Strategic Interactions on Networks: An Experimental Approach*

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Abstract

This paper experimentally investigates how global and local characteristics of a network influence the equilibrium selection and behavior in a network public goods game. Bramoulle et al (2014) shows that the equilibrium of the public good game can be characterized according to the simple characteristics of the underlying network. Precisely, guided by the theoretical predictions from Bramoulle et al(2014), I explore whether underlying networks can predict equilibrium selection and subjects' behavior in the controlled laboratory. The data implies that 1) there is some aspect in which agents' actions are consistent with the claims of Bramoulle et al(2014), but 2) local, rather than global, characteristics of the network are more fundamental in influencing behavior and equilibrium selection. Specifically, I show that asymmetry inside of network is a major factor in explaining the actions of individual economic agents.

Keywords: Network, local public good games, experiment, strategic substitute
JEL classification: C91, D00, D81, D85, C72, H41

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1 Introduction

Traditional economics model yields a number of insights about implications of rational decisions for resource allocation and welfare. However, it seems not to be able to explain some tenacious empirical results like patterns of diffusion related with technology and segregation of neighborhood. In the recent past traditional model of human behavior with anonymous interaction has been developed in micro economic theory. However there is another literature trends that take into account the network in which the actors are embedded. In fact, the economics of social networks has gained attention from the new economics trend. In a real world, wide variety settings where social network play a role leads to an almost endless set of interesting avenues to investigate (Jackson 2005). As predictions from models proliferate, I test these network theories whether they truly understand the behavior of economic agents.

In Bramoulle and Kranton (2007, henceforth BK), they made a set up for local public good games in which individuals are part of networks and invest the contribution of local public goods. Their model is characterized by two main features: First, agents are embedded in a fixed network. Second, agents' payoff are directly affected by their partners' actions only. In BK, they suggests networks can lead to specialization which means some agents fully contribute to the public good provision while remaining agents free-ride. However, the evidence is not supported in empirical data. In Rosenkranz et al (2012), they study a lab experiment to find the empirical evidence of BK. However, the specialized action and specialized equilibrium is rarely presented in some networks. Instead, all agents made a positive contribution.

In Bramoulle et al (2014), they suggest the theory explaining the impact of global network structure to the equilibrium selection. They study the setting in line with BK. Agents are positioned in a fixed network and play the local public good games. However, the difference with the BK is that they have a "decay" factor between agents which means that there is a smoothed impact of each players' action to their connected neighbors. Their main result is that the structure of network can affect the amplification of agents' action. Their analysis leads to these insights. First when the global networks structure amplifies enough the contributions of agents (override the decay factor between agents), networks can lead to specialization and that in any network there is a multiple Nash equilibria. Second, when the global networks structure cannot amplify the strategic substitution of action between agents, then the network has unique and stable Nash equilibrium. These theoretical results show that the global network property is critical to equilibrium prediction and individual behavior.

I designed an experiment to explicitly address and identify the impact of local and global network to the equilibrium selection and behavior of agents described in Bramoulle et al (2014). I tested hypothesis which contains the core of the model in Bramoulle at al (2014). First, I test a hypothesis regarding the lowest eigenvalue of networks of networks "$|\lambda_{min}|$". In Bramoulle et al (2014), This is a measure of amplification of network structure. I find that there are some data trend which is consistent with the theory of Bramoulle et al (2014). When the global network structure amplifies the strategic substitute between agents well enough, the behavior of agents changed in a more specialized way what Bramoulle et al (2014) described. However, there is no significant difference in equilibrium selection. Second, I test a hypothesis regarding the decay factor, "δ". In Bramoulle et al (2014), they find the the interaction between δ and $|\lambda_{min}|$. If δ is low enough in comparison to the $|\lambda_{min}|$, then there is unique equilibrium. Likewise $|\lambda_{min}|$, δ affects the amplification of agents' action. I made a design to test this theory. Although Charness et al(2014) have an interest in equilibrium selection in networks, their focus does not lies on the the global characteristics of network. In that sense, This paper has a contribution which is the first to show the effect of global and local network characteristics to the equilibrium selections in a systematic way.

