 1, one unit of extraction returns fixed amount w. For market 2, payoff depends on both aggregate extraction and individual own extraction measured in proportion. The characteristic of CPR is represented by market 2.

Let x_i be the extraction level in common pooled resource.[3] $G(\sum x_i)$ is the return from

[3]The term of “extraction” I use here is equivalent to “investment” in Ostrom et al. (1992).

extraction in common pooled resource. Assume that G is a concave function where $G'(0) > w$ and $G'(ne) < 0$. Subject's payoff function is

$$\pi_i = \begin{cases} we & \text{if } x_i = 0 \\ w(e - x_i) + \frac{x_i}{\sum x_i} G(\sum x_i) & \text{if } x_i > 0. \end{cases} \tag{3.1}$$

The meaning of this equation is straightforward. If an agent puts all their endowment in market 1, the payoff is we for sure. On the other hand, if subject extracts in both market, the payoff from market 1 is $w(e - x_i)$ and sharing payoff from CPR which is $(x_i / \sum x_i) G(\sum x_i)$.

To analyze the characteristics of investment in CPR, I assume an interior solution. The individual's problem of extraction in CPR is

$$\max_{0 < x_i \leq e} w(e - x_i) + \frac{x_i}{\sum x_i} G(\sum x_i)$$

The first order condition is

$$-w + \frac{1}{n} G'(\sum \hat{x}_i) + G(\sum \hat{x}_i)[\frac{n-1}{n^2 \hat{x}_i}] = 0 \tag{3.2}$$

Since all subjects are symmetric, $\hat{x}_i$ satisfied by equation 3.2 is the symmetric Nash equilibrium. To solve the social optimal outcome, the social planner sums all individual payoff.

$$\max_{0 < \sum x_i \leq ne} wne - w \sum x_i + G(\sum x_i)$$

The first order condition is

$$-w + G'(\sum x_i^*) = 0 \tag{3.3}$$

where x_i^* is social optimal investment in CPR. To achieve the social optimum, the marginal

Table 3.1: Summary of parameters

Number of tokens	10
Number of subjects	8
Nash equilibrium	8
Social optimum	4.5

return from CPR must equal the opportunity cost. Assume the quadratic form of G.

$$G(\sum x_i) = a \sum x_i - b(\sum x_i)^2$$

with $a > w$ and $a/2b < \sum x$. Applying the specific form of G to equation 3.2, the (aggregate) Nash equilibrium is $\sum \hat{x}_i = [n/(n+1)](a-w)/b$. Since all subjects are symmetric, the extraction in CPR is $\hat{x}_i = [1/(n+1)](a-w)/b$. Likewise, the social outcome is $\sum x_i^* = (a-w)/2b$ and $x_i^* = (a-w)/2bn$.

3.3.2 Parameterization

Like Abatayo and Lynham (2016), Cardenas et al. (2000) and Cardenas (2004), I ignore the role of market 1; then, $w = 0$. Numerically, I set $a = 72, b = 1, e = 10$ and $n = 8$. Therefore, $\hat{x}_i = 8$ and $x_i^* = 4.5$ are symmetric Nash equilibrium and social optimum, respectively. Replacing $w = 0$, the appropriator's profit function is

$$\pi_i = ax_i - bx_i(\sum x_i) \tag{1'}$$

The profit is $\hat{\pi}_i = 64$ and $\pi_i^* = 162$ corresponding to $\hat{x}_i$ and x_i^*, respectively. The payoff table is shown in Appendix B.1. Table 3.1 summarize the parameters.

Table 3.2: Summary of treatments

Treatment	# of groups	Subjects per group	# of subjects in communication	Commitment (quota)	Probability of being audited
Open access	2	8	No	No	-
External regulation	3	8	No	Yes/imposed externally	1/16
Partial communication	5	8	6 out of 8	Yes/imposed internally	1/16
Full communication	3	8	8 of 8	Yes/imposed internally	1/16

3.4 Experimental Design

Subjects play the common pooled resource game for 20 rounds that are divided into 2 stages. In the first stage,$1-10$ round, all subjects play the same game. In the second stage, $11-20$ round, subjects play based on the treatment group that they are assigned to. There were three treatments and one baseline in our experiment; open access (baseline), external regulation, partial and full communication treatment. Table 3.2 provides a summary of the treatments.

3.4.1 Stage 1

At the beginning of each session, the experimenter gave instructions of the game to all subjects and asked them to read together. Once the experimenter finished reading aloud, all subjects were requested to answer a questionnaire. The experimenter explained individually to subjects who could not answer correctly. Also, the experimenter gave subjects a game card, decision record sheet, and payoff table with an explanation on how to use them. The game instructions are provided in Appendix B.2. The following is a summary of the stage 1 instructions.

"You are going to play a series of decision game. Each subject is endowed with 10 tokens in each round. You cannot transfer your endowment from the current period to future period. You have to make a decision on how many tokens you want to extract in each round. Extraction is allowed in integer amounts only. The earning depends on your own extraction level and the group extraction level. The more individual extractions, the more earnings you will receive. However, the more the group extracts, the less of a share you obtain. The net earning in each round is calculated from those. Subjects make a decision individually and results are anonymous. "

Once stage 1 finished, subjects played stage 2 under treatment they were assigned in. The following subsection will be the details of base case and other treatments in stage 2.

3.4.2 Open access

In open access, the rule of the game was the same as stage 1. There was an eight minute breaks after round 10. Communication was not allowed in open access.

3.4.3 External regulation

In the external regulation treatment, the experimenter imposed an individual quota of extraction. The experimenter assigned a quota of 5 units of extraction to each individual in stage 2.[4] The quota was not allowed to be trade and no communication was allowed among subjects. As in Cardenas et al. (2000), the probability of an audit is 1/16. The audit was done by drawing balls from a box with replacement. If the subject was audited and extracted more than the quota, he was penalized by a fine that depends on the amount over the quota. The subject's expected payoff in external regulation is

$$\pi_i = \begin{cases} ax_i - bx_i(\sum_i x) & \text{if } x_i \leq 5 \\ ax_i - bx_i(\sum_i x) - \frac{1}{16}f(x_i - 5) & \text{if } x_i > 5. \end{cases}$$

, where f is the per unit deviation fee.

Determining the fee is subjective. Most of the literature treats it as an exogenous parameter. However, I apply the idea of Becker (1968). He proposes that the fine is optimal when

[4] The paper use "quota" and "commitment" interchangeably

it keeps social loss from illegal activities at the minimum. The policy implication is that without constraint from "outside" the government should set the fine as much as possible.[5] Then, the fine is defined by

$$F = \pi^d - \pi^* \tag{3.4}$$

where π^d represents cheater's payoff, given that others play the socially optimal level. The intuition is that fine should cancel out the benefit of cheating. Since all players are homogeneous, I ignore subscript i. Given other subjects choose the socially optimal level, the subject i cheats by choosing $x_i^d = (a - 7bx_j^*)/2b$, where

$$x_i^d \equiv \arg\max_{x_i} ax_i - bx_i(\sum_{j \neq i} x_j^* + x_i)$$

According to the parameters, $x_i^d = 10$ and $\pi_i^d = 305$.[6] Therefore, $F = 143$.

Since F is the total amount of the fee that would equalize cheating and cooperation payoff, $f = 29 (= 143/5)$. Since the fine is equal to the extra payoff from cheating, risk neutral subjects will not cheat if the probability of being caught is 1. However, the probability of being audit here is 1/16, which means the expected fine is not strong enough to induce compliance with the regulation. In other words, the risk neutral individual's best response is non compliance. Cardenas et al. (2000) and Cardenas (2004) calls this enforcement regime as "weak enforcement".

The reason I apply weak enforcement here is because legal enforcement has limitations, especially in developing countries. For example, there is a group of fishermen around Songkhla lake in Thailand that permanently set standing traps, a type of fishing gear, in the lake. Legally, standing traps over the lake infringes upon marine legislation and water and sea

[5]Becker (1968) shows that this conclusion is true under the assumption that there is no cost of punishment. In the case of costly punishment, the optimal fine and equilibrium of crime depend on the elasticity of response to illegal activities with respect to change in probability of inspection and size of punishment.

[6]Actually, our parameter returns $x_i^d = 20.25$ which is greater than the endowment. Then, I apply the corner solution.

laws. However, local government officers fail to enforce the law because they are confronted with strong protest.

3.4.4 Partial communication

In the first stage, participants played the baseline, open access. After round 10, the experimenter randomly divided all subjects into communicator group (6 subjects) and outside subjects (2 subjects). The experimenter gave the new instructions to subjects and asked them to read together. All subjects were asked to read the following instruction.

"Subjects are divided into 2 groups, 6 subjects as communicators and 2 subjects as outside subjects. For communicators, subjects have 8 minutes to talk together. They can talk anything except (i) no physical threat (ii) no monetary transfer and (iii) cannot look at the record table of other subjects. At the end of the conversation, the group has to set a commitment extraction level and informs the experimenter. Before the next round, subjects have 2 minutes to communicate with each other. The group can change the commitment level but they have to inform the new level to the experimenter. During communication, the experimenter will take note of the conversation for research purposes only.

For outside subjects, communication is not allowed. The experimenter will inform the commitment extraction level and update it if it changes.

All decisions are made independently and privately. At the end of the round, the experimenter announces the total extraction level. "

After the experimenter read the instruction aloud and subjects answered all questions, outside subjects moved to another room. To compare between partial communication and external regulation, the exactly same fine scheme and probability of inspection is imposed. Probability of being audited was 1/16 and the marginal fine was 29. The monitoring and fine scheme would apply to both the communicators and outside subjects.

Since the experimenter read the same instructions in front of both communicators and outside subjects, there was no asymmetric information about the rule between communicators and outside subjects. The only restriction on outside subjects was that they were not allowed to communicate with other subjects.

3.4.5 Full communication

I apply the standard communication experiment, proposed by Ostrom et al. (1992) and Ostrom et al. (1994). The only difference is the exogenous fine. It is exactly the same as the partial communication treatment, except all subjects communicate with each other. There were no outside subjects. At the end of the communication session, subjects informed the experimenter of the commitment extraction level. Subjects knew the total investment at the end of each round. The probability and fine scheme were exactly the same as in the external regulation and partial communication treatment.

3.5 Experimental procedure

The experiment was conducted at the Prince of Songkla University in Thailand.[7] All subjects were recruited from Principles of Economics, Science for Life and Introduction to Business classes.[8] Prior to recruitment, subjects were informed to play an economic decision making game. They received approximately \$1.4 (50 Baht) as a show up fee plus earnings from the game which depends on their own decisions. The experiment was non computerized and lasted for approximately two hours. There were two unpaid groups as a pilot experiment which was conducted by 4^{th} year Economic major students.

Subjects knew the round number that the round they were playing but they did not know the total number of rounds. At the end of each round, the subject was informed the total extraction and was requested to calculate his own payoff. The experimenter randomly checked the subject's payoff. The subjects used the record table to check their extraction level, payoff and total extraction in the previous round. At the end of the experiment, the

[7] The experiment had done by pen and paper. All instructions were translated to Thai language.
[8] All of those classes are general education. Students are from several majors including Economics.

subject received his earning privately.

3.6 Results

There were 104 participants in this experiment. The average earning of all participants was \$4.34 (152 Baht). The maximum was \$6.62 (234 Baht) and the minimum \$3.02 (106 Baht), including show up fee \$1.42 (50 Baht).

The organization of this section is as follows. Subsection 3.6.1 provides basic overview statistics. Next, the effect of each treatment is analyzed in subsection 3.6.2. Individual compliance behavior is analyzed in 3.6.3. Finally, the discussion of the results is provided in 3.6.4.

3.6.1 Descriptive statistic

In stage 1, the average extraction level is 7.63 tokens. The average payoff is 80.72 experiment dollar or 49.83% of the efficient outcome. Efficiency is defined as :

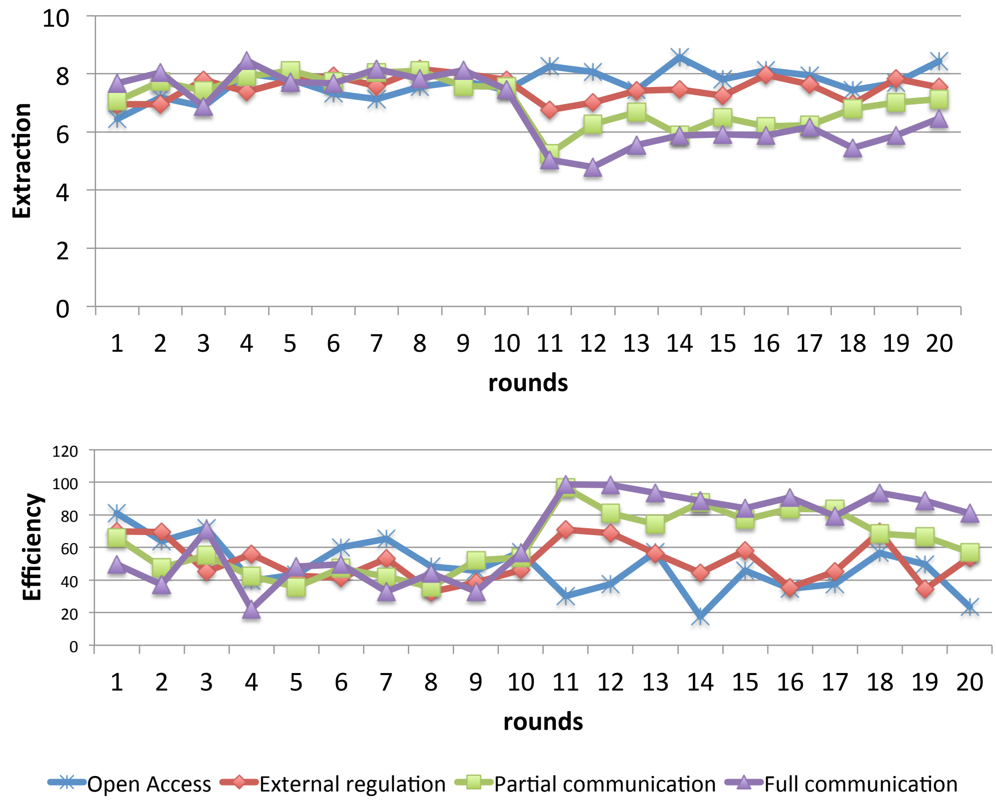
$$\text{Efficiency} = \frac{\sum_{i=1}^{8} \text{individual payoff}}{\sum_{i=1}^{8} \text{maximum payoff}}$$

where the maximum payoff is the social optimal outcome (164 experiment dollar).

The lowest average level of extraction occurs in the 1^{st} round and slightly increases thereafter. The lowest extraction in the 1^{st} round is consistent with the literature of common pooled resources and public goods contribution because subjects need time to learn how to play the game strategically.

Figure 3.1 shows the result of extraction level and payoff across treatments. In stage 1, the extraction level in all treatments appears to be similar and approaching the Nash equilibrium level of 8. After imposing treatments, the average extraction are $7.98, 7.38, 6.4$ and 5.7 tokens for open access, external regulation, partial communication and full communication treatments, respectively. The lowest efficiency is 38.49% for open access, whereas

Figure 3.1: Average extraction and payoff across treatments



the highest efficiency is 88.93% for the full communication treatment. The average efficiency for partial communication (76.57%) is higher than that of external regulation (52.98%). The subject's extraction level in external regulation treatment is the highest among the other two treatments. The role of the treatment is described in the following subsection.

3.6.2 Treatment effect

Table 3.3 shows the average extraction level between stage 1 and 2 for all treatments. The extraction in stage 2 is higher only in open access, whereas the extraction of other treatments drops in stage 2. In addition, Table 3.4 shows the average efficiency between stage 1 and 2 for all treatments.

Table 3.3: Extraction in stage 1 and 2 across treatments.

	Open access	External regulation	Partial communication	Full communication
Social optimum	4.5	4.5	4.5	4.5
Nash eq.	8	8	8	8
Stage 1	7.35	7.63	7.72	7.8
	(0.15)	(0.13)	(0.1)	(0.14)
Stage 2	7.98	7.38	6.4	5.7
	(0.12)	(0.12)	(0.17)	(0.15)
Difference	0.625	-0.25	-1.33	-2.1

Note: Standard errors in parentheses. The last row is the difference between stage 1 and 2.

Table 3.4: Efficiency in stage 1 and 2 across treatments.