I also have a concern that there will be another local and global characteristics of networks which is not captured by the theory also can affect the equilibrium selection and individual behavior. More specifically, I have a conjecture that the behavior of agents can be largely depend on their local network characteristics. There are many experimental evidence that people react to the local network structure. In Rosenkranz et al(2012), they show that adding links to agents increases significantly the behavior of free-riding. With this same consensus, I focus on the asymmetry of network structure. asymmetry means the unequal distribution of local degree. For example, In core-periphery networks, some agents are benefited from many neighbors while other agents are connected with small numbers of neighbors. This local characteristics are not captured by the theory of Bramoulle et al (2014). This paper is the first paper finds the empirical evidence of the impact of asymmetry to the equilibrium selection in networks. Another network characteristics which is not captured by the theory of Bramoulle et al (2014) is average degree of networks. Average degree means how many neighbors each agent have on average in the network. This is related with the density of networks which means that how close the network is with the complete network. This feature is also not considered in theoretical model in Bramoulle et al (2014). In Rosenkranz et al (2012) find the significant increased of free-riding behavior of agent when the degree of agent is increased.

This paper consists of two parts. First analysis is equilibrium convergence of group behavior. The main result of this paper is that there is no significant difference in Nash equilibrium convergence across treatment regarding $|\lambda_{min}|$. However, there is significant difference in equilibrium selection regarding δ. This implies that δ has more fundamental effect to the equilibrium selection in comparison to the $|\lambda_{min}|$. Not only δ but also asymmetry and average degree have significant treatment effect on the equilibrium convergence. Second analysis is individual behavior. The reason why I focus on individual level data is that the frequency of Nash equilibria convergence is quite low (On average 20% of data). This patterns are also presented in Charness et al (2014) and Rosenkranz et al (2012). In Charness et al (2014), about 50% of group level data converged on the equilibrium. In Rosenkranz et al (2012), less than 3% of group level data converged on the exact Nash equilibrium. To understand the incentive of individual, it is important to analyze the behavior of individual contribution.

2 Theory

In this section, I briefly summarize the model and findings of Bramoulle et al (2014) and bringing the theory into testable hypothesis. Suppose that there are N agents who are located in fixed networks and let $x_i \geq 0$ denote agent i's level of actions while x_{-i} denote the actions of all agents other than i. Agents play the simultaneous local public good games.

Agents are arranged in a network which is represented by an undirected network g, $g_{ij} \in \{0, 1\},\ g_{ij} = g_{ji},\ for\ all\ i, j \in N$. By collecting this link information we can construct the $n \times n$ adjacency matrix G. A payoff parameter $\delta \geq 0$ measures how much i and j affect each others' payoffs given they are connected. Each agent receives benefit from their neighbors' action given network structure and her marginal cost to her own contribution is constant. Therefore, agent i's payoff can be represented as below.

$$u_i(x_i, x_{-i}, \delta, G) = b(x_i + \delta \sum g_{ij}x_j) - \kappa_i x_i \ with\ b' > 0, b'' < 0.$$

They assume $b'(0) > \kappa_i$ to avoid trivial cases. It is straightforward to show that agents have linear best reply form.

$$f_i(x_{-i}, \delta, G) = \begin{cases} \bar{x}_i - \delta \sum_j g_{ij}x_j & if \quad \delta \sum_j g_{ij}x_j < \bar{x}_i \\ 0 & if \quad \delta \sum_j g_{ij}x_j \geq \bar{x}_i \end{cases}$$

The amount of action between neighbors are strategic substitutes ; the more action an agent take, the less incentive neighbors' take. In Nash equilibrium, all agents in the network take the linear best reply from described as above. The action profile of a network is active when the amount of actions are strictly positive for all agents. This means that there is no free-rider in a network. The action profile in a network is specialized when the action of agents in a network is either 0 or $\bar{x}$. This means specialization between agents. Some agents fully contribute to the public goods, while some agents free ride to their contribution.

Before investigate main results of Bramoulle et al (2014), there are global and local graph structural notations in networks. First, the absolute value of lowest eigenvalue of adjacency matrix G , $|\lambda_{min}|$. Intuitively, as $|\lambda_{min}|$ is larger, the more agents' actions rebound in network. This means that the global network structure can be measured its amplification by the value of $|\lambda_{min}|$. It is crucial to the shape of equilibria set because if the network amplifies enough the strategic substitute, the more incentive to free-ride each agent has. Second, the degree of each agent i, $\eta_i(G) = |N_i(G)|$. It denotes the number of neighbors what agent i has. Third, we refer $|\eta_{avg}|$ as average degree of network. It means how many neighbors each agent has on average perspective. Fourth, a network is *symmetric* if every agent in network has the same number of neighbors, i.e. $\eta_i(G) = \eta \; \forall i \in N$.