	Open access	External regulation	Partial communication	Full communication
Social optimum	100	100	100	100
Nash eq.	39.51	39.51	39.51	39.51
Stage 1	56.94	48.87	47.17	43.89
	(20.10)	(22.10)	(16.79)	(19.6)
Stage 2	38.49	52.98	76.57	88.93
	(18.48)	(22.54)	(20.48)	(10.72)
Difference	-18.45	4.11	29.4	44.64

Note: Standard errors in parentheses. The last row is the difference between stage 2 and 1.

Next, I turn to consider treatment effect by means of regression analysis. Since the number of independent observations (sessions) is small, bootstrapping is applied.[9] In addition, individual observations in each session are not statistically independent both in time and across subjects. To address the problem of interdependence in observations, the clustering standard error is applied. Hence, all regressions will be clustered by *session*. To measure the treatment effect, I conduct the statistical inference and hypothesis testing by OLS regression analysis. The Difference-in-Difference approach is applied. I perform OLS estimation, using a subject's decision per round as the unit of observation. The equation is as follows

$$\begin{aligned} y_{it} = &\beta_0 + \beta_1 Stage2 + \beta_2 Ext + \beta_3 Partial + \beta_4 Full + \\ &\beta_5 Stage2 * Ext + \beta_6 Stage2 * Partial + \beta_7 Stage2 * Full + \epsilon_{it} \end{aligned}$$

The dependent variable is subjects's extraction per round in Table 3.5. Similarly, I estimate group efficiency per round; see Table 3.6. *Stage2* is a dummy variable. It takes the value of 1 if the observation is from stage 2 and 0 if stage 1. *Ext*, *Partial* and *Full* are dummy variables for all treatments. *Ext* takes 1 if the observation is from external regulation and 0 if otherwise. *Partial* takes 1 if the observation is from partial communication and 0 if otherwise. *Full* takes 1 if the observation is from full communication and 0 if otherwise. Hence, the base case is open access in stage 1. Finally, *Stage2*Ext*, *Stage2*Partial* and *Stage2*Full* are interaction dummy variables to capture the interaction effect between *Stage2* and each treatment.

Table 3.5 shows the regression results of the subject's extraction. The coefficient of *Stage2* is positive and significant. It means that subjects in open access significantly increase extraction when they are in stage 2. In other words, subjects extract more when they are familiar with the game. Ostrom et al. (1992) calls this result the "strategy learning effect".

Finding 5 *(Strategic Learning Effect) There exists strategy learning effect. Subjects increase*

[9]The idea of bootstrapping is creating the distribution, based on the number of observation. Hence, the sample size is not an important issue when the regression is run by bootstrapping. One of the advantage is it works well for small sample size. For more discussion, see Casella and Berger (2002) pp. 478 − 480.

Table 3.5: Difference-in-Difference estimation of individual extractions in all treatments

Subject's extraction	coefficient	Std. Error	z statistic	p-value
Constant	7.35***	0.061	120.35	0.000
Stage2	0.625***	0.092	6.82	0.000
Ext	0.28***	0.122	2.33	0.02
Partial	0.373***	0.118	3.16	0.002
Full	0.45***	0.076	5.94	0.000
Stage2*Ext	-0.879***	0.174	-5.06	0.000
Stage2*Partial	-1.953***	0.284	-6.87	0.000
Stage2*Full	-2.725***	0.251	-10.85	0.000
Adj R^2	0.148			
Num Obs.	2080			

Note : Bootstraped std. error. The regression is clustered by 13 sessions. The baseline is open access in stage 1. ***$p < 0.01$, **$p < 0.05$, *$p < 0.01$.

Table 3.6: Difference-in-Difference estimation of efficiency in all treatments

Efficiency	coefficient	Std. error	z statistic	p-value
Constant	56.944***	1.118	50.91	0.000
Stage2	-18.445***	2.219	-8.31	0.000
Ext	-8.067**	3.479	-2.32	0.02
Partial	-9.773***	2.637	-3.71	0.000
Full	-13.051***	1.993	-6.55	0.000
Stage2*Ext	22.556***	6.498	3.47	0.001
Stage2*Partial	47.845***	6.146	7.78	0.000
Stage2*Full	63.092***	4.219	14.95	0.000
Adj R^2	0.415			
Num Obs.	260			

Note : Bootstraped std. error. The regression is clustered by 13 sessions. The baseline is open access in stage 1. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

extraction significantly, when they play in stage 2.

Finding 5 is confirmed by the efficiency regression Table 3.6. The coefficient of *Stage2* in Table 3.6 is negative and significant. That means decreasing efficiency is the result of increasing extraction.

The coefficient of *Ext*, *Partial* and *Full* in Table 3.5 are positive and significant. It means that in stage 1 subjects in all treatments have more extraction than those in open access, significantly. To confirm the difference in extraction, I restrict $H_0 : \beta_2 = \beta_3 = \beta_4 = 0$ on the regression and find that this null hypothesis is rejected (χ^2 p value =0.000). Therefore, extraction in open access is significantly lower than all treatments. Similarly, the coefficient of *Ext*, *Partial* and *Full* in Table 3.6 are negative and significant. That means efficiency is lower under all treatments than under open access in stage 1. Because extraction in open access is lower than that in other treatments in stage 1, I apply Difference-in-Difference to measure the treatment effect.

Now I consider the stage 2. I start with the effect of external regulation. The coefficient of *Stage2*Ext* shows whether changing from stage 1 to stage 2 affects the subject's extraction differently in external regulation and open access. From Table 3.5, the coefficient of *Stage2*Ext* is significant and negative. It indicates that after imposing the regulation, change in extraction is significantly lower under external regulation than under open access.

Finding 6 *(External regulation effect) External regulation reduces the subject's extraction. In particular, the change in extraction is significantly lower under external regulation than under open access.*

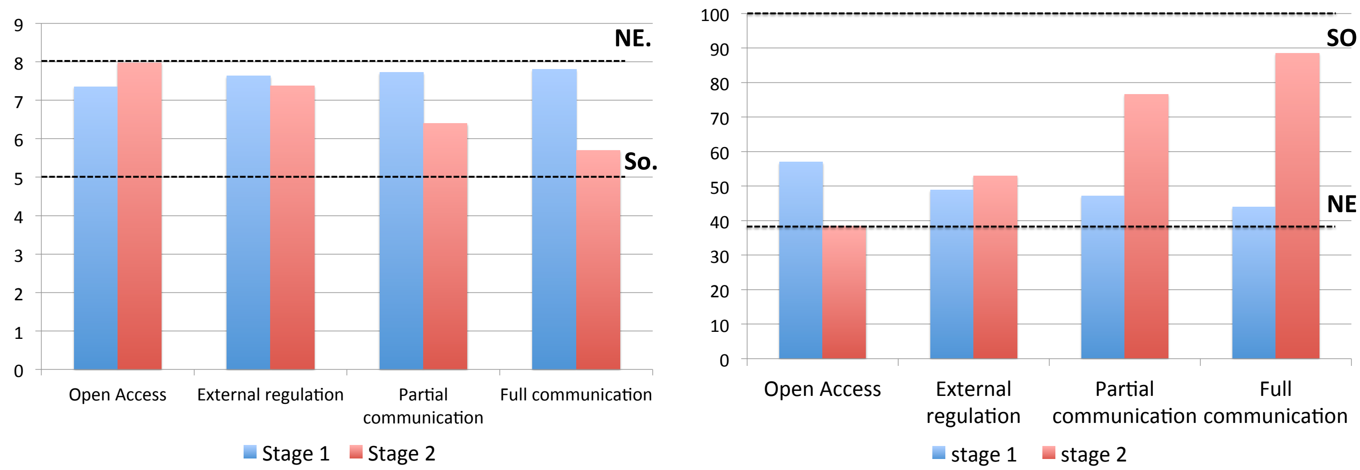
The external regulation effect is confirmed by the significance of *Stage2*Ext* in Table 3.6 which means external regulation increases efficiency.

Next, I examine the effect of communication in partial and full communication treatments. According to Figure 3.2(a), it is likely that communication has an effect on a subject's extraction. The coefficient of *Stage2*Partial* is negative and significant. It means that

Figure 3.2: Mean of efficiency and extraction across treatments

(a) Mean of extraction

(b) Mean of efficiency



after communicators (6 subjects) have an opportunity to communicate with each other, the change in extraction in partial communication treatment is significantly lower than that in open access. As for the full communication treatment, the coefficient of *Stage2*Full* is negative and significant. It means that after all subjects have an opportunity to communicate with each other, the change in extraction in full communication treatment is significantly lower than that in open access.

Finding 7 *(Communication effect) Communication reduces the subject's extraction. After subjects have the opportunity to communicate, the change in extraction level in both partial communication and full communication treatments are significantly lower than that in open access.*

Finding 7 is consistent with the result in Table 3.6. The coefficient of *Stage2*Partial* and *Stage2*Full* are positive and significant, meaning that both partial and full communication increase efficiency.

Next, I compare all three treatments among each other. I consider both absolute extraction levels in stage 2, and differences in changes from stage 1. Since I focus on treatment,

Table 3.7: OLS estimation of absolute extraction level in each treatment.

Subject's extraction	coefficient	Std. Error	z statistic	p value
Constant	7.379***	0.235	31.34	0.000
Partial	-0.984***	0.307	-3.21	0.001
Full	-1.679***	0.344	-4.89	0.000
Adj R^2	0.188			
Num Obs.	880			

Note : Bootstraped std. error. The regression is clustered by 11 sessions. Open access is dropped. The base case is external regulation. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

open access observations are dropped. The definition of *Partial* and *Full* are the same as above. Hence, the base case is external regulation.

From Table 3.7, the coefficient of *Partial* and *Full* are negative and significant. That means subjects in partial and full communication have lower absolute extraction level than those in external regulation. In addition, I test whether extraction level change between partial and full communication. I restrict H_0 : *Partial=Full* to the regression of Table 3.7 and find that the hypothesis is rejected at 5% significance level, χ^2 p value = 0.022. That means extraction in the full communication treatment is significantly less than that in the partial communication treatment. Therefore, I can conclude that in terms of absolute levels the highest extraction occurs under external regulation, followed by partial communication and full communication, respectively.

In addition, I test whether change in extraction among treatments are different. I restrict H_0 : *Stage2*Partial=Stage2*Full*, H_0 : *Stage2*Partial=Stage2*Ext* and H_0 : *Stage2*Ext=Stage2*Full* to the regression of Table 3.5. The χ^2 p values are 0.035, 0.000 and 0.000, respectively. This leads to rejecting the null hypotheses of no differences in changes between any two treatments at 5% significance level. Compared with open access, the greatest decrease in extraction occurs under full communication, followed by partial communication and external regulation, respectively.

To confirm the result, I restrict H_0 : *Stage2*Partial=Stage2*Full*, H_0 : *Stage2*Partial=Stage2*Ext* and H_0 : *Stage2*Ext=Stage2*Full* to the regression of Table 3.6. All null hypotheses are rejected at 5% significance level, χ^2 p value = 0.027, 0.002 and 0.000, respectively. That means compared with open access, the highest increase in efficiency is full communication, followed by partial communication and external regulation, respectively.

Finding 8 *(External regulation vs. Communication) In terms of absolute levels, the highest extraction occurs under external regulation, followed by partial communication and full communication, respectively. In terms of changes in extraction, compared with open access, the greatest decrease in extraction occurs under full communication, followed by partial communication and external regulation, respectively. In addition, compared with open access, the highest increase in efficiency occurs under full communication, followed by partial communication and external regulation, respectively.*

Finding 8 formally states that the change in extraction in both absolute levels and differences in change is different across treatments. It is natural to ask why the subject's extraction is different across treatments. The next section investigates individual behavior in compliance.

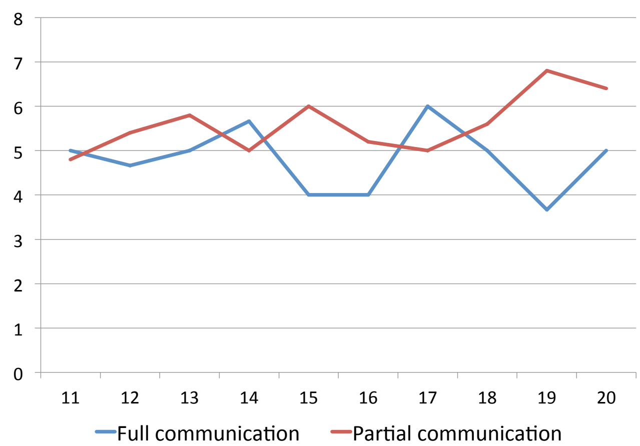
3.6.3 Individual's behavior in compliance

There are two factors that make extraction different across treatments: commitment level and compliance. I start by considering the effect of commitment levels. The average commitment level is 5.6 and 4.8 in the partial and full communication treatments, respectively. Note the commitment level in external regulation is fixed at 5. Figure 3.3 shows the average commitment level.

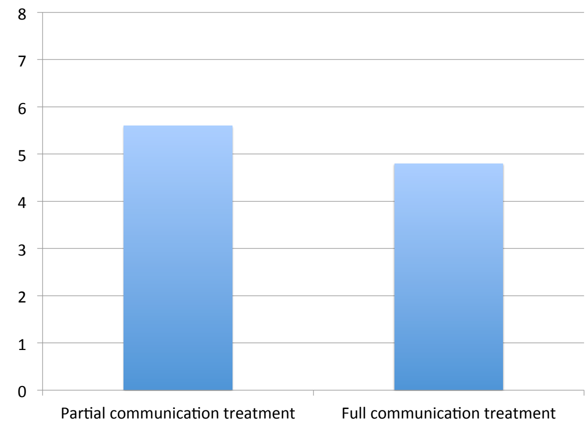
Table 3.8 reports the regression result, where the dependent variable is group commitment level per period in the partial and full communication treatments. I drop the external regulation observation from the regression because the commitment level is fixed at 5 in that treatment. Hence, the base case is the full communication treatment at round 11. The definition of *Full* and *Partial* are the same as above. *Time* is round variable which adjusts

Figure 3.3: Commitment level in partial and full communication treatments

(a) The mean of commitment level per round



(b) The mean of commitment level



round 11 to be 0.[10] The coefficient of *Partial* is not significant. That means the commitment level in partial and full communication are statistically the same at the beginning. Moreover, I test whether the commitment level is different from social optimum. I restrict H_0 : constant+Partial = 5 to the regression of Table 3.8 and find that the null hypothesis is not rejected (χ^2 p value = 0.959). In addition, I restrict H_0 : constant=5 to the regression of Table 3.8 and find that the null hypothesis is not rejected (χ^2 p value = 0.888). That means commitment levels in both partial and full commitment are not different from social optimum at the beginning. The coefficient of *Full*Time* is not significant. However, the coefficient of *Partial*Time* is significant at 10% significance level. That means the commitment level increases over time under partial communication, whereas it remains at social optimum under the full communication.

Finding 9 *(Commitment level) At the beginning, the commitment levels in both partial and full communication are not different from social optimum. However, the commitment level increases over time in partial communication, whereas it does not change over time in full communication.*

[10] I adjust 11 to be 0 because I am considering time trend. Although the result does not change much, it is more accuracy to normalize the starting point at 0.

Table 3.8: OLS estimation of commitment level in partial and full treatments.

commitment level	constant	Std. error	z statistic	p value
Constant	4.964***	0.276	17.99	0.000
Partial	0.025	0.346	0.07	0.941
Partial*Time	0.136*	0.076	1.79	0.073
Full*Time	-0.036	0.062	-0.58	0.559
Adj. R^2	0.103			
Num. Obs.	80			

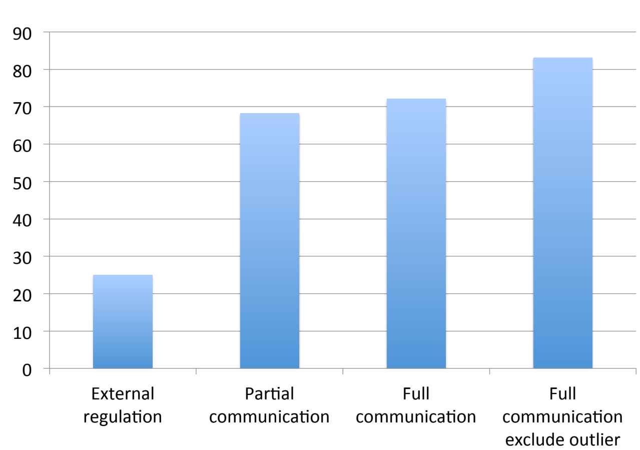
Note : Bootstraped std. error. The regression is clustered by 8 sessions. The base case is commitment level in full communication at round 11. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$

Next, I consider compliance behavior. I introduce two variables, compliance and deviation, which capture the individual's compliance. For the compliance variable, it is a qualitative variable. It takes on a value of 1 if an individual's extraction is not greater than the commitment level and 0 if otherwise. Deviation is defined as

deviation = actual extraction - commitment level

Figure 3.4: Compliance rate and deviation across treatments

(a) Compliance rate



(b) Deviation

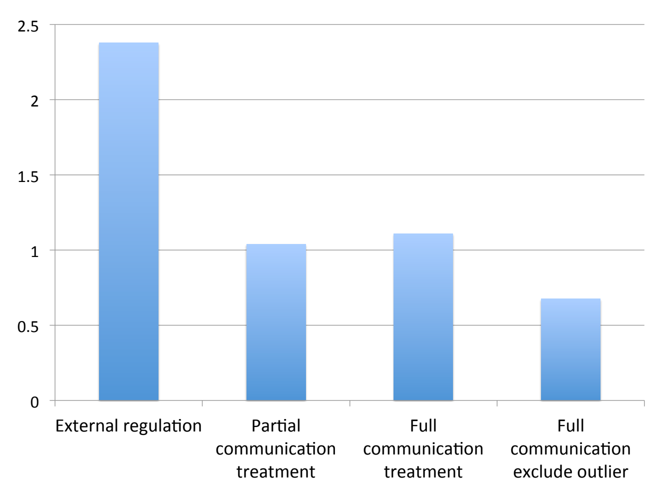


Figure 3.4 illustrates that the external regulation treatment are the least obedient. In

particular, the compliance rate and deviation are 25% and 2.38, respectively. The compliance rate in partial communication and full communication are very close, 68.25% and 72.08%, respectively.

In the full communication treatment, there is one outlier group in which subjects set the commitment level much lower than the social optimum. They set the commitment level at $1, 2$ and 3 in round $15 - 17$, respectively. All subjects extract more than that level. Consequently, the deviation in this group is so high that the average deviation is close to that of partial communication. The following is a summary of the conversation in round 15 of that session.

"We should set the commitment level very low like 1, 2 or 3 to increase the cheater's punishment. In particular, the cheater sets his extraction at 10. If he is caught, his penalty is very high. He will probably reduce his extraction to 4, 5 or 6, which is around the social optimum. We will play 4 or 5 and take our own risk."

However, this commitment level does not lead to the expected level. The group commits to 5 in round 18 and maintains that target until the experiment finishes. The following is a summary of conversation in round 18 of that session.

"It seems that the low commitment strategy does not work. Should we set the new target at 10? If so, it means there is no rule. We are back to the first ten rounds and obtain a low payoff. Why do we not set at 5 and ignore the cheaters? Even if there is cheating, our earnings is still higher than what we get in the first ten rounds."

If this outlier group is dropped, the deviation under full communication treatment is 0.675, which is the lowest, whereas the compliance rate is 83.125%, which is the highest.

To investigate formally the differences in deviation across treatments, I perform OLS estimation, using an individual's deviation as the dependent variable. Since each session of partial and full communication has different commitment levels, the variation in deviation might be from the variation in commitment levels. To address the variation in commitment levels, I add the set of dummy variables which represents the difference in commitment levels.

Table 3.9: OLS estimation of deviations from commitment across treatments

Subject's deviation	coefficient	Std. Error	z statistic	p-value
Constant	2.379***	0.265	8.95	0.000
Partial	-1.197***	0.311	-3.84	0.000
Full	-1.715***	0.306	-5.48	0.000
Commit-L	2.907***	0.743	3.91	0.000
Commit-H	-0.672***	0.091	-7.39	0.000
Commit-N	-2.527***	0.525	-4.81	0.000
Adj. R^2	0.285			
Num. Obs.	880			

Note : Bootstrapped std. error. The regression is clustered by 11 sessions. Open access is excluded. The base case is external regulation. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Commit-L is dummy variable. It takes the value of 1 if the observation is from the round that set the commitment level less than or equal to 3. *Commit-H* takes 1 if the observation is from the round that sets the commitment level at 6 or 7. *Commit-N* is dummy variable. It takes the value of 1 if the observation is from round that has the commitment level at 8 or more. Also, there is a set of dummy variables for treatment. *Partial* is dummy variable. It takes the value of 1 if the observation is from the partial communication treatment. *Full* takes 1 if the observation is from the full communication treatment. Hence, the base case is external regulation which has commitment level at 5. Table 3.9 reports the result of the following regression,

$$y_{it} = \beta_0 + \beta_1 Partial + \beta_2 Full + \beta_3 (Commit - L) + \beta_4 (Commit - H) + \beta_5 (Commit - N) + \epsilon_{it}$$

According to Table 3.9, the coefficient of *Commit-L* is positive and significant. It means that when the commitment level is less than 3, the deviation is statistically higher than when the commitment level is set at 4 or 5. The coefficient of *Commit-H* and *Commit-N* are negative and significant. It indicates that the deviation is lower than the base case when the commitment level is greater than 5. Moreover, the coefficient of *Commit-N* is less

Table 3.10: Estimation of Compliance probability across treatments in all treatments.

Subject's compliance	Model 1 (Logit)	Model 2 (Probit)
Constant	1.099**	0.674***
	(0.481)	(0.234)
Partial	1.550***	0.967***
	(0.56)	(0.267)
Full	2.357***	1.432***
	(0.567)	(0.346)
Commit-L	-2.513***	-1.499***
	(0.865)	(0.512)
Commit-H	0.755***	0.436***
	(0.162)	(0.121)
Commit-N	1.939***	1.084***
	(0.4)	(0.234)
Psuedo R	0.185	0.184
Num Obs.	880	880

Note : Bootstrapped standard error in parenthesis. The regression is clustered by 11 sessions. Open access is excluded. The base case is external regulation. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.01$.

than *Commit-H*, statistically (p value = 0.007).[11] That means the deviation is negatively monotonic in commitment level.

The coefficient of *Partial* and *Full* are negative and significant. It indicates that subjects in partial and full communication treatments have less deviation than those in the external regulation, significantly. In addition, I test the difference between the deviation in partial and full communication by adding the restriction $H_0 : \beta_1 = \beta_2$ to the regression of Table 3.9. This hypothesis is rejected at 5% significance level (χ^2 p value = 0.013). That means the deviations are lower under full communication than under partial communication.

To confirm the deviation results, I perform Logit and Probit estimation, using an individual's decision per round as the unit of observation. The dependent variable is the subject's compliance in stage 2. It takes the value of 1 if the observation is from a subject who extracts less than or equal to the commitment level and takes 0 if otherwise.

Model 1 is estimated using the logistic distribution, while Model 2 is estimated under

[11] I restrict H_0 : Commit-H = Commit-N in Table 3.9 and χ^2 p value = 0.007.

the normal distribution. According to Table 3.10, *Commit-L* is negative and significant. The coefficient of *Commit-H* and *Commit-N* are positive and significant. Moreover, the coefficient of *Commit-N* is significantly higher than *Commit-H* (p value = 0.002 and 0.005 in Model 1 and 2, respectively).[12] Therefore, the compliance probability is positively monotonic in commitment level.

The coefficient of *Partial* and *Full* in both models are positive and significant. It indicates that subjects in partial and full communication have a statistically higher probability of complying with the commitment level than those in external regulation. Similarly, I test H_0 : Partial=Full in both models and find that the null hypothesis is not rejected, χ^2 p value =0.174 and 0.104 for Logit and Probit models, respectively. That means the probability of compliance is not statistically different between partial and full communication.

Finding 10 *(Compliance behavior) Cooperation is higher when subjects have a chance to communicate. In particular, the deviation from commitment of partial and full communication treatments are less than those of external regulation. Compliance under partial and full communication treatments is higher than under external regulation. Moreover, I observe that subjects in partial communication deviate from commitment level more than those in full communication. However, the compliance probability of partial and full communication are not different. Finally, deviation is negatively monotonic in commitment level, while compliance probability is positively monotonic in commitment level.*

So far, I know that partial communication has large deviations and a commitment level that increases over time, compared with full communication. Next, I analyze deeper this result by considering an outside subject. I add dummy variables which represent outside subjects. *Outsider* is dummy variable. It takes the value of 1 if the observation is from outside subjects in partial communication and 0 if otherwise. *Ext* is dummy variable. It takes the value of 1 if the observation is from external regulation and 0 if otherwise. *Full*

[12] I restrict H_0 : Commit-H = Commit-N to both regressions of Table 3.10 and χ^2 p value = 0.002 and 0.005 in Model 1 and 2, respectively.

Table 3.11: OLS estimation of deviations from commitment across treatments: communicators and outside subjects

Subject's deviation	coefficient	Std. Error	z-statistic	p-value
Constant	1.022***	0.175	5.83	0.000
Ext	1.356***	0.295	4.59	0.000
Outsider	0.633*	0.328	1.93	0.054
Full	-0.359*	0.212	-1.69	0.091
Commit-L	2.907***	0.756	3.84	0.000
Commit-H	-0.672***	0.089	-7.52	0.000
Commit-N	2.527***	0.499	-5.06	0.000
Adj. R^2	0.292			
Num Obs.	880			

Note : Bootstrapped std. error. The regression is clustered by 11 sessions. Open access is excluded. The base case is communicators setting commitment level at 4 or 5. $***p < 0.01$, $**p < 0.05$, $*p < 0.01$.

is dummy variable. It takes the value of 1 if the observation is from full communication and 0 if otherwise. Hence, the base case is the observation from communicators in partial communication. *Commit-L*, *Commit-H* and *Commit-N* are dummy variables which capture the variation in commitment level. Table 3.11 reports the result of the deviation regression,

$$
\begin{aligned}
y_{it} =& \beta_0 + \beta_1 Ext + \beta_2 Outsider + \beta_3 Full + \beta_4(Commit - L) + \beta_5(Commit - H) \\
& + \beta_6(Commit - N) + \epsilon_{it}
\end{aligned}
$$

According to Table 3.11, the coefficient of *Ext* is positive and significant. It means that subjects in external regulation significantly deviate more than communicators in partial communication. This result is consistent with the communication effect in Finding 7. Next, the coefficient of *Outsider* is positive and significant at 10% significance level. It means that outside subjects have higher deviations than communicators do.

Since outside subjects treat the commitment extraction level as an external rule, it is interesting to compare the behavior of outside subjects with subjects in an external regulation treatment. The null hypothesis, $H_0 : \beta_1 = \beta_2$, is rejected at 10% significance level (χ^2 p value =0.091). It means that deviation in external regulation is significantly higher than those of communicators in partial communication. The coefficient of *Full* is negative and significant at 10% significance level. It means that the deviation behavior of subjects in the full communication treatment is significantly lower than communicators in the partial communication treatment. Finally, I observe positive monotonicity in commitment level.

To confirm the result, I perform Logit and Probit estimation, using individual's compliance as the dependent variable. According to Table 3.12, the coefficient of *Ext* is negative and significant. It means that the probability of compliance is statistically lower in external regulation. However, *Outsider* and *Full* are not significant. That means the probability of compliance is statistically the same between outside subjects and communicators and between communicators and subjects in full communication. To compare the behavior of compliance between outside subjects and subjects in external regulation, I find that the compliance probability under outside subjects is significantly higher than that under subjects in external regulation at 10% significance level (χ^2 p value = 0.069 and 0.0479 for logit and probit, respectively). The following Finding formally state the result of Table 3.11 and 3.12.

Finding 11 *(Communicators, outside subjects and full communication)The compliance rate of subjects in partial and full communication are higher than that of subjects in external regulation. On the other hand, the deviation from commitment level of subjects in partial and full communication are lower than that of subjects in external regulation. There is weak evidence (10% significance level) that outside subjects have more deviations than communicators. Therefore, conditional on the decision to deviate, the highest deviation occurs under external regulation, followed by outside subjects, communicators and subjects in full communication, respectively.*

3.6.4 Discussion

In this part, I compare the result of the behavior of communicators and outside subjects between this paper and Schmitt et al. (2000). In Schmitt et al. (2000), subjects in commu-

Table 3.12: Estimation of compliance probability across treatments: communicators and outside subjects

Subject's compliance	Model 1 (Logit)	Model 2 (Probit)
Constant	0.622*	0.398
	(0.349)	(0.272)
Ext	-1.721***	-1.073***
	(0.561)	(0.387)
Outsider	-0.656	-0.413
	(0.524)	(0.359)
Full	0.635	0.359
	(0.566)	(0.349)
Commit-L	-2.517***	-1.509***
	(0.825)	(0.469)
Commit-H	0.768***	0.448***
	(0.19)	(0.144)
Commit-N	1.964***	1.119***
	(0.433)	(0.266)
Psuedo R^2	0.1906	0.1906
Num Obs.	880	880

Note : Bootstrapped standard error in parenthesis. The regression is clustered by 11 sessions. Open access is excluded. The base case is communicators setting commitment level at 4 or 5. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.01$.

nication group cheat the commitment level but blame the over extractions are from outside subjects. The outside subjects do not have an opportunity to respond strategically because the total extractions are close to Nash equilibrium. However, outside subjects here have more extraction than communicators (Finding 11). The difference is from information structure. The outside subjects in Schmitt et al. (2000) do not know the commitment level of communicators; however, they do know the level in this model. Since communicators announce the commitment level, outside subjects can choose the extraction to maximize their payoff, given that level. That is the reason outside subjects' extraction is higher than communicators' extraction. On the other hands, the communicators respond outside subject's extraction by increasing the commitment level. The communicators' response is the explanation of increasing in commitment level in partial communication treatment (Finding 9).

To check communicators' response, I test the behavior of communicators. I perform OLS estimation using the current commitment level as the dependent variable. The regression is as follows.

$$y_t = \beta_0 + \beta_1 x_{t-1} + \beta_2 Time + \epsilon_t$$

, where y_t is current commitment level, x_{t-1} is one period lag of total deviation (total extraction-(8*commitment level)) and $Time$ is time variable which adjusts round 11 to be 0. The coefficient of x_{t-1} and $Time$ are positive and significant at significance level 10% ($\hat{\beta}_1 = 0.413$, p value = 0.088 and $\hat{\beta}_2 = 0.120$, p value = 0.071). It indicates that communicators increase the commitment level when they observe increasing in total deviation in last round.Moreover, the significance of $Time$ is consistent with Finding 9.

To check the dynamic behavior of outside subjects, I perform OLS estimation using the current outside subjects' extraction as the dependent variable. The regression is as follows.

$$y_{i,t} = \beta_0 + \beta_1 x_{1i,t} + \beta_2 x_{2i,t-1} + \beta_3 x_{3i,t-1} + \epsilon_{i,t}$$

, where $y_{i,t}$ is outside subjects' extraction, $x_{i,t}$ is current commitment level, $x_{2i,t-1}$ is one period lag of commitment level and $x_{3i,t-1}$ is the one period lag of total extraction. The coefficient of $x_{1i,t}$ is positive and significant ($\hat{\beta}_1 = 0.392$ and p value $= 0.007$). It indicates that outside subjects increase their extractions when communicators increase the commitment level. However, the coefficient of $x_{2i,t-1}$ and $x_{3i,t-1}$ are not significant ($\hat{\beta}_2 = -0.046$, p value $= 0.841$ and $\hat{\beta}_3 = 0.039$, p value $= 0.487$). It implies that when outside subjects make a decision, the decision only depends on the current commitment level.

3.7 Conclusion

This paper investigates the following questions (i.) Does partial communication reduce individual's extraction?; (ii.) Comparing partial communication and external regulation treatment, which one is better in term of both maintaining high resource levels and supporting cooperation behavior? and (iii.) Is there a difference in extraction and cooperation behavior between partial and full communication? To answer these questions, I separate the 104 participants to four treatments which are external regulation, partial communication and full communication treatments. Open access, the no rule case, is treated as a benchmark.

To compare the effect of each treatment with open access, a Difference-in-Difference approach is applied. The paper finds that external regulation and communication can reduce extraction. Compared across regulatory schemes in both absolute extraction level and change in extraction, I find that the highest extraction is subjects in external regulation, followed by those in partial communication and full communication treatments, respectively.

The paper investigates more thoroughly about the factors which make extraction different across treatments. I consider two factors: commitment levels and compliance. For commitment level, although subjects in both partial and full communication treatments set the same commitment level at the beginning, the commitment level increases over time in partial communication, whereas it remains at social optimum under full communication treatment.

For compliance, the probability of compliance in partial and full communication treatments are higher than those of external regulation. Subjects have the highest deviation in external regulation, followed by partial communication and full communication, respectively. Moreover, I find that conditional on the decision to deviate, the highest deviation is subjects in external regulation, followed by outside subjects, communicators and subjects in full communication, respectively.