Bramoulle et al (2014) describes the properties of equilibria set. When the distribution of actions is specialized (all agents choose 0 or $\bar{x}$), this is called as specialized equilibrium. (Those who choose 0 called free-rider and those who choose $\bar{x}$ called full-contributor). On the other hand, the equilibrium profile which all gents i choose non-zero actions is called active equilibrium. Active equilibrium is more equal than specialized equilibrium.

[Theorem 1] If $|\lambda_{min}| < \frac{1}{\delta}$, *there is a unique and active Nash equilibrium.*

This means that, for multiple equilibria, the network should amplify the strategic substitution of each agent captured by the lowest eigenvalue of the network. This result in on the basis that the agents can rationally recognize the structure of global network.

Furthermore, in Bramoulle et al (2014), they emphasize the role of lowest eigenvalue amplifying strategic substitutes between agents.

[Proposition 4] For $|\lambda_{min}| > \frac{1}{\delta}$,. there are multiple equilibria including specialized equilibrium.

In summary, these theoretical prediction represent $|\lambda_{min}|$ of network plays important role in characterizing the equilibria. Specifically, $|\lambda_{min}|$ increases, the network amplifies the strategic substitute between players. This paper's main goal is to test this theoretical prediction and find another structure of network can affect the equilibrium selection of agents. Following hypotheses are formulated on the basis of this theory of prediction Bramoulle et al (2014).

2.1 Direction of Analysis

First hypothesis is about the main result of Bramoulle et al (2014). In their theory, as the lowest eigenvalue increases, specialized equilibrium profile is added to the equilibria set. Therefore, the prediction of equilibrium selection is that agents coordinate on the specialized equilibrium profile more easily. In Rosenkranz et al (2012), their results say that the frequency of converging specialized equilibria is less than 0.5% even though the specialized equilibria is in the theoretical prediction. This means that agents have a tendency to avoid the asymmetric equilibrium. However, they did not control the global and local network characteristics. To test this concern more systematically, I controlled global and local characteristics except the lowest eigenvalue. Following hypothesis is

(H.1) As the lowest eigenvalue increases, individuals are able to coordinate on the corresponding specialized equilibria.

Second hypothesis is about the role of δ. Different from the $|\lambda_{min}|$, δ is related with more directly to the agent's payoff. In Rosenkranz et al (2012) and Charness et al (2014), they did not have variation of δ. In theoretical perspective, as δ increases, the incentive to free-ride on the other player's contribution will increase. In Bramoulle et al (2014), the increase of δ is interpreted as the magnitude of amplifying the strategic substitute between players increases. This effect is same with the increase of $|\lambda_{min}|$ in theory. Therefore this paper is to test whether the equilibrium selection changes following the change of δ.

(H.2) As the δ increases, Individuals are able to coordinate on the corresponding specialized equilibria.

Third hypothesis is to capture the behavioral aspect in equilibrium selection which is not described in a Bramoulle et al (2014). In BK, they made statement about the asymmetry of network : On any core-periphery graph, there exists following Nash equilibrium: No core agent exerts effort, each peripheral agent exerts effort. This results implies that in core-periphery network, the specialized equilibrium becomes salient. Therefore, I test the impact of asymmetry of network to the specialized equilibrium selection.

(H.3) In core-periphery network, individuals are able to coordinate on specialized equilibria more frequently.

Fourth hypothesis is that I focused on the average degree of networks. In Rosenkranz et al (2012) they find out the contribution decreases as link is added to the agent. This means that increase of average degree also increase the incentive of free-riding. I hypothesized that the behavior of agents are specialized easily when the average degree is higher. Therefore, the specialized equilibria are selected more frequently.

(H.4) As average degree increases, individuals are able to coordinate on the specialized equilibrium more frequently.

3 Experimental Design

3.1 Network games

In experimental set-up, each agent plays a simultaneous game which is implemented by random positioning and random matching. To prevent people from recognizing the game as the form of repeated game, I recruited 24 or 12 people in each session and divide them into groups which is composed of 12 people. Inside of that group people are randomly assigned in each position by every period. Randomly matched 6 individuals in a 12 people group formed a connected network g. In the game, individuals' pure strategies at each stage are one of the choice of 0,1 or 2. Agents can choose among free-riding action (choose 0), moderate action (choose 1), and full action (choose 2). Payoffs at each period are calculated using the following benefit function.

$$u_i(x_i, x_{-i}, G, \delta) = 1000(x_i + \delta \sum g_{ij} x_j + 0.3)^{\frac{1}{2}} - 432.7x_i$$

The above utility function satisfies the assumptions of Bramoulle(2014). The exchange rate of real money is 10 :1. As treatments, I considered a series of 7 combinations of δ and different network structures, as depicted in the following figure 1. In the figures there are 6 circles and lines. circles means the position of players. Line means that two agents are connected.