Based on the findings in this paper, local government should relax the existing rule and encourage communities to set up self governance institution. However, communication which is the key of institution in reality is not easy as in the paper. The key factor to obstruct the communication is transaction cost. Therefore, the role of government officers should change from regulatory to facilitator. For example, the local officers can be the host of meeting or can be the coordinator to announce the rule to non communicator resource users.

Finally, I discuss the way to improve the result. The deviation result regarding from commitment level between outside subjects and communicators is weak (10% significant level). In particular, the deviation behavior of outside subjects and communicators is explained by the increasing commitment level over time in partial communication. It is possible that outside subjects deviate more than communicators in the beginning of stage 2 and communicators respond the deviation by increasing commitment level. The way to make this argument clearer is to separate the analysis to rounds $11-15$ and $16-20$ and consider the compliance of each group or look at the experiment log of partial communication treatment.

Chapter 4

Network Formation in Cost Distance Function

4.1 Introduction

"Social networks permeate our social and economic lives", Jackson (2010). There are countless examples showing how networks apply to social and economic problems. Networks play a key role in transmitting job information in the labor market.[1] They are also important in determining which product one buys, how criminal gangs form and organize, [2] how people vote, how financial crises spread,[3] and so forth.

In this paper, I study network formation in which agents not only receive benefit from links they are connected with but also bear the cost of maintaining these connection. The paper focuses on the situation where agents obtain benefits from their direct connection, such as their friend, but are faced with costs from direct and indirect friend, i.e. friend of friends.

[1]The role of social network in employment is discussed in Calvo-Armengol and Jackson (2004)

[2]Network is important for buyers and sellers in term of bidding (Kranton and Minehart (2003)), criminal organization (Mastrobuoni (2013))

[3]The financial crisis propagate throughout the financial network Elliott et al. (2013))

Well known examples include epidemic[4] and financial contagion, where the disease spreads through the social network, and the latter, across other sectors, or countries. For the case of an epidemic, the probability of getting sick depends both on direct friends and friends of friends. The probability is represented by the *decay* in distance. The paper models the cost function that captures the decay in distance and is referred to as the *cost distance function.*

Agents benefit from direct connections but bear the cost from both direct and indirect connections. I define the formation of link between two agents as *two way flow connection*, as following Bala and Goyal (2000). The two way flow connection requires both agents to equally share the cost of maintaining their connection. In other words, the link is formed under mutual agreement of both agents. To capture the decay effect, I assume that the cost of friends closer in distance is higher than those that are farther away.

From the general cost distance function, the configuration of the network is sensitive to the number of agents and the magnitude of benefits that range from direct connections. The configuration consists of independent components, for all possible cases.

Next I consider the special case where the cost is a linear function. In particular, the cost function is affected by only two distances, a friend and a friend of a friend. The net benefit of making a direct connection plays a key role. If the net benefit of the direct connection is high enough, starting from an empty network, the stable network converges to many components in which there are four agents. Furthermore, each component is complete network.

The intuition of the result is straightforward from the asymmetry between the benefit and cost of making connection. Since agents attain benefits only from the direct connection but bear costs from both the direct and indirect connection, the best strategy for all agents is to remove the indirect connection. In other words, they will form more direct connections, which eventually make up their complete network. However, since the network starts from empty, agents need time to secure their complete network. Before reaching that state, there is some point in time at which agents have many indirect connections and higher costs

[4] Jackson (2010) provides an excellent survey is chapter 5 and 7 in

than they can handle. In this situation, the equilibrium is for agents to form the small component, usually four agents, and make direct connections with each other. However, the component size is not necessarily exactly four agents. If the net marginal benefit of the direct connection is high enough, then agents can form connections across components and create larger components.

There is a large literature on network formation in economics and computer science. Most of literature considers cases where the benefit function depends on distance. The paper first contributes to the literature by examining network formation through the cost distance function. The result is reasonable in the sense that it is opposite from the benefit distance model. Rather than minimal connection like star network, the equilibrium is maximal connection (complete network).

The second contribution is introducing the double best response algorithm to analyze the network formation. The criterion agents use to make a connection is very important in network formation. The literature commonly applies a myopic algorithm in which agents make a connection as long as that link returns positive payoff. The current paper, however, adds more restriction in the way that agents will offer and accept the proposal from his top choice.

Since the paper proposes an alternative algorithm, the double best response algorithm, the last part of this paper is devoted to justifying the double best response algorithm. In particular, I compare the efficiency characteristic between double best response and the standard myopic algorithm commonly present in the literature. The result shows that double best response algorithm is more efficient than the myopic algorithm in specific circumstances, when algorithm has one by one component selection.

The rest of the paper is organized as follows: Section 4.2 presents the related literature; Section 4.3 represents the model; Section 4.4 documents the double best response algorithm. Section 4.5 presents the general cost function. Section 4.6 provides the linear distance cost function, which is special case. Section 4.7 presents properties of the limit network and

Section 4.8 is devoted to justify the double best response algorithm. Finally, the conclusion is in section 5.

4.2 Literature Review

Recently, there are many theoretical research in network formation area. The literature of network formation starts from Aumann and Myerson (1988). They construct the extensive form game that players are randomly drawn and asked whether or not they make a connection. The game continues until either all links are formed or no one wants to form a link anymore. Although there always exists a solution, it is very difficult to solve the equilibrium. To simplify the network formation game, Myerson (1977) changes the game to a simultaneous game in which each player announces the set of players whom he want to connect with. It is much easier to solve for equilibrium in this environment and the result is equivalent to the result from Aumann and Myerson (1988). However, the main drawback of this method is an empty network is always one of Nash equilibria.

In order to maintain the simplicity of a simultaneous game and remove the drawback of an empty network, Jackson and Wolinsky (1996) introduce the new concept of equilibrium, *stable pairwise*. The stable pairwise is the equilibrium such that no player neither wants to make additional connections nor sever existing links. Moreover, they show there exists a trade off between efficiency and stability. The example is star network. The star network equilibrium is stable but not efficient. Moreover, the star network is sensitive to the range of values of the direct benefit parameter. According to Jackson and Wolinsky (1996), the star network is the basic result in network formation literature when agent receives benefit from both direct and indirect connections and only bares cost from direct connections. Jackson and Watts (2002) replicate the model of Jackson and Wolinsky (1996) and check the robustness of star network by assuming there exists small perturbation in agents' decision. They find that the topology of network in that circumstance converges to either a star network or another efficient network.

Watts (2003) extends Jackson and Wolinsky's model to the dynamic process. He finds that the number of players play a crucial role forming an efficient network. The efficeint network emerges only if the ordering of connections is correct. Bala and Goyal (2000) study network formation in dynamic process. However, their model is different from the literature. In particular, the connection is unilateral the initiator does not need the permission from others to make a connection. The only requirement is the intiator can bare the cost of connection. They classify the benefit into two categories, one and two ways. In one way case, only one agent attains the benefit, empty and wheel network are the equilibrium. On the other hand, periphery-sponsored star network is the equilibrium when two agents have mutual agreement. In particular, the periphery-sponsored star is the network that the center player does not bare cost of connection whereas other players have a single link with the center player and bare the cost of connection. Hojman and Szeidl (2008) shows the crucial of periphery-sponsored star when agents can make a monetary transfer and bargain over the network.

Goyal and Joshi (2003) apply the network formation model to explain the colloration in industry. The connection saves firm's cost. Consequently, the more links (or collaboration) a firm has, the less cost he incurs. They find that in the moderate competition, there are many components in which firms have the same cost to collaborate with each other. On the other hand, in aggressive competition the equilibrium where is the lowest cost firm connects while the rests of firms are separated. Galeotti et al. (2006) study the heterogeneity in cost function. They find that the stable network is the network that has a short average distance between agents and the equilibrium has high centrality.

4.3 The Model

Let $N = \{1, 2, \ldots, n\}$ be the set of players. I define (N, G) as a network, where G is the set of all link.[5]. A *path* between player i and j is the sequence of links $\overline{m_1 m_2}, \overline{m_2 m_3}, \ldots, \overline{m_{k-1} m_k}$ such that $m_1 = i$ and $m_2 = j$ and such that $m_p \neq m_q$ for all p, $q \in \{1, 2, \ldots, k\}$. I say that i and j are *connected* if there exists a path between any i and j in (N, G). The *direct connection* between i and j is a path of size one. If agents i and j are connected indirectly, I call it *indirect connection*. The network is *complete* if all agents are connected. The *distance* between i and j is the shortest path between them. I say (N', G') is subnetwork of (N, G) if $N' \subset N$ and $G' \subset G$, $\forall \overline{ij} \in G'$ and $i, j \in N'$. A *component* is a nonempty subnetwork (N', G') such that

- (N', G') is connect.
- if $i \in N'$ and $\overline{ij} \in G$, then $j \in N'$ and $\overline{ij} \in G'$

If G is composed of many components, $G = [A_1, A_2, \ldots, A_n]$, I denote $|A_i|$ as the size of component i or the number of agent in component i. To complete the normal form game, I define the payoff function. Let l_k^i be the number of players who are at k distance from i. Let π^i be i's payoff function. The payoff function is

$$\pi_i(G) = vl_{i1} - c(l_{i1}, l_{i2}, \ldots, l_{ik})$$

Players receive benefit, v, only from direct connection but the cost function also depends on indirect connections. The example of this cost function is the epidemic or financial crisis. The disease can be passed from "friend of friend." The probability to getting sick depends on how many connection players have, both direct and indirect. However, the probability is low when the source of disease is far from player. I assume that $c(.)$ is strictly increasing in l_m^i, for all $m \in \{1, 2, \ldots, k\}$, whereas v is constant across players.

[5]The formal strategy and the way players make a connection will be explained in next part.

4.4 Double Best Response Algorithm

In this part, I explain the algorithm that players make a connection and network configuration is formed. This algorithm will be applied throughout the paper.

Definition 3 *Player j is top choice of player i if and only if*

$$\pi_i(G) = \underset{j/\overline{ij}\notin G}{\arg\max}\, vl_j^i - c(G \cup j)$$

At every stage, the following steps happen:

1. A random ordering of the agents with uniform probability is selected.

2. Following this ordering, agents make a proposal to an agent to form a link given the network that is currently formed. If there are multiple agents at his top choice, he selects one at random.

3. An agent who receives a proposal accepts it if and only if it is coming from an agent who is at the top of his preferences given the network that is currently formed.

4. The algorithm continues with the following agents in the list.

5. Once all the agents had a chance to propose, the algorithm moves to the next stage. The algorithm finishes once no one does not create a link.

Since $\overline{ij}$ is formed only they are top choice of each other, I call this algorithm as "double best response algorithm". Note given the i's proposal, the connection depends on j's decision. I call player j as "responder player" and call player i "proposer player". Formally, given network G, the strategy of responder player is $a_j : G \times \{N/j\} \rightarrow \{0, 1\}$. On the other hand, the strategy of proposer player is $p_i : G \rightarrow N/i$.

The double best response algorithm is different from the centralized algorithm. In the centralized algorithm, players reveal the preference and the algorithm matches players in order to attain the maximum payoff. On the other hand, players in double best response algorithm are not requested to reveal their preference to algorithm. Player chooses the connection which attains the maximum payoff. However, the algorithm requires more restriction which is the connection will be created if it is from the top choice of both parties. By this restriction, the double best response is also different from decentralized algorithm in which the connection will be created only from one top choice such as myopic algorithm. Therefore, the double best response algorithm lies in between centralized and decentralized algorithm. For the comparison between double best response and myopic algorithm, I will show in section 4.8.

4.5 General Cost Function

Assumption 12 *[Submodularity Cost Function] The cost function is increasing function in l_i where $\{i = 1, \ldots, k\}$ such that for all K and L*

$$c(K, L) - c(K-1, L+1) \geqslant c(K+1, L-1) - c(K, L)$$

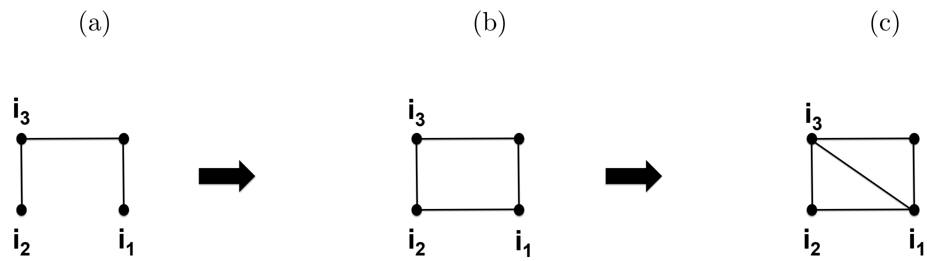
, where K is the number of direct connection (l_1) and L is the number of indirect connection ($l_2, \ldots, l_k$).[6]

Assumption 12 states that marginal cost is decreasing in direct connection. The submodularity assumption implies that the marginal cost of changing from farther to closer distance is monotonically decreasing function.

Figure 4.1 shows the marginal cost of agent i_1 when he changes an indirect connection to direct connection. The marginal cost of $\overline{i_1 i_2}$ equals $c(2,1,0) - c(1,1,1)$ and the marginal cost of $\overline{i_1 i_3}$ equals $c(3,0,0) - c(2,1,0)$. By the submodularity cost function, $c(2,1,0) - c(1,1,1) \geqslant c(3,0,0) - c(2,1,0)$.

[6]Generally, I denote $c(l_1, l_2, \ldots, l_k)$ as the cost function. However, since this assumption focuses on the number of direct and indirection connection, I ignore the distance of indirect connection and use L denotes the number of indirect connection.

Figure 4.1: Submodularity Cost Function



I start from an important lemma to explain maximize direct connection is a key role in the main results. This lemma comes from the critical assumption on the submidularity of the cost function.

Lemma 3 *Consider the network $G = [A, B]$ composed of two fully connected components A and B. Let $a_k = |A|$ and $b_k = |B|$. If $v > c(a_k, b_k - 1) - c(a_k - 1, 0)$, then the double best response algorithm starting from G converges to the complete network.*

Proof. Consider the first step of the algorithm. Since $v > c(a_k, b_k - 1) - c(a_k - 1, 0)$, every agent in A is willing to connect to any agent in B.

Now, suppose that there are s links between A and B. I will show that another link between A and B will be created. In order to do this, I consider two cases.

Case 1: The algorithm selects an agent i in A who is not directly connected to an other agents in B. Agent i's marginal cost of the first link is $c(a_k, b_k-1) - c(a_k-1, s, b_k-s)$. Since $v > c(a_k, b_k-1) - c(a_k-1, 0)$, agent i will make a link because $c(a_k-1, 0) < c(a_k-1, s, b_k-s)$.

Case 2: The algorithm selects an agent i in A who has already directly connected to at least one agent in B. Suppose that i has already connected to $t-1$ links in B. Then, the agent i's marginal cost of $t - 1^{th}$ link is $c(a_k + t - 2, b_k - t + 1) - c(a_k + t - 3, b_k - t + 2)$. Since agent i is connected to $t-1$ agents in B, it implies that $v \geq c(a_k+t-2, b_k-t+1) - c(a_k+t-3, b_k - t + 2)$. Once the agent evaluates to make an offer or accept an offer, he considers his increment in marginal cost, $c(a_k + t - 1, b_k - t) - c(a_k + t - 2, b_k - t - 1)$. By submodularity,

$c(a_k+t-2, b_k-t+1) - c(a_k+t-3, b_k-t+2) \geq c(a_k+t-1, b_k-t) - c(a_k+t-2, b_k-t)$. Hence, $v \geq c(a_k+t-1, b_k-t-1) - c(a_k+t-2, b_k-t)$.

This analysis is similar if the agent i is in an element B. Therefore, the limit of the algorithm is the complete graph. ■

Since the network starts from an empty network, every point in time the network composes of many components. Lemma 3 can therefore be applied to every point in time.

Next, I will show the configuration of network depends on the size of N. Consider the case $N = 2^k$, for some $k \geqslant 0$. I define sequences $\{p_m\}$ as the passive component in stage m which offers to merge with another component and $\{a_m\}$ is the active component which accepts/rejects the offer from passive component in stage m. If $\{a_m\}$ accepts the offer from $\{p_m\}$, the two components will merge together. Therefore, $|a_m| \leqslant |p_m|$ for all stage. Let K_m be a sequence of partition of N at stage m in which there are many complete components. The next three propositions cover all possibilities of N.