$-Figure1-$

The first network characteristic is the lowest eigenvalue. Turtle, Circle and Core-periphery network have the same lowest eigen value 2, while Wheel network has 3. The second network characteristic is regularity. Turtle, Wheel, and Circle network has a symmetric degree distribution which means that all of the agents in the networks have same number of agents. However, In core-periphery network the degree distribution is asymmetric. There exists core-position players those of who have more neighbors than periphery-position. The third one is average degree. Turtle, Wheel and Core-periphery network have 3 average degree for all agents, while circle network has 2 average degree. The characteristics of each networks are defined as a table below.

$$-Table 1-$$

In table 1, network characteristics are presented. When $\delta \times |\lambda_{min}|$ is greater than 1, there exists multiple equilibria. On the other hand, when $\delta \times |\lambda_{min}|$ is less than 1, there exists unique equilibrium. More specific equilibrium profile is in Table 2.

$$-Table 2-$$

In Table 2, there are equilibrium profile of each networks. when $\delta \times |\lambda_{min}|$ is less than 1, there exists unique equilibrium and in the equilibrium, all agents contribute positive amount. As δ increases from 0.35 to 0.75, the equilibria set are multiple and span including specialized equilibrium profile. For example, in Circle network, $|\lambda min|$ is 2. When δ is 0.35, $\delta \times |\lambda_{min}|$ is less than 1. Therefore, (1,1,1,1,1,1) is unique and stable equilibrium. While δ is greater than 0.75, (1,1,1,1,1,1) and (2,0,2,0,2,0) are equilibria. This setting is to test the main results of Bramoulle et al (2014) which means players can coordinate this specialized equilibrium (2,0,2,0,2,0) also as δ increases because the equilibria set include this new profile.

3.2 Risk Assessment

We measure risk attitudes following Holt and Laury(1998). Players made a decision between two lotteries: one of the alternatives is a safe lotteries which pay player a certain amount, the other is a probabilistic lottery. The sequence of decisions is in a line according to an increasing certain payment while probabilistic lottery remains same. An agent's risk attitude is measured by the indifferent point between the two alternatives. For each pair, one of the alternatives is more safe alternative in comparison to the other. The sequence of decisions was ordered according to an increasing the expected payoff of risky alternative. An agent's risk aversion should determine at which decision he/she indifferent between the two alternatives and for any further decision he should prefer the risky alternative. The below table shows the screen of risk assessment.

3.3 Procedural details

In total 17 sessions were run at the experimental laboratory at CEBSS at Seoul National University in December 2015 and April 2016. Participating subject came from the online website which can be used only Seoul National University students. The procedure during the sessions was kept same and all sessions are computerized, using a program written with z-tree (Fischacher, 1999). 256 subjects participated and were seated in a random order at PCs in laboratory. Instructions(see Appendix1) were then read aloud and questions were answered in private. Subject were randomly assinged to groups of size N=12, inside of that group, Subejct were randomly positioned in the network N=6. Throughout the sessions students were not allowed to communicate each other and could not see others' screen. These are summary statistics for each network.

$$-Table 3-$$

In the experiment, each subject played 3 independent parts of experiment. First is the network games each player made a decision, the second part is risk assessment and the last part is understanding of networks test. In the first part, subject should make a decision in the certain specific network for 40 Periods. Each period, they are assigned in a random position in a network. I decided neighbors can be changed by the same random assignment rule. At last, their payment is decided by the sum of earnings they earn by each period. This design is a direct translation from the original settings in Bramoulle(2014). Every period, subjects were informed about their position and payoff matrix on the screen and determine how much they will take actions among 0,1, and 2 in that period. After each period ends, each player get a detailed feedback about what his/her neighbors choose (not all the players in networks) and payoff at that period. On average, player can receives a secure option giving exact amount of money, however, Option B is a probabilistic lotteries. To be specific e \$17.3 for 65 minutes in the first part. Moreover, in the second part, each subject had to answer what option they want to choose between Option A and Option B. Option A is a probabilistic lottery between 2000 won (about \$2) and 1600 won (about \$1.6) and Option B is a probabilistic lottery between 3850 won (about \$3.85) and 100 won (about \$0.1). As the row of table goes below, the probability is different. What I have an interest is that when players can be indifferent between these two options. The last part of my experiment is testing the understanding of the effect of networks. Agents play the games with computers which can rationally understand the whole network structures. The sequence of treatments for the 17 sessions has been processed by several concerns: I decide to implement the network games to prevent the effect of revelation of lottery result. Also, I used a random assignment rule in the 12 agents not 6 agents to reduce the probability to match people each other again. This set-up is crucial to understanding game rule because this Bramoulle(2014) assumes simultaneous game with strangers. To prevent the issue with ordering effect, I designed the experiment in a between treatment. Thus, agents will select their choice only in a certain network and given delta for 40 periods.

4 Empirical Results

4.1 The Impact of Lowest eigenvalue

4.1.1 Equilibrium selection

In this section, I will compare the equilibrium convergence between (Turtle, $\delta_{0.35}$) and (Wheel,$\delta_{0.35}$). The difference between these two networks is the lowest eigenvalue. all other network characteristics are controlled. The summary of these network characteristics and convergence ratio are presented below.

$-Table4-$

In the circumstance of $\delta = 0.35$, there is an active unique equilibrium in (Turtle, $\delta_{0.35}$) while (Wheel, $\delta_{0.35}$) has multiple equilibria. there are multiple equilibria including specialized equilibrium ((2,0,2,0,2,0)). To be specific, (1,1,1,1,1,1) is active equilibrium which are compatible in both networks. However, (2,0,2,0,2,0) is only compatible in the wheel network. First, the overall convergence rate is not different under 5% level. In (Turtle,$\delta_{0.35}$) the frequency of choosing (2,0,2,0,2,0) is 1. however, the overall frequency on the specialized equilibria between (Turtle, $\delta_{0.35}$) and (Wheel, $\delta_{0.35}$) is not different under 5% level. This results is in line with Rosenkranz et al (2012). They also find that the convergence of specialized equilibrium is less than 1% under continuous action space. Although this paper choose discrete action space, the frequency is also not significant. After control the fixed effect of period , the frequency of converge to specialized equilibrium is not significant. Therefore, the conclusion is that in both case, agents coordinate on the active equilibrium.

$-Figure2-$

Figure 2 checks the convergence ratio across period flows. In Figure 2, there is a convergence ratio across period. First, in both (Wheel, $\delta_{0.35}$) and (Turtle, $\delta_{0.35}$), there is an increase in convergence ratio. (In (Turtle, $\delta_{0.35}$), represent the convergence ratio of active equilibrium.) The correlation between convergence rate and Period is 0.254

which is statistically significant at 1% level in both treatments. They have very same trend of convergence ratio which is not statistically different at 5% level across first 10 period, period 11 29, and last 10 period. This means that the trend is same for all period. Second, the convergence ratio of specialized equilibrium is statistically different at 5% level between first 10 period is 7.9% and last 10 period 0%. This difference is statistically significant at 5% level. This results implies that the convergence to the specialized equilibrium decreases as period goes.

4.1.2 Individual Behavior

In the previous section, regarding equilibrium selection, agents choose the active equilibrium not specialized equilibrium in both case. However, the equilibrium convergence is possible only if when all 6 agents in the group chose the best response to each other. Therefore, in this section, I check whether the individual behavior of agents between these two treatments is different. In this section, let specialized action means that 0 (Free-ride) or 2 (full contribution). In theoretical perspective, the individual behavior changes in a more speicalized way because specialized equilibrium is in the theoretical prediction in (Wheel, $\delta_{0.35}$) while not in (Turtle, $\delta_{0.35}$). Below Figure is about the ratio of choice between the (Wheel, $\delta_{0.35}$) and (Turtle, $\delta_{0.35}$).

$$-Figure 3-$$

Figure 3 shows the contribution across (Wheel, $\delta_{0.35}$) and (Turtle, $\delta_{0.35}$) there is 14.3% decreases those of who select 1. This also means that there is increase on the proportion those of who select 0 or 2.On average there is 1.10 contribution in (Wheel, $\delta_{0.35}$) and 1.04 in (Turtle, $\delta_{0.35}$). They are statistically different at 5% level. To test this in a regression table, setting the dependent variable c_{spec} as follows.