Definition 4 *Given $N = 2^k$. The definition of the sequences $\{a_i\}$, $\{p_i\}$ and partition $[K_i]$ are following :*

In the case that $N = 2^k$,

$a_m = 2^m, p_m = 2^m$ *and* $K_m = [2^m, 2^m, \ldots, 2^m]$ *for all* $m \leqslant k$

$a_{m+1} = 2^{m+1}, p_m = 2^{m+1}$ *and* $K_{m+1} = [2^{m+1}, 2^{m+1}, \ldots, 2^{m+1}]$

Proposition 5 *Given $N = 2^k$. Let m^* be the smallest number such that*

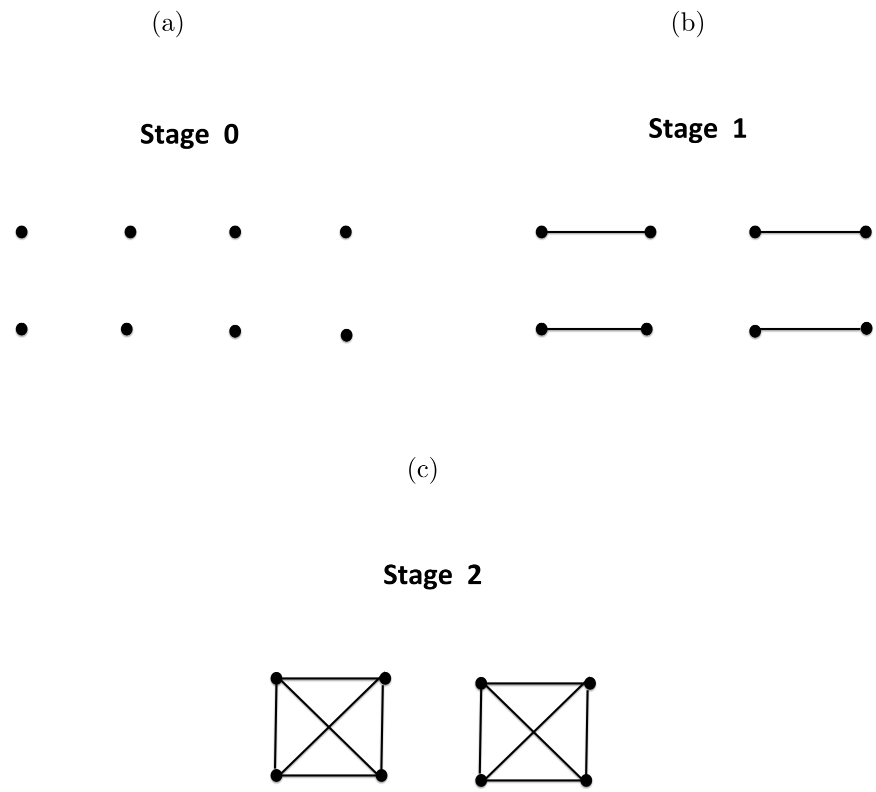
$$v < c(a_{m^*}, p_{m^*} - 1, 0, \ldots, 0) - c(a_{m^*} - 1, 0, \ldots, 0).$$

The final partition given by double best response strategy is composed of complete subnetwork of sizes given by K_{m^*}

Proof. see Appendix C.1 ■

This proposition shows the condition of final partition when $N = 2^k$. The next example will show the configuration of network in this case.

Figure 4.2: Network Formation when $N = 2^k$



Example 4 *Consider the case $N = 8$. From Figure 4.2 Stage 0 is empty network. Stage 1, $K_1 = [2, 2, 2]$ will be final stage, if $v < c(2, 1) - c(1, 0)$. Otherwise, the network moves to stage 2, Stage 2, $K_2 = [4, 4]$ will be the final state if $c(2, 1) - c(1, 0) < v < c(4, 3) - c(3, 0)$. However, if $v > c(4, 3) - c(3, 0)$, the network is complete in stage 3 (not show in figure).*

Next I will consider in the case that N is odd. Let $[N]_{2^k}$ be the remainder of dividing N by 2^k.

Definition 5 *Let N be an odd number and $k \geqslant 2$. The definition of sequences $\{a_i\}$, $\{p_i\}$ and partition $[K_i]$ are following :*

In the case that $N = 2^k(I+1) + [N]_{2^k}$ *and* I *is even,*

$a_k = 2^k, p_k = 2^k$ *and* $K_k = [2^k, \ldots, 2^k, 2^k + [N]_{2^k}]$,

$a_{k+1} = 2^k + [N]_{2^k}, p_{k+1} = 2^{k+1}$ *and* $K_{k+1} = [2^{k+1}, \ldots, 2^{k+1}, 2^k + [N]_{2^k}]$

and

$a_{k+2} = 2^{k+1}, p_{k+1} = 2^{k+1}$ *and* $K_{k+2} = [2^{k+1}, \ldots, 2^{k+1}, 3(2^k) + [N]_{2^k}]$

In the case that $N = 2^k(I+1) + [N]_{2^k}$ *and* I *is odd,*

$a_k = 2^k, p_k = 2^k$ *and* $K_k = [2^k, \ldots, 2^k, 2^k + [N]_{2^k}]$,

$a_{k+1} = 2^{k+1}, p_{k+1} = 2^k + [N]_{2^k}$ *and* $K_{k+1} = [2^{k+1}, \ldots, 2^{k+1}, 2^k, 2^k + [N]_{2^k}]$

and

$a_{k+2} = 2^{k+1}, p_{k+1} = 2^{k+1}$ *and* $K_{k+2} = [2^{k+1}, \ldots, 2^{k+1}, 2(2^k) + [N]_{2^k}]$

Proposition 6 *If* N *is odd, let* k^* *be the smallest number such that* $k \geq 2$ *and*

$$v < c(a_{k^*}, p_{k^*} - 1, 0, \ldots, 0) - c(a_{k^*} - 1, 0, \ldots, 0)$$

The final partition given by double best response strategy is composed of complete component of sizes given by K_{k^*}

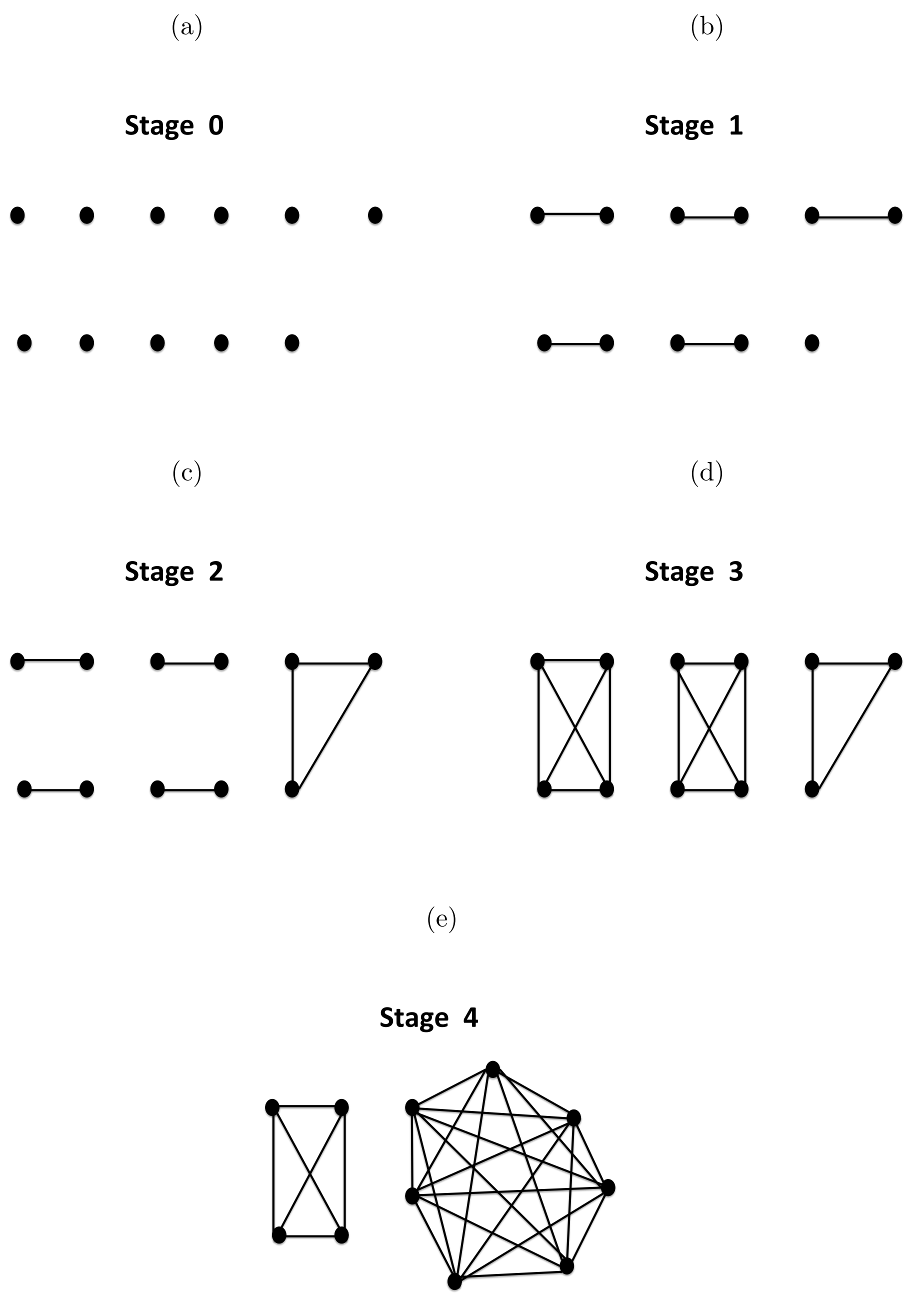
Proof. see Appendix C.2 ■

This proposition shows the condition of final partition. Since there are two cases when N is odd, I have two conditions for final network configuration. The next two examples provide the network configuration in both cases.

Example 5 *Consider the case* $N = 11$. *It can write* $11 = 2(I+1) + [11]_2$, *where* $I = 4$. *From Figure 4.3, at stage 1, given* $a_1 = 1$ *and* $p_1 = 2$ *the* $K_1 = [2, 2, 2, 2, 2, 1]$. *The single node is the top choice of everyone. If* $v > c(2, 0) - c(1, 1)$, *then the* $K_1 = [2, 2, 2, 2, 3]$. *From this point of time, proposition 6 can be applied. Since* $a_2 = 2$ *and* $p_2 = 2$, *the last component will not be changed. Then* $K_2 = [4, 4, 3]$, *if* $c(2, 1) - c(1, 0) < v < c(3, 3) - c(2, 0)$. *Now* $a_3 = 3$ *and*

$p_3 = 4$, $K_3 = [4, 7]$, *if* $c(3,3) - c(2,0) < v < c(4,6) - c(3,0)$. *Finally, if* $v > c(4,6) - c(3,0)$, *the network will be complete network.*

Figure 4.3: Network Formation when N is odd and $I = 4$



Example 6 *Consider* $N = 13$. *It can write* $13 = 2(I+1) + [13]_2$, *where* $I = 5$. *From Figure 4.4 in stage 0, 1 and 2, the configuration is the same as example 5. However, in*

stage 3 since I is odd number, there is a pair who cannot form component size 4. Then, $K_3 = [4, 4, 2, 3]$ where $a_3 = 2$ and $p_3 = 3$. The component size 5 will be formed and stop at stage 4 if $c(2, 2) - c(1, 0) < v < c(4, 3) - c(3, 0)$. In stage 4, $K_4 = [4, 4, 5]$ where $a_4 = 4$ and $p_4 = 4$. The network will stop at stage $K_5 = [8, 5]$ if $c(4, 3) < v < c(5, 7) - c(4, 0)$ Finally, if $v > c(5, 7) - c(4, 0)$, the network will be complete.

From example 5 and 6, it can be observed that although the both of them are odd number, the configuration after state 2 is different.

The last case is $N = 2^m h$, where h is odd. This case is the extension of N is odd.

Definition 6 *Given $N = 2^m h$, where h is odd. Let $i = m + h$. The definition of sequences $\{a_i\}$, $\{p_i\}$ and partition $[K_i]$ are following :*

In the case that $N = 2^m[2^k(I + 1) + [N]_{2^k}]$ and I is even,

$a_i = 2^i, p_i = 2^i$ *and* $K_i = [2^i, 2^i, \ldots, 2^i, 2^m(2^k + [N]_{2^k})]$,

$a_{i+1} = 2^m(2^k + [N]_{2^k}), p_{i+1} = 2^{i+1}$ *and* $K_{i+1} = [2^{i+1}, \ldots, 2^{i+1}, 2^m(2^k + [N]_{2^k})]$

and

$a_{i+2} = 2^{i+1}, p_{i+2} = 2^{i+1}$ *and* $K_{i+2} = [2^{i+1}, \ldots, 2^{i+1}, 3(2^i) + 2^m[N]_{2^k}$

In the case that $N = 2^m[2^k(I + 1) + [N]_{2^k}]$ and I is odd,

$a_i = 2^i, p_i = 2^i$ *and* $K_i = [2^i, \ldots, 2^i, 2^m(2^k + [N]_{2^k})]$,

$a_{i+1} = 2^i, p_{i+1} = 2^m(2^k + [N]_{2^k}$ *and* $K_{i+1} = [2^{i+1}, \ldots, 2^{i+1}, 2^i, 2^m(2^k + [N]_{2^k})]$

and

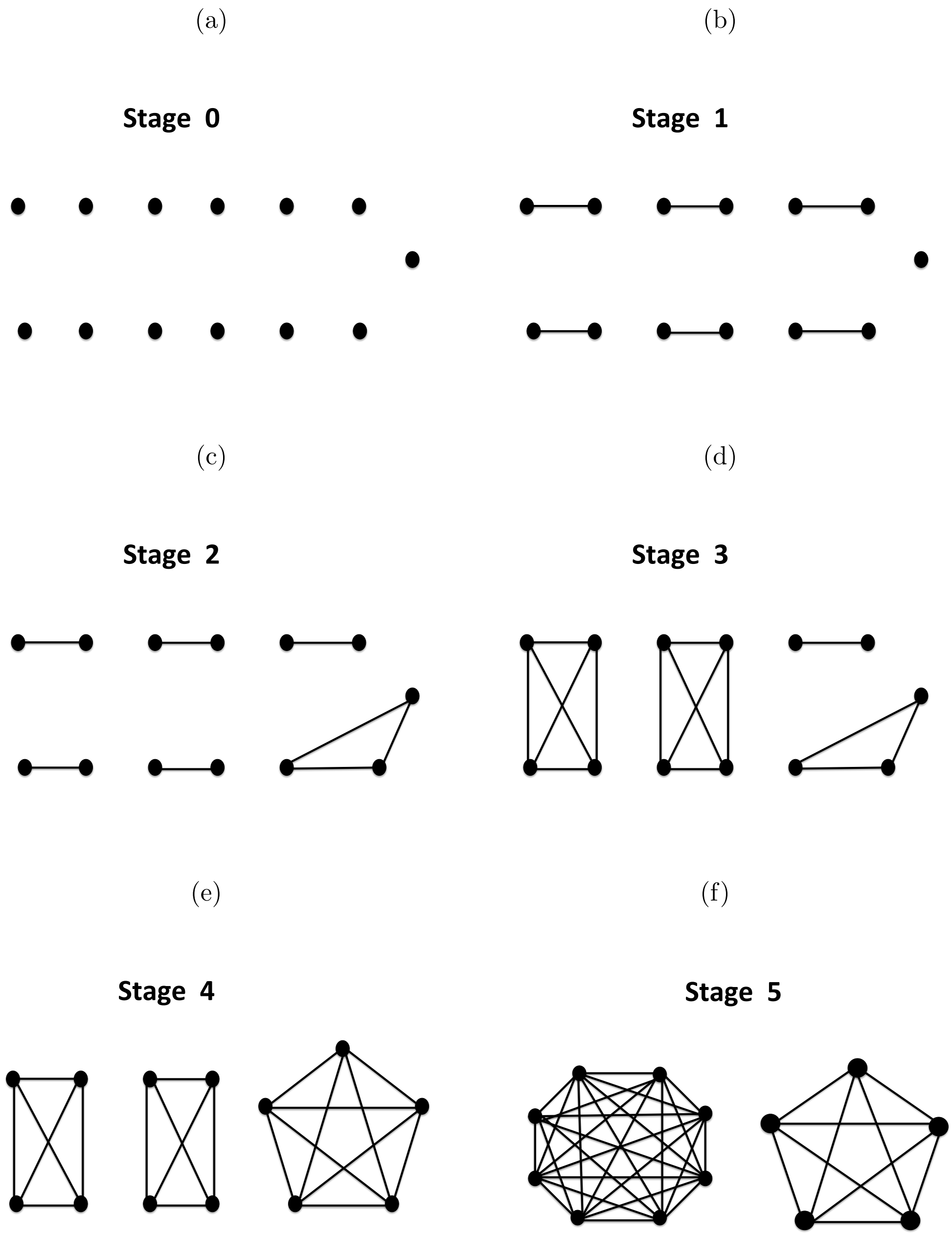
$a_{i+2} = 2^{i+1}, p_{i+2} = 2^{i+1}$ *and* $K_{i+2} = [2^{i+1}, \ldots, 2^{i+1}, 2(2^i) + 2^m[N]_{2^k}]$

Proposition 7 *If $N = 2^i(I + 1) + [N]_{2^i}$, let i^* be the smallest number such that*

$$v < c(a_{i^*}, p_{i^*} - 1, 0, \ldots, 0) - c(a_{i^*} - 1, 0, \ldots, 0).$$

The final partition given double best response strategy is composed of complete subnetwork of sizes given by K_{i^*}

Figure 4.4: Network Formation when N is odd and $I = 5$



Proof. see Appendix C.3 ■

This proposition shows the condition of final partition when $N = 2^m h$. I now complete the condition of final partition for all possible cases.