$$c_{spec} = \begin{cases} 1 & if \;\; c \in \{0, 2\}, \\ 0 & O.W \end{cases}$$

This dependent variable captures the specialized behavior of agents which is not captured by the equilibrium selection part. Below regression table shows the effect of increased lowest eigenvalue to the specialized equilibrium. Average degree and symmetry is controlled as described in the previous section. Therefore, the wheel network dummies means that the effect of lowest eigenvalue on the specialized action. Fixed effect includes period dummies and position dummies. Standard errors are clustered by each individuals.

$$-Table 5-$$

Above table 5 shows the effect of the increased $|\lambda_{min}|$ on the specialzied behavior. In all specification, the proportion of agent who chose specialized action increased about 14.4% which is significant at 1% level in model (1). After controlling the woman and risk aversion and period fixed effect, there is 18.6% increase which is significant at 1% level on the specialized action. This regression table shows that the specialized action of agents increase in wheel network. This is consistent with the theory of Bramoulle et al (2014). This is the first results of finding the changes of individual behavior caused by global network characteristic after controlling the local network characteristics.

4.2 The Impact of δ in Networks.

4.2.1 Equilibrium selection

In the previous sectiom, I showed the impact of $|\lambda_{min}|$ in the equilibrium selection. In this part, I test the theory related with the δ, payoff decay factor. In the theory, δ has an interaction with $|\lambda_{min}|$. This means that in theoretical perspective, there is no difference between the two parameters. We have 3 networks variation according to the increase of δ. In Turtle and Circle network, the equilibrium set expand while, Wheel has the same.

$$-Table 6-$$

Table 6 represents the amount of equilibrium convergence in each networks. First, Regardless of δ, there is a trend to converge on the active equilibrium. In multiple equilibria case, there is a strong trend to converge on the active equilibrium which is significant at 1% level for all networks. [In this part, the data trends with other literature should be added]. Therefore, the first observation is that agents coordinate on the active equilibrium regardless of δ. Second, In all 3 network there is significant increases on the convergence to specialized equilibrium which is significant at 1% in Turtle 5% in Wheel and Circle. This means that the increased effect of δ is significant on both three network. Specifically, in Turtle and Circle network, their theoretical equilibrium spans including the specialized equilibrium while Wheel network's equilibrium selection set remains as same. Therefore, The data trend is consistent with the theoretical perspective. However, in Wheel network, the theoretical equilibrium set remains same. Therefore, theoretically we cannot predict what equilibrium will be selected. Empirical evidence shows that there is significant increase on the converging trends to the specialized equilibrium.

4.2.2 Individual Behavior

This parts is about the individual behavior in each networks. First, In the equilibrium selection parts, there is a significant increase on the specialized equilibrium. Below graphs shows the amount of contribution chosen by agents. In all three networks, There is a significant increases at 1% level on the specialized action as we did same regression in Table 2. This means that like $|\lambda_{min}|$ did, there is a significant increase on the specialized action. This effect cause the increase of convergence to the specialized equilibrium. Specifically, in Wheel network, there is 8% increase on the specialized action. In Wheel network, there is 12% increases on the specialized action. In these two network, there is a significant increases on the free-riding action not full contribution. This means that the increase of specialized action mostly comes from the free-riding actions. The difference of free-riding action is statistically increases at 1% level in both case, while the ratio of full-contribution is not statistically difference in both case. Theoretically, the increase of δ increase the incentive to free-riding and simultaneously increase the full contribution. Our empirical evidence shows that the increase of δ primarily increase the free-riding effect. In Circle network, there is 22.1% increases on the specialized action which is the most effective. In Circle network, the increases on the specialized action comes from the free-riding and full contribution both. They are increased about 11.2% and 8.6% respectively which is significant at 1% level.

$$-Figure 4-$$

This results shows that the increase of δ cause the individual's specialized actions more frequently. This is consistent with the theory because Bramoulle et al(2014) point out the specialized action is more prevalent when the δ is high.

4.3 The Impact of Asymmetry in Networks

In this section, I will check the impact of asymmetry in the networks. This features is not captured by the theory. The asymmetry means the degree distribution is unequal inside the network. For example, Circle, Turtle, and Wheel network is symmetric network because all agents in the circle network has the same amount of neighbors. However, core-periphery network is asymmetric network because some of agents in the network have 4 neighbors while some of agents have 2 neighbors. Core-periphery network has average degree 3 and $|\lambda_{min}|$. These are same characteristics with Turtle network. The sole difference between Core-periphery and Turtle networks is the asymmetry in the network.

4.3.1 Equilibrium selection

$-Table7-$

When δ is 0.75, in the equilibria set, Turtle and Core-periphery networks have multiple equilibria set with active and specialized equilibria. Their global network characteristics including average degree and $|\lambda_{min}|$ are controlled. First, in Core-periphery network, every equilibrium selection were done in the specialized equilibrium. This is striking results because in all case they are coordinate on the specialized equilibrium. The difference between the convergence ratio to the specialized equilibrium is significant at 1% level. The difference is also presented as the period flows.

$-Figure5-$

Above Figure shows that the amount of equilibrium convergence to the specialized equilibrium by first 10 period , 10 30, and last 10 period. In the Core-periphery network, the convergence ratio increase as period goes. This means that agents' learning effect is toward the specialized equilibrium, while, in Turtle network, agents' learning effect is toward the active equilibrium. In the three classification, they are all different across all specification. I set the dependent variable 1 if agents are coordinate on the specialized equilibrium , 0 if not. Below Table 8 represents the regression results for the convergence on the specialized equilibrium.

$-Table8-$

Above Table 8 shows the regression results for the convergence on the core-periphery networks. There are significant increase on the converging on the specialized equilibrium. There is 8.4% increases on the specialized equilibrium selection on the Core-periphery. After I controlled the period dummies for fixed effect, the results is also roubst at 5% level. This result clearly shows that the changes of symmetry inside of agents affects the specilaized equilibrium selections between agents.

4.3.2 Individual behavior

Asymmetry also affects the specialzied actions on the agents. In the (Turtle, $\delta_{0.75}$) 56.8% of agents chose 1. However, about 23.1% of agents chose 1 in Core-periphery networks. The ratio of action are presented below Figure. The ratio of agents who chose free ride increase about 13.2%. Also the ratio of agents who chose full contribution increase about 21.2%. This results means that there is 33.4% decrease in the proportion who chose 1. The above difference results between (Turtle, $\delta_{0.75}$) and (Core-periphery, $\delta_{0.75}$)

is different for all contribution, 0,1, and 2, at 1%. This results is clearly shows that the local characteristics (Asymmetry) have more effective than the theoretical prediction to the individual contribution.

$$-Figure 6-$$

$$-Figure 7-$$

In the core position, 64.1% of agents chose 0 (free-ride), while 74.6% of agents chose 2(full-contribution) in periphery position. This is clearly shows that the local degree distribution of agents plays as a power law of agent. This behavior is an empirical evidence that the role of local chracteristics can play important role to the individual contribution which is not captured by the global network characteristics. Below regression table is for the specialized action in each network.

$$-Table 9-$$

Above Table 9 shows the regression results for the specialized action in core-periphery networks. Fixed effect includes the period dummies. Across all specification, there is a significant increase on the specialized action in core-periphery networks. It is the first paper to find the relationship between the specialized action and local network characteristics after we control the global network characteristics. Therefore, the conclusion of this section is there exists strong impact of asymmetry of degree distribution on the specialized action and equilibrium selection.

4.4 The Impact of Average Degree

In the theoretical perspective, it does not say about the absolute number of links which each agent has. Therefore, I control the global network characteristics and check how the changes of average degree in networks affects the equilibrium selection on the networks and individual behavior.

4.4.1 Equilibrium selection

$$-Table 10-$$

Above Talbe 10 shows the equilibrium selection comparison between (Circle, $\delta_{0.35}$) and (Turtle, $\delta_{0.35}$). In both network has a same unique active equilibrium. What I want to focus on is the frequency of convergence. the frequency of convergence decrease 6.7%

which is significant at 5% level.

The two network have a same active and unique equilibrium set when they are belong to $\delta_{.35}$. What I want to test in the case of $\delta_{.35}$ is that whether there is a difference of convergence frequency even though they have a same equilibrium set. It could be important because we can verify in what circumstance people can coordinate on the equilibrium frequently. In the circumstance of $\delta_{.75}$, they belongs to the multiple equilibria situation. Specifically, Both networks have one active equilibrium and one specialzied equilibrium. In the circle network, each agent has the same number of neighbors as 2. On the other hand, in the Turtle network, each agent has 3 neigbors. Turtle and Circle networks belong to the regular graph which means that all the agents in each networks have the same number of neigbors. They have same lowest eigenvalue thus their theoretical prediction are not quite different. because they have unique and active action profile in the $\delta_{.35}$ case, while in the $\delta_{.75}$ case, they have Active and Specialized equilibria respectively.