The equilibrium behavior of double best response algorithm is pairwise stable.[7] According to Jackson and Wolinsky (1996), the network is pairwise stable if

$$(i)\forall i,j \in G,\ \ \pi_i(G) \geq \pi_i(G-\overline{ij}) \ \text{ and } \ \pi_j(G) \geq \pi_j(G-\overline{ij})$$

$$(ii.)\forall i,j \in G,\ \text{ if } \pi_i(G+\overline{ij}) \geq \pi_i(G),\ \text{ then } \pi_j(G+\overline{ij}) < \pi_j(G)$$

Proposition 8 *Given the assumption of submodularity cost function, the network which satisfies proposition 5, 6 and 7 is pairwise stable.*

Proof. To show $(i.)$. Suppose that $\overline{ij}$ is formed already. It means that $v \geq c(l_1, 0, \ldots, 0) - c(l_1 - 1, 0, \ldots, 0)$, where l_1 is the number of direct connection. The marginal benefit of severing $\overline{ij}$ is $c(l_1, 0, \ldots, 0) - c(l_1 - 1, 0, \ldots, 0)$, whereas the marginal cost is v. Therefore, i and j will not delete the connection $\overline{ij}$.

To show $(ii.)$. Suppose that $\overline{ij}$ is not formed. It means that i and j belong in different component. Since the last partition K_{m^*} satisfies $v < c(a_{m^*}, p_{m^*} - 1, 0, \ldots, 0) - c(a_{m^*} - 1, 0, \ldots, 0)$. Therefore, $\overline{ij}$ will be not created. ■

4.6 Linear Cost Function

The purpose of this section is to illustrate the configuration of network with the simple cost linear function. I first consider the simplest case that $c(.) = \delta l_1^i + \delta^2 l_2^i$. The payoff function is $\pi^i = v l_1^i - \delta l_1^i - \delta^2 l_2^i$. Since player bares a cost from indirect connections, he has to consider not only benefit from l_1 but also the cost from l_1 and l_2. Player then increases one direct connection if

$$\frac{v-\delta}{\delta^2} \geqslant \Delta l_2^i \tag{4.1}$$

[7] The failure of Nash equilibrium in network formation is discussed in Jackson (2010) pp. 154 – 156.

for all $i \in N$. The left hand side represents the (net) marginal benefit from having one more direct link. The right hand side represents the marginal cost. This equation reveals that the player only considers how l_2 changes when he make a connection. Furthermore, it implies that a player is better off if he connects with an agent who has a low number of l_2. The lower the number of l_2, the smaller marginal cost, Δl_2, he has. Therefore, agent i lists the connecting player that makes the δl_2 lowest as his top choice.

Proposition 9 *Consider the cost function $c(.) = \delta l_1^i + \delta^2 l_2^i$. Given $N \geqslant 5$. Starting from an empty network, the double best response strategy converges to*

i. if $0 \leqslant \frac{v-\delta}{\delta^2} < 1$, many independent lines with at most 2 players.

ii. given $N = 4b + l$ where $0 \leqslant l < 4$ where b and l are natural number and given $1 \leqslant \frac{v-\delta}{\delta^2} < 3$, the network converges to

1. if $N = 4b$, b components with 4 players and every component is a complete network.

2. if $N = 4b+1$, $b-1$ components with 4 players and one component with 5 players and every component is a complete network.

3. if $N = 4b+2$, b components with 4 players and one line and every component is a complete network.

4. if $N = 4b+3$, b components with 4 players and one component with 3 players and every component is a complete network.

iii. if $3 \leqslant \frac{v-\delta}{\delta^2} < k$, many independent components with more than 4 players; in particular, any two components can merge together and the merging process will stop when the next merging has $\frac{v-\delta}{\delta^2} < k$.

Proof. see Appendix C.4 ■

By the double best response algorithm, an agent minimizes marginal cost measured in term of indirect connection (Δl_2). Once a component is formed, the direct connection is created by reducing the indirect connection. That means the first indirect connection has the highest cost and the cost will decrease with every additional more direct connection. Since the network starts from an empty network, the first indirect connection is the first link across components. Once a player forms a component, the top choice is other players in the same component. If a player can accept the cost of the first link across components, every connection from there has less cost. The network then ends up with the complete network. However, the size of network depends on the size of (net) marginal benefit, $\frac{v-\delta}{\delta^2}$. Every two components merge together and form bigger components as long as the equation 4.1 is satisfied.

Example 7 *Consider the case that $N = 10$, $v = 0.3$ and $\delta = 0.2$. With this numerical example, $1 \leqslant \frac{v-\delta}{\delta^2} < 3$.*

Step 1, *Starting from an empty network. Every agent is the same.*

Step 2, *Since $1 < \frac{v-\delta}{\delta^2}$, agents make a link and components with two agents are formed.*

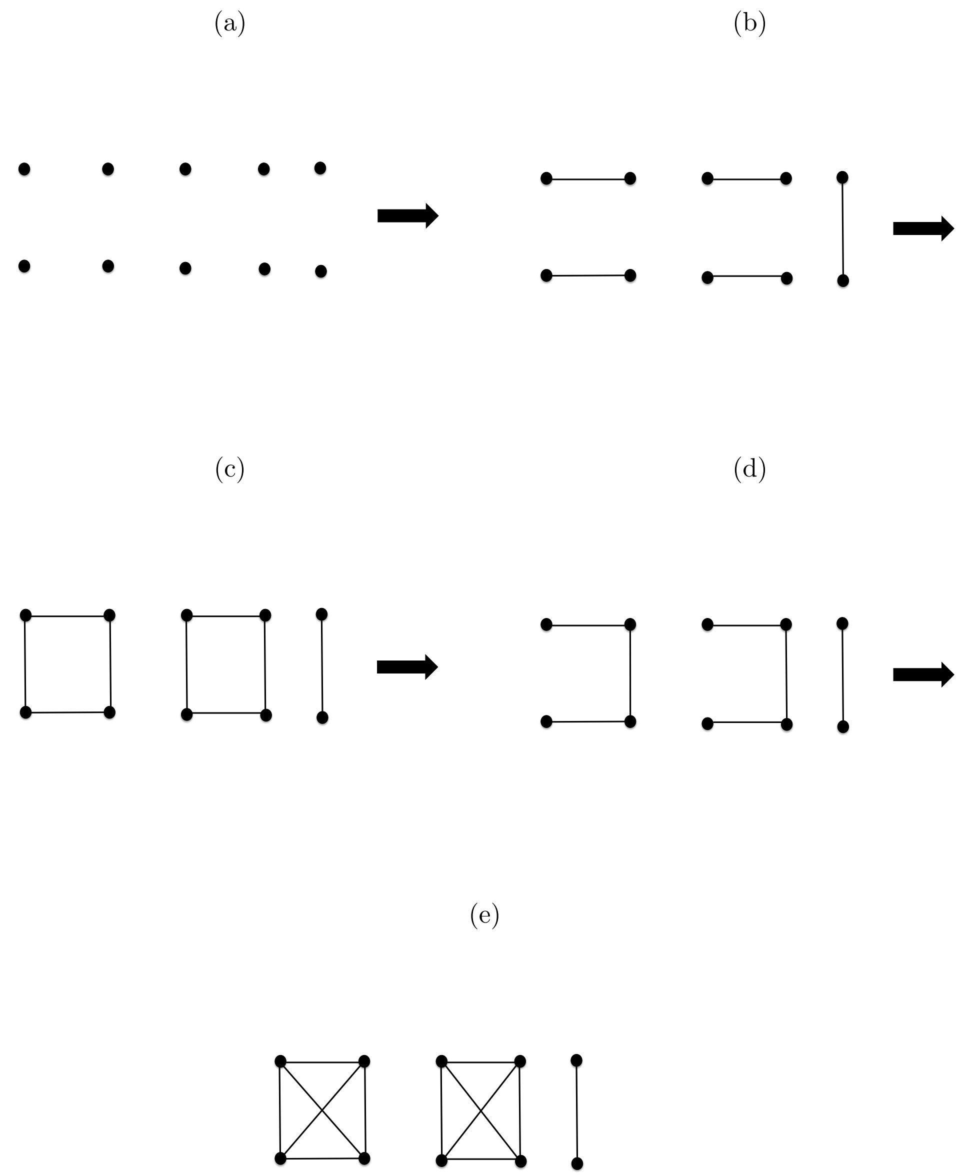
Step 3, *agent makes link across pairs and two components with four players are formed. Since there is a pair who cannot make link, they will have only one direct connection.*

Step 4, *agents in components size four make a link within component. If they establish link within component, the $\Delta l_2 = 0$, whereas the $\Delta l_2 = 1$, if they make link with component size of two.*

Step 5, *agents make the direct connection as much as possible because the benefit is only on direct link and also they save cost by reducing the indirect connection. Then, the complete network are formed. Agents will not make more links because now the top choice is two agents in line but those agents cannot accept the extra three indirect links, then they reject any offers. Finally, the stable network is two complete independent components with four agents and a connection with two agents.*

From proposition 9, some point in time the network is formed in many independent components. If they merge together, they will merge one-by-one component. The intuition is that players attain benefit from the existing across component link. Indeed, the first link

Figure 4.5: Network Formation when $N = 10$, $v = 0.3$ and $\delta = 0.2$



between two independent components has a positive externality to the latter players. For other players, creating the connection across these two components is better than making new connection with other components. Hence, the distance of cost which is farther than two distances does not affect merging process. Consequently, the result from proposition 9 can apply to the general case $c(G) = \delta l_1^i + \delta^2 l_2^i + \delta^3 l_3^i \cdots + \delta^k l_k^i$.

An agent now makes one more direct connection if and only if

$$\frac{v-\delta}{\delta^2} \geqslant \Delta l_2^i + \delta \Delta l_3^i \cdots + \delta^{k-2} \Delta l_k^i \tag{4.2}$$

and his top choice is the one who minimize the right hand side of this equation.

Corollary 13 *The network formation of* $c(.) = \delta l_1^i + \delta^2 l_2^i$ *is exactly the same as the formation of finite cost distance function,* $c(.) = \delta l_1^i + \delta^2 l_2^i + \cdots + \delta^k l_k^i$.

Proof. I will consider only part [ii.] and [iii.] in proposition 9.

Part [ii.] $\frac{v-\delta}{\delta^2} < 3$. In this case, all players do not want to make a connection across components. The maximum of the indirect connection is the second degree. Obviously, the result is the same as proposition 9 in part [ii.].

Part [iii.] $\frac{v-\delta}{\delta^2} \geqslant 3$. From the proposition 9 part [iii.], I know that players merge one-by-one component (see detail in proof [iii.] of proposition 9). Therefore, the maximum indirect all players consider is the second degree. ■

4.7 Efficiency of network

Definition 7 *The network* G *is efficient if* $\sum_{i=1}^{n} \pi_i(G) \geqslant \sum_{i=1}^{n} \pi_i(G')$ *for all possible of* G.

Assumption 14 *[Subadditive Cost Function] The cost function is subadditive, if*

$$c(s_i - 1, 0) + c(s_j - 1, 0) \geq c(s_i + s_j - 1, 0), \forall i, j$$

The subadditive cost function states that the bigger the component, the lower cost of connection agent. The following proposition is the inefficiency in the general cost function case.

Proposition 10 *Consider the cost function* $c(G)$ *that is submodular and subadditive, then the efficient network is the complete network.*

Proof. From lemma 3, every component is fully connected. Now, suppose that the network is composed of fully connected components of size $[s_1, s_2, \ldots, s_k]$. By Subadditive assumption, I have

$$\begin{aligned}
v &\geq c(s_i + s_j - 1, 0) - [c(s_i - 1, 0) + c(s_j - 1, 0)] \\
v(s_i + s_j - 1) - c(s_i + s_j - 1, 0) &\geq v(s_i - 1) - c(s_i - 1, 0) + v(s_j - 1) - c(s_j - 1, 0) \\
(s_i + s_j - 1)[v(s_i + s_j - 1) - c(s_i + s_j - 1), 0] &\geq (s_i + s_j - 2)[v(s_i - 1) - c(s_i - 1, 0) \\
&\quad + v(s_j - 1) - c(s_j - 1, 0)] \\
&\geq (s_i - 1)[v(s_i - 1) - c(s_i - 1, 0)] \\
&+ (s_j - 1)[v(s_j - 1) - c(s_j - 1, 0)]
\end{aligned}$$

The left hand side of the last equation implies that $N - 1 = argmax_{s_m}[v(s_m - 1) - c(s_m - 1, 0)](m - 1)$. Therefore, the efficient network is complete network. ■

This proposition points out the limitation of double best response algorithm in general cost distance function. The limit network will not be efficient if v is not so high that the complete network is created. The next corollary states this point formally.

Corollary 15 *The limit network obtained in propositions 5, 6 and 7 are not efficient if they stop before forming the complete graph.*

Proof. Let $K_m = [A_1, \ldots, A_k]$ be network in stage m. The network in stage $m + 1$ is $K_{m+1} = [A'_1, \ldots, A'_n]$. By subadditive cost function, $c(|A'_l| - 1, 0) \leq c(|A_i|, 0) + c(|A_j|, 0)$. Hence, $\sum_{l=1}^{n} c(|A_l| - 1, 0) \leq \sum_{i=1}^{k} c(|A'_i| - 1, 0)$. On the other hand, I have

$$[|A'_l| - 1]v = [|A_i| + |A_j| - 1]v \geq [|A_i| - 1]v + [|A_j| - 1]v$$

The RHS of this equation is the beefit of A_i and A_j in stage m, whereas the LHS is the benefit of A'_l in stage $m+1$. Hence, $\sum_{l=1}^{n}[|A'_l| - 1]v \geq \sum_{i=1}^{k}[|A_i| - 1]v$. The total net payoff of K_m is less than the total net payoff of K_{m+1}. Therefore, K_m is not efficient as long as K_m

is not completed network. ■

4.8 Myopic vs. Double Best Response Algorithm

In this part, I compare the double best response to the myopic algorithm which is common in the literature. In the myopic algorithm, the proposer only offers to his top choice. Formally, agent i proposes connection to agent j if

$$\pi_i(G) = \underset{j/\overline{ij}\notin G}{\arg\max}\, vl_j^i - c(G \cup j)$$

The myopic algorithm is more flexible than double best response algorithm. In particular, responder j will accept proposal as long as $\Delta\pi_j > 0$, while the double best response algorithm requires that j accepts only proposal from his top choice. For simplicity, I restrict the analysis in the case that the algorithm selects agents one by one component process. The following definition explains the one by one process.

Definition 8 *(One by one component selection) The algorithm is one-by-one component selection, if the following step is completed.*

1. *The algorithm randomly choose a component with uniform probability.*
2. *The algorithm makes list of players in that component and randomly selects a proposer. Once a link is formed.*
3. *The algorithm continues to the next player in the list.*
4. *Once all agents in that component have an opportunity to form a link, the algorithm moves to another component and repeats the process again.*

Proposition 11 *Assume that the algorithm uses the one by one component process and lists the components from minimum to maximum size, the limit network of myopic algorithm converges to the limit network of double best response algorithm.*

Proof. Since the network starts from empty, there is some point in time that network is $[A_1, A_2, \ldots, A_n]$, where A_i is component i. Assume $|A_1| \leq |A_2| \leq \cdots \leq |A_n|$, where $|A_i|$ is size of completed component i. Suppose that $v \geq c(|A_1|, |A_2|-1) - c(|A_1|-1, 0)$. $|A_1|$ have pontential to merge $|A_2|$. Agent in $|A_2|$ is agents in $|A_1|$' s top choice because $|A_2| \leq |A_3| \cdots \leq |A_n|$. Then agent in $|A_1|$ will propose the link to agent in $|A_2|$. On the other hand, agent in $|A_1|$ is agents in $|A_2|$' s top choice. Note since agents are pessimistic, there is no difference whether or not $|A_2|$ is complete component. Then agent in A_1 and A_2 are top choice of each other. The merging procedure is the same for A_3 and so on as long as $v \geq c(|A_m|, |A_n|-1) - c(|A_m|-1, 0)$, where $|A_m| < |A_n|$. Therefore, myopic algorithm is equivalent to double best response algorithm. ■

This proposition shows that double best response algorithm is a special case of myopic algorithm and the limit network are exactly the same under circumstance in which algorithm list component from the minimum. The next example shows the case when algorithm randomly chooses component.

Example 8 *Suppose that the network at stage* $m-1$ *is* $[2,3,3,4,5]$ *when the final stage is* m *and the cost function is linear. Since agents offer and accept the offer from their top choice the network stage* m *of double best response algorithm is* $[(2+3),(3+4),5]$ *and the total payoff is* $82(v-\delta)$*. Note the total payoff is calculated from* $[(4*5)+(7*6)+(4*5)](v-\delta)$

On the other hand, if the algorithm randomly lists component such as choose size 4 *component first and then size* 3 *component, the network in stage* m *is* $[(2+4),(3+3),5]$ *and the total payoff is* $80(v-\delta)$*, which is less than* $82(v-\delta)$*. However, if the algorithm lists components from the maximum to minimum size, the network in stage* m *is* $[2+5, 3+4, 3]$ *and the total payoff is* $90(v-\delta)$*, which is greater than* $82(v-\delta)$*.*

Clearly, the result of comparison between myopic and double best response algorithm is ambiguous. Actually, it depends on the number of components at stage before the final stage. The general result is stated in the following proposition.

Lemma 4 *Suppose that the network in final stage is $[A_1, \ldots, A_n]$, where $|A_1| \leq |A_2|, \ldots, \leq |A_n|$ and the cost function is linear. The total utility is increasing in size of A_n.*

Proof. Let m be final stage. Since m is final stage, the component cannot merge together. When algorithm selects agent, he will make links in the same component. Then each component converges to completed component. Consider the limit network $[A_1, \ldots, A_{n-1}-x, A_n+x]$ and there is no loss of generality to assume that $v - \delta = 1$, where x is positive number. The utility in $A_{n-1} - x$ and $A_n + x$ are $(A_{n-1} - x)(A_{n-1} - (x+1))$ and $(A_n + x)(A_n + x - 1)$, respectively. Due to the fact that $(A_{n-1} - x)(A_{n-1} - (x+1)) < (A_n + x)(A_n + x - 1)$, the total utility is increasing in A_n. ■

Proposition 12 *Assume that algorithm follows one component selection process and the cost function is linear. Let m be the final stage where the network is $[A_1, \ldots, A_n]$ at stage $m-1$, where $|A_1| \leq \cdots \leq |A_n|$. Given $v \geq c(|A_i|, |A_n| - 1) - c(|A_i| - 1, 0)$.*

1. *If n is odd, the efficient algorithm is ambiguous.*
2. *If n is even, the double best response algorithm is not less efficient than myopic algorithm.*

Proof. Case 1 : n is odd. Clearly the example 8 shows the efficiency algorithm is ambiguous. The efficiency depends on the selection of algorithm.

Case 2 : n is even. Assume that m is the final stage where the partition in stage $m-1$ is $[A_1, A_2, \ldots, A_n]$. Since $v \geq c(|A_i|, |A_n| - 1) - c(|A_i| - 1, 0)$ and n is even, all components can merge and form $[A'_1, \ldots, A'_n]$ in the final stage, m , where $A'_i = A_m + A_j$ is the result of merging between A_i and A_j in stage $m-1$.

According to Lemma 4, the most efficient is the limit network which have the biggest size of A'_n. By the double best response algorithm, the limit network is $[A_1 + A_2, A_2 + A_3, \ldots, A_{n-1} + A_n]$. Since $A_{n-1} + A_n = \max_{i,j} A_i + A_j$, the double best response algorithm is not less efficient than the myopic algorithm. ■

4.9 Conclusion

This paper investigates the network configuration when cost of connection depends on distance, cost distance function. To characteristic the network, I propose the "double best response algorithm", where an agent offers/accepts an offer from his top choice. I find that if direct benefit is greater than the marginal cost of merging the two biggest components, the limit network will be complete. Otherwise, the limit network will be composed of many components, each of which is complete. In particular, I apply the general case to the specific case, a linear cost function. In the linear cost function, the distance of agents does not affect to the network configuration. I also justify the double best response algorithm by comparing it with myopic algorithm, where an agent offers/accepts an offer as long as the connection give him positive payoff, rather than maximum payoff. I find that the network configuration is sensitive to the number of agents and the way that algorithm randomly selects the agents.

In the model, the network configuration is formed from an empty network. In addition, I do not allow an agent to delete the existing connection. There are rooms to investigate the network configuration in which the agent is a part of the network already. Deleting the existing link will be crucial in that environment. In addition, the justification of double best response algorithm is based on one by one component selection process. The result might be challenged if algorithm has random selection process.

Chapter 5

Conclusion Remarks

This dissertation, “Essays on Environmental Management and Network Economics”, studies cooperation in common pooled resource. The chapter 2 applies a two part punishment scheme, punishment and resume to cooperation, to Bioeconomic model. I study the cooperation in a dynamic game taking into account the effect of resource dispersal between patches. The environment of this paper is different from the standard common pooled resource in the sense that agents have property rights over their patch but the resource disperses across patches. By applying a worst perfect equilibrium, I state the strategy that cooperation is supportable Subgame Perfect equilibrium. An agent who deviates from cooperation will be severely punished and drive the payoff to the minimum. Moreover, I find that level of cooperation depends on the pattern of fishing dispersal. The main reason is that the bargaining power among agents depends on the pattern of dispersal (i.e. which patch the fish migrates to or from). In particular, the patch which only receive fish migration from others does not have bargaining power. That patch owner cannot make a punishment. In this scenario, Subgame Perfect equilibrium is not supported and a side payment mechanism to sustain cooperation is needed.

Chapter 3investigates the following questions (i.) Does partial communication reduce individual’s extraction?; (ii.) Comparing partial communication and external regulation treatment, which one is better in term of both maintaining high resource levels and supporting cooperation behavior? and (iii.) Is there a difference in extraction and cooperation behavior between partial and full communication? To answer these questions, I separate the 104 participants to four treatments which are external regulation, partial communication and full communication treatments. Open access, the no rule case, is treated as a benchmark.

To compare the effect of each treatment with open access, a Difference-in-Difference approach is applied. The paper finds that external regulation and communication can reduce extraction. Compared across regulatory schemes in both absolute extraction level and change in extraction, I find that the highest extraction is subjects in external regulation, followed by those in partial communication and full communication treatments, respectively.

The paper investigates more thoroughly about the factors which make extraction different across treatments. I consider two factors: commitment levels and compliance. For commitment level, although subjects in both partial and full communication treatments set the same commitment level at the beginning, the commitment level increases over time in partial communication, whereas it remains at social optimum under full communication treatment.

For compliance, the probability of compliance in partial and full communication treatments are higher than those of external regulation. Subjects have the highest deviation in external regulation, followed by partial communication and full communication, respectively. Moreover, I find that conditional on the decision to deviate, the highest deviation is subjects in external regulation, followed by outside subjects, communicators and subjects in full communication, respectively.

Based on the findings in this paper, local government should relax the existing rule and encourage communities to set up self governance institution. However, communication which is the key of institution in reality is not easy as in the paper. The key factor to obstruct the communication is transaction cost. Therefore, the role of government officers should change from regulatory to facilitator. For example, the local officers can be the host of meeting or can be the coordinator to announce the rule to non communicator resource users.

Chapter 4 explores the network configuration when cost of connection depends on distance, cost distance function. To characteristic the network, I propose the "double best response algorithm", where an agent offers/accepts an offer from his top choice. I find that if direct benefit is greater than the marginal cost of merging the two biggest components, the limit network will be complete. Otherwise, the limit network will be composed of many components, each of which is complete. The intuition of result is straightforward from the asymmetry between the benefit and cost of making connection. Since agents attain benefits only from the direct connection but bear costs from both the direct and indirect connection, the best strategy for all agents is to remove the indirect connection. However, since the network starts from empty network, agents need time to secure their complete network. Before reaching that state, there is some point in time at which agents have many indirect connections and higher costs than they can handle. In this situation, the equilibrium is for agents to form the small component and make direct connections with each other. If the net marginal benefit of the direct connection is high enough, then agents can form connections across components and create larger components.

Appendix A

Appendix to Chapter 1

A.1 Show that $e^*_{it} < \hat{e}_{it}$ when $c'(.) = 0$.

This part will show that fisherman will harvest less in corporation case when the (unit) cost is fixed for all patches, $c_i(s) = c_i$ for all i.

Cooperation case

Since $c_i(s) = c_i$, we can write the fisherman's profit as $a_i h_{it}$, where $a_i = (p - c_i)$. In addition, since $h_{it} = s_{it} - e_{it}$, the joint rent maximization is

$$\begin{aligned} \underset{\{e_t\}_{t=0}^{\infty}}{\text{maximize}} \quad & \sum_{t=0}^{\infty} \beta^t \sum_{i=1}^{N} a_i (s_{it} - e_{it}) \\ \text{subject to} \quad & s_{it+1} = e_{it} + \sum_{j=1}^{N} g_i(e_{i,t}) D_{ji}, \qquad \forall i \end{aligned}$$

The Bellman equation is

$$V(s_t) = \max_{0 \le e_{it} \le s_{i,t}} a_i (s_{it} - e_{it}) + \beta V(s_{t+1})$$

The necessary condition for all periods is

$$-a_i + \beta \sum_{j=1}^{N} \frac{\partial V(s_{t+1})}{\partial s_{jt+1}} \frac{\partial s_{jt+1}}{\partial e_{it}} = 0 \qquad , \forall i$$

The constraint equations can be substituted to the necessary condition as

$$-a_i + \beta \{ a_i + \sum_{j=1}^{N} a_j g_i'(e_{it}^*) D_{ji} \} = 0 \quad , \forall i$$

Algebraically, we can write it as

$$g_i'(e_{it}^*) = \frac{a_i k}{\sum_{j=1}^{N} a_j D_{ji}} \quad , \forall i$$

where $k = \frac{1-\beta}{\beta}$.

Non-cooperation case

The individual fisherman's problem is

$$\begin{aligned} \underset{\{e_{it}\}_{t=0}^{\infty}}{\text{maximize}} \quad & \sum_{t=0}^{\infty} \beta^t a_i (s_{it} - e_{it}) \\ \text{subject to} \quad & s_{it+1} = e_{it} + \sum_{j=1}^{N} g_i(e_{it}) D_{ji}, \end{aligned}$$

The necessary condition is

$$-a_i + \beta \sum_{j=1}^{N} \frac{\partial V(s_{t+1})}{\partial s_{jt+1}} \frac{\partial s_{jt+1}}{\partial \hat{e}_{it}} = 0$$

which is the same as the cooperation case. However, since the agent does not take into account other patches, we can set $a_j g_i'(e_{it}) D_{ji} = 0$ for all $j \neq i$. The necessary condition can rewritten as

$$-a_i + \beta[a_i + a_i g_i'(\hat{e}_{it}) D_{ii}] = 0$$

Algebraically, we can write it as

$$g_i'(\hat{e}_{it}) = \frac{k}{D_{ii}}$$

Therefore, $\frac{a_i k}{\sum_{j=1}^{N} a_j D_{ji}} = g_i'(e_{it}^*) < g_i'(\hat{e}_{it}) = \frac{k}{D_{ii}}$ as long as $D_{ii} < 1$. It means that the non cooperation and non cooperation case are different when the larvae of one patch affects fish stock of other patches. Since $g(.)$ is concave, it implies that $e_{it}^* > \hat{e}_{it}$.

Appendix B

Appendix to Chapter 2

B.1 Payoff Table

The Table B.1 represents the payoff table. The columns are individual extraction $1 - 10$, and the rows are other subjects' extraction $7 - 70$. According to our parameters, the payoff can be negative when subjects extract more than the Nash equilibrium. The negative payoff reflects the fact of short run extraction. For example, the revenue from fish might not cover fishing costs, if fish are less abundant.

Table B.1: Payoff Table

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
7	64	126	186	244	300	354	406	456	504	550
8	63	124	183	240	295	348	399	448	495	540
9	62	122	180	236	290	342	392	440	486	530
10	61	120	177	232	285	336	385	432	477	520
11	60	118	174	228	280	330	378	424	468	510
12	59	116	171	224	275	324	371	416	459	500
13	58	114	168	220	270	318	364	408	450	490
14	57	112	165	216	265	312	357	400	441	480
15	56	110	162	212	260	306	350	392	432	470
16	55	108	159	208	255	300	343	384	423	460
17	54	106	156	204	250	294	336	376	414	450

Continued on next page

Table B.1 – continued from previous page

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
18	53	104	153	200	245	288	329	368	405	440
19	52	102	150	196	240	282	322	360	396	430
20	51	100	147	192	235	276	315	352	387	420
21	50	98	144	188	230	270	308	344	378	410
22	49	96	141	184	225	264	301	336	369	400
23	48	94	138	180	220	258	294	328	360	390
24	47	92	135	176	215	252	287	320	351	380
25	46	90	132	172	210	246	280	312	342	370
26	45	88	129	168	205	240	273	304	333	360
27	44	86	126	164	200	234	266	296	324	350
28	43	84	123	160	195	228	259	288	315	340
29	42	82	120	156	190	222	252	280	306	330
30	41	80	117	152	185	216	245	272	297	320
31	40	78	114	148	180	210	238	264	288	310
32	39	76	111	144	175	204	231	256	279	300
33	38	74	108	140	170	198	224	248	270	290
34	37	72	105	136	165	192	217	240	261	280
35	36	70	102	132	160	186	210	232	252	270
36	35	68	99	128	155	180	203	224	243	260
37	34	66	96	124	150	174	196	216	234	250
38	33	64	93	120	145	168	189	208	225	240
39	32	62	90	116	140	162	182	200	216	230
40	31	60	87	112	135	156	175	192	207	220
41	30	58	84	108	130	150	168	184	198	210
42	29	56	81	104	125	144	161	176	189	200
43	28	54	78	100	120	138	154	168	180	190
44	27	52	75	96	115	132	147	160	171	180
45	26	50	72	92	110	126	140	152	162	170
46	25	48	69	88	105	120	133	144	153	160
47	24	46	66	84	100	114	126	136	144	150
48	23	44	63	80	95	108	119	128	135	140
49	22	42	60	76	90	102	112	120	126	130
50	21	40	57	72	85	96	105	112	117	120
51	20	38	54	68	80	90	98	104	108	110

Continued on next page

Table B.1 – continued from previous page

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
52	19	36	51	64	75	84	91	96	99	100
53	18	34	48	60	70	78	84	88	90	90
54	17	32	45	56	65	72	77	80	81	80
55	16	30	42	52	60	66	70	72	72	70
56	15	28	39	48	55	60	63	64	63	60
57	14	26	36	44	50	54	56	56	54	50
58	13	24	33	40	45	48	49	48	45	40
59	12	22	30	36	40	42	42	40	36	30
60	11	20	27	32	35	36	35	32	27	20
61	10	18	24	28	30	30	28	24	18	10
62	9	16	21	24	25	24	21	16	9	0
63	8	14	18	20	20	18	14	8	0	-10
64	7	12	15	16	15	12	7	0	-9	-20
65	6	10	12	12	10	6	0	-8	-18	-30
66	5	8	9	8	5	0	-7	-16	-27	-40
67	4	6	6	4	0	-6	-14	-24	-36	-50
68	3	4	3	0	-5	-12	-21	-32	-45	-60
69	2	2	0	-4	-10	-18	-28	-40	-54	-70
70	1	0	-3	-8	-15	-24	-35	-48	-63	-80

B.2 Experiment instruction

B.2.1 Baseline

Assume that you are an investor. You desire how many investment units you want to invest in each round. All subjects are endowed with 10 investment units. You can choose $1, 2, \ldots, 10$ investment units. Decimal are not allowed. Once you make a decision, you write it in the game card. Your decision is independent and private.

The return of investment depends on 2 things.

1. **Individual investment** : The more investment, the more benefit you receive.

2. **Gross investment** : The more gross investment, the less benefit you receive. In this point, you can understand that everyone's share (including your share) decrease when there are lots of investment.

The return you receive is calculated from the net effect of those. For simplicity, let's think that you are fishermen in Songkla lake. Every day, you decide how many hours you want to harvest. Of course, the more hours, the more fish you get. However, if all fishermen harvest many hours, you can get less.

Next, I will explain how investment return is calculated. See payoff table.

Example 1. If other subjects's investment is 35 unit, and you invest 6 units, your return is 186 experiment dollar.

Example 2. If other subjects's investment is 70 unit, and you invest 8 units, your return is -48 experiment dollar. In this case, instead of receiving, you have to pay 48 experiment dollar.

Note the grey column in payoff table represents your best response, given other subjects' investment.

When the round end, I will collect game card and announce the total investment. You must record the following in decision record sheet. (*i.*) gross investment (*ii.*) individual investment and (*iii.*) the return of investment.

The cash you earn at the end of experiment is the summantion of investment earning in each round.

B.2.2 External regulation

From now on, the experimenter will change the rules of the game as follows. All subjects have quota 5 units of investment. Your decision in investment unit is still independent and private. When you have already desired, experimenter will monitor randomly by drawing balls.

I draw with replacement a ball from ballots in which there are 2 balls, one is orange and another one is white. If I have white ball, there is no monitoring in that round. On the other hand, if I have orange ball, that round has monitoring. Each subject has to draw a ball with replacement from another ballot in which there are 8 balls, 7 white balls and one orange ball. If you have orange ball and you invest more than 5, you have to pay 29 experiment dollar per investment unit.

For example, If you invest 10 units and are monitored, the fine is $145(= 5*29)$ experiment dollar. On the other hand, if you are not monitored, you do not have fine. **The random monitoring is applied for all subjects.**

When the monitoring process is finished, experimenter will announce the total investment.

B.2.3 Partial Communication

From now on, experimenter will change the rule of game as following. All subjects are divided to 2 groups, 6 subject group and 2 subject group.

For communication group, all 6 subjects have 8 minutes to talk together in communication session. In communication session, you can talk anything except (1.) making agreement on monetary transfer (2.) looking game card of other subjects (3.) looking decision record sheet of other subjects. At the end of communication session, group has to agree on individual investment target. Before next round starts, all 6 subjects have 2 minutes to talk together. You can change investment target. If so, group has to inform experimenter. The individual investment is still independent and private. During communication session, all of communication are recorded for research purpose. All names are anonymous.

I recommend that the optimal investment is less than 8 tokens. The optimal investment is the level at which the aggregate earning is the maximum. However, it might not be your best choice. For example, if the individual target is 5 tokens and everyone invest that level, everyone equally receives the same earning 160 experiment dollar and the aggregate earning will be $1280(= 160 * 8)$. However, if there is one subject invest 10 tokens, he will receive 270 experiment dollar, while other subjects will attain 135 experiment dollar. The aggregate earning is $1215(= 270 + (135 * 7))$.

Please remind yourself the fact that you can invest more than the target. Similarly, everyone can do the same thing. If so, you are back to round $1 - 10$.

For outside subjects, you are not allowed to talk. Experimenter will inform communication group's investment target. Also, you will be updated all of changing in investment target.

Once you have already desired investment, experimenter will monitor randomly by drawing balls. Experimenter will draw a ball with replacement from ballots in which there are 2 balls, one is orange and another one is white. If I have white ball, there is no monitoring. On the other hand, if I have orange ball, monitoring is applied. Each subject has to draw a ball with replacement from another ballot in which there are 8 balls, 7 white balls and one orange ball. If you have orange ball and you invest more than 5, you have to pay 29 experiment dollar per investment unit.

For example, If you invest 10 units and are monitored, the fine is $145(= 5*29)$ experiment dollar. On the other hand, if you are not monitored, you do not have fine. **The random monitoring is applied for all subjects.**

When the monitoring process is finished, experimenter will announce the total investment.

B.2.4 Full Communication

The instruction is the same as partial communication treatment, except the part of outside subjects.

Appendix C

Appendix to Chapter 3

C.1 Proof of proposition 5

In stage m, the agent $a_m = 2^k$ makes a decision to accept/reject the offer from $p_m = 2^k$. He will accept if

$$v > c(2^{m-1}, 2^{m-1} - 1, 0, \ldots, 0) - c(2^{m-1} - 1, 0, \ldots, 0) \tag{C.1}$$

and forms the partition $K_{m+1} = [2^{m+1}, \ldots, 2^{m+1}]$.

In state $m + 1$, the agent a_m make a decision to accept/reject the offer from p_m. He will accept if

$$v > c(2^{m+1}, 2^{m+1} - 1, 0, \ldots, 0) - c(2^{m+1} - 1, 0, \ldots, 0) \tag{C.2}$$

and form the partition $K_{m+2} = [2^{m+2}, 2^{m+2}, \ldots, 2^{m+2}]$.

The merging algorithm stops at K_m if v is not satisfied equation C.1 and will stop at K_{m+1} if v is in between equation C.1 and equation C.2.

C.2 Proof of proposition 6

Since N is odd, it can write in form $N = 2^k(I+1) + [N]_{2^k})$. There is some point in time, say state k, that the network is

$$K_k = [2^k, \ldots, 2^k, 2^k + [N]_{2^k}]$$

Case a : I is even.

In stage k, agent in active component, 2^k, makes a decision to accept the offer from the agent in the passive component, 2^k. The agent in the active component will accept if

$$v > c(2^k, 2^k - 1, 0, \ldots, 0) - c(2^k - 1, 0, \ldots, 0) \tag{C.3}$$

and forms the partition $K_{k+1} = [2^{k+1} \ldots, 2^{k+1}, 2^k + [N]_{2^k}]$

In state $k+1$. Now the $a_{k+1} = 2^k + [N]_{2^k}$ makes a decision to accept the offer from $p_{k+1} = 2^{k+1}$. The agent in a_{k+1} will accept the offer if

$$v > c(2^k + [N]_{2^k}, 2^{k+1} - 1, 0, \ldots, 0) - c(2^k + [N]_{2^k} - 1, 0, \ldots, 0) \tag{C.4}$$

and form the partition $K_{k+2} = [2^{k+1}, \ldots, 2^{k+1}, 3(2^k) + [N]_{2^k}]$.

The merging algorithm stops at K_k if v is not satisfied C.3 and stops at K_{k+1} if v is between equation C.3 and C.4 and the network converges to K_{k+1}. For the stage $k \geq k+2$, the pattern of merging is the same with this process.

Case b : I is odd

In stage k. The agent in the active component, 2^k component, make a decision to accept the offer from the agent in the passive component, 2^k. The agent in the active component will accept if equation C.3 is satisfied. The partition is

$$K_{k+1} = [2^{k+1}, 2^{k+1}, \ldots, 2^{k+1}, 2^k, 2^k + [N]_{2^k}]$$

in stage $k+1$. Now the $a_{k+1} = 2^k$ makes a decision to accept the offer from $p_{k+1} = 2^k + [N]_{2^k}$. The agent in a_{k+1} will accept the offer if

$$v > c(2^k, 2^k + [N]_{2^k} - 1, 0, \ldots, 0) - c(2^k - 1, 0, \ldots, 0) \tag{C.5}$$

and form the partition $K_{k+2} = [2^{k+1}, 2^{k+1}, \ldots, 2^{k+1}, 2(2^k) + [N]_{2^k}]$.

The merging algorithm stops at K_k if v is not satisfied equation C.3 and stops at K_{k+1}, if v is in between equation C.3 and C.5.

C.3 Proof of proposition 7

Since the $N = 2^m h = 2^{m+k}[(I+1) + [N]_{2^k}]$, the proof is very close to proposition 6. There is some point in time, say state $m+k$, that the network is

$$K_i = [2^i), 2^i), \ldots, 2^m(2^k), 2^m[2^k + [N]_{2^k}]]$$

Case a : I is even.

In stage k. The agent in active component, 2^i, makes a decision to accept the offer from the agent in the passive component, 2^i. The agent in the active component will accept if

$$v > c(2^i, 2^i - 1, 0, \ldots, 0) - c(2^i - 1, 0, \ldots, 0) \tag{C.6}$$

and form the partf ition $K_{i+1} = [2^{i+1}, \ldots, 2^{i+1}, 2^m(2^k + [N]_{2^k})]$.

In stage $k+1$. Now the $a_{i+1} = 2^m(2^k + [N]_{2^k})$ makes a decision to accept the offer from $p_{i+1} = 2^i)$. The agent in a_{i+1} will accept the offer if

$$v > c(2^m(2^k + [N]_{2^k}), 2^i - 1, 0, \ldots, 0) - c(2^m(2^k + [N]_{2^k}) - 1, 0, \ldots, 0) \tag{C.7}$$

and form the partition $K_{i+2} = [2^{i+1}, \ldots, 2^{i+1}, 3(2^i) + 2^m[N]_{2^k}]$.

The merging algorithm stop at state $k+1$, if v is in between equation C.6 and C.7 and the network converges to K_{i+1}.

Case b : I is odd

In stage k. The agent in active component, 2^i component, makes a decision to accept the offer from the agent in passive component, 2^i. The agent in the active component will accept if equation C.6 is satisfied. The partition is $K_{i+1} = [2^{i+1}, \ldots, 2^{i+1}, 2^i, 2^m(2^k + [N]_{2^k})]$

In state $k+1$. Now the $a_{i+1} = 2^i$ makes a decision to accept the offer from $p_{i+1} = 2^m(2^k + [N]_{2^k})$. The agent in a_{i+1} will accept the offer if

$$v > c(2^i, 2^m(2^k + [N]_{2^k} - 1), 0, \ldots, 0) - c(2^i - 1, 0, \ldots, 0) \tag{C.8}$$

and forms the partition $K_{i+2} = [2^{i+1}, \ldots, 2^{i+1}, 2(2^i) + 2^m[N]_{2^k}]$.

The merging algorithm stops at state k if v is between equation C.6 and C.8 and the network converges to K_{i+1}.

C.4 Proof of proposition 9

To prove [**i.**], Show that no agent has second degree connection.

Stage 1 : Since the network is empty in stage 0, all players are indifferent. They then match randomly.

Stage 2 : There are 2 possible cases. First, there are many pairs, say $\overline{ij}$ and $\overline{kl}$. Player i and j will not offer to k or l because $\Delta l_2^i = 1 > \frac{v-\delta}{\delta^2}$. Second, the network is composed of many pairs and a separated agent, namely $\overline{ij}$ and k. In this case, player k is top choice but he cannot accept the proposal because $\Delta l_2^i = 1 > \frac{v-\delta}{\delta^2}$. Therefore, the network converges to either many independent lines or many independent lines and one separated player. In particular, if N is even, the network is many lines and if N is odd, there is one separated player.

To prove [**ii.**1], There are 3 steps.

Step 1 *Players make link between* 2 *paris and form component size* 4.

Stage 1 : Since $N = 4b$, there are $2b$ pairs (no separatd agent).

Stage 2 : Since all players have one direct connection, they are exactly the same. They can match randomly. Players will make a link between 2 pairs and the components with 4 players are formed. In particular, for any line $\overline{ij}$ and $\overline{kl}$. Making a link between lines create $\Delta l_2 = 1$ which is equal to $\frac{v-\delta}{\delta^2}$. It satisfy equation 4.1.

I now have a link between 2 lines. Assume that $\overline{ik}$ is formed. Let C_1 be component which composes of $\{\overline{ij}, \overline{kl}, \overline{ik}\}$. Consider the choice of j. Player j can form a link $\overline{jl}$ or she form a link $\overline{jo}$ where player o is from another component, C_2. If j makes link with o, then $\Delta l_2^j = 1$. But if j makes link with l, then $\Delta l_2^j = 0$ because before and after l_2^j is the same, who is k. Player j prefers to make link with l to o. Note it is the same if agent l is selected. Then $\overline{jl}$ is formed. Therefore, the component C_1 has exactly 4 players.

Step 2 *Each component is complete network.*

Stage 3 : Let us consider component C_1. Now I have $\{\overline{ik}, \overline{ij}, \overline{jk}, \overline{jl}\}$. In particular, all players have one direct and one indirect connection. Each player will either offer or accept the offer from her indirect connection. Player i wants to make a link with l because $\overline{il}$ make $\Delta l_2^i = -1$. Note Δl_2^i can be negative if the link decrease the number of l_2^i. Player i is better off and $\overline{il}$ is formed. It is the same as i for all players.

Step 3 *: Players will not make link across components.*

Now there are size 4 of b components. It means that every player has 3 direct connections. If i who is in C_1 match with o who is in C_2, then $\Delta l_2^i = 3$ which is greater than $\frac{v-\delta}{\delta^2}$. It contradicts with equation 4.1. Therefore, players will not match across components. The proof [ii.1] is done.

According to proof [ii.1], it is straightforward that agents' top choice is always others who is in the same component. The intuition is that agents consider only the marginal of l_2. Consequently, linking within his own component not only increases the benefit from the direct connection but also reduces the number of l_2. Note this fact is true, regardless of size of component. The next lemma states this fact formally.

Lemma 5 *Once the component is formed. The agent's top choice is others who is in his own component.*

To prove [ii.2], $N = 4b + 1$.

Stage 1 Since $N = 4b + 1$ is odd, there are $2b$ pairs and one separated player.

Stage 2 Let i be a separated player. Player i is the top choice of everyone because making link with him make $\Delta l_2 = 0$. Assume $\overline{ij}$ is formed. Now a component with 3 players is formed, namely C_1. In particular, C_1 is composed of $\{\overline{ij}, \overline{jk}\}$ where $\overline{jk}$ has existed since stage 1.

Now consider the rest $2b-1$ pairs. Since $2b-1$ is odd, agents can form $b-1$ components of size 4 and one pair left. Assume that o is agent in a pair left. Note $\overline{om}$ exists already. Suppose that o is selected by algorithm. He has 2 choices, proposing to size 4 or to size 3. However, an agent of size 4 will not accept because o is not his top choice by lemma 5. Then the only way to make a link is proposing to agent k who is of size 3 component and did not make any link in this stage. On the other hand, k will accept the proposal because it makes $\Delta l_2 = 1$. Consequently, the network composes of $b - 1$ size 3 and one size 5 component.

Stage 3 and so on : The agents maximize the link within his component by lemma 5. The complete network in component is network finally. There is no agent who can make a link across component by the same reason as step 3 in part [ii.1].

To prove [ii.3], $N = 4b + 2$.

Stage 1 Since $N = 4b + 2$ is even, there are $2b + 1$ pairs.

Stage 2 Agents can form $2b$ size 4 component and one pair left. Again, once the size 4 component is formed, the agent in a pair will not be top choice. Consequently, the network has b complete component of size 4 and one pair.

To prove [ii.4], $N = 4b + 3$

Stage 1 Since $N = 4b+3$ is odd, there are $2b+1$ pairs and one separated player. Stage 2 Let i be a separated player. Every player want to make connection with i because connecting with her make $\Delta l_2 = 0$. Assume that $\overline{ij}$ is formed. Now the component with 3 players, $C_1 = \{\overline{ij}, \overline{jk}\}$ where $\overline{jk}$ has been formed since stage 1. Then the rest of players is $N = 4b$. The result is the same as part [ii.1]. Therefore the equilibrium is many components with 4 players and one component with 3 players.

To prove [iii.],

Since $\frac{v-\delta}{\delta^2} \geq 3$, agents can make a link across components. Let $\#C_m$ be the number of players in component m associating with the result of part [ii.]. I can rank $\#C_1 \leqslant \#C_2 \leqslant \cdots \leqslant \#C_m$. Then $\#C_1$ is the top choice of the rest agents. On the other hand, agent in $\#C_1$ will accept only the proposal from the agent in $\#C_2$ because it is the minimum of Δl_2. For the rest of agents, the merging pattern is exactly the same. Therefore, the merging process is done as one-by-one component. Again, by lemma 5, each component is a complete network.

Let $\#C'_m$ be the number of players in component m which is the result of merging process. Note $\#C'_m \geq \#C_m$ for all m. The merging will stop when $k > \min \#C_m$.

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