In the equilibrium selection part, the effect of choosing moderate behavior in the equilibrium has increased also. Table 10 shows the amount of frequency coordinate on the equilibrium. It is quite interesting that the frequency of convergence in the active equilibrium is much higher in Circle Network. This is because people have more equal contribution on the equilibrium set. This result is in line with the result with Rosenkranz et al (2012). They showed that in public good games played on network, people have a tendency to locally coordinate more on the network which has lower average degree. In the same spirit,

4.4.2 Individual behavior

In the individual behavior, The percentage of choosing the specialized action is different across the Network. There is significant increase on the behavior of choosing the specialized action in the high degree cases. The graph shows the proportion of action selected by agents. As you can see below about 90% who belongs to the Circle Network choose moderate contribution. There was about 16% increase those of who select moderate contribution. The percentage of full contribution and free-rider decreased. In the regression they are statistically significant at 5% level In summary, There was a significant increase on the number of people those who select moderate contribution.

$$-Table 11-$$

5 Concluding Remarks

This paper explore the effect of global and local network characteristics in network position in an experiment when actions are strategic substitutes. The game theoretic base for experiment is the model of Bramoulle et al (2014). We observed the equilibrium selection in each treatment. We find that some aspect that consistent with the theory especially when the lowest eigenvalue of network is larger then the frequency of specialized behavior of agents increases. However, this is not presented in the equilibrium selection parts. Moreover, there are another aspect related with local network structure might plays critical role to the contribution of each agent. Specifically, local degree of agents plays important role to the specialized actions and equilibrium selection. Also average degree of networks plays important role to select the positive contribution equilibrium. These finding might suggest that although individuals are situated in a perfect information of networks, they use quite simple heuristics to their decision-making.

References

Bramoulle, Yann, Rachel Kranton, and Martin D'amours. 2014., Strategic interaction and networks. The American Economic Review 104.3: 898-930.

Bramoulle, Y., Kranton, R., 2007. "Public goods in networks". J. Econ. Theory 135, 478-494.

Charness, Gary, et al. Experimental games on networks: Underpinnings of behavior and equilibrium selection.", 2014., Econometrica 82.5: 1615-1670.

Fischbacher, U., 2007. Z-Tree. Zurich toolbox for ready-made economic experiments. Exper. Econ. 10, 171-178.

Foster, A.D., Rosenzweig, M.R., 1995. Learning by doing and learning from others: Human capital and technical change in agriculture. J. Polit. Economy 103 (6), 1176-1209.

Goeree, J.K., Holt, C.A., Palfrey, T.A., 2005. Regular quantal response equilibrium. Exper. Econ. 8, 347-367.

Goeree, J.K., Riedl, A., Ule, A., 2009. In search of stars: Network formation among heterogeneous agents. Games Econ. Behav. 67 (2), 445-466.

Rosenkranz, Stephanie, and Utz Weitzel. Network structure and strategic investments: An experimental analysis., 2012, Games and Economic Behavior 75.2: 898-920.

Jackson, M.O., 2006. The economics of social networks. In: Blundell, Richard, Newey, Whitney, Persson, Torsten (Eds.), The Proceedings of the 9th World Kosfeld, M., 2004. Economic networks in the laboratory: A survey, review of network. Economics 3, 20-41.

Table 1: Network Characteristics of treatments.

Network	δ	$\lvert\lambda_{min}\rvert$	Equilibrium	Average Degree	Regularity
Turtle	0.35	2	Unique	3	Regular
	0.75		Multiple		
Wheel	0.35	3	Multiple	3	Regular
	0.75		Multiple		
Cricle	0.35	2	Unique	2	Regular
	0.75		Multiple		
Core-periphery	0.75	2	Multiple	3	Irregular

Table 2: Equilibrium Prediction

Network	δ	$\lvert\lambda_{min}\rvert$	Equilibrium profile	Characterization
Turtle	0.35	2	(1,1,1,1,1,1)	Active
	0.75		(1,1,1,1,1,1)	Active
			(2,1,0,2,1,0)	Specialized
Wheel	0.35	3	(1,1,1,1,1,1)	Active
			(2,0,2,0,2,0)	Specialized
	0.75		(1,1,1,1,1,1)	Active
			(2,0,2,0,2,0)	Specialized
Circle	0.35	2	(1,1,1,1,1,1)	Active
	0.75		(1,1,1,1,1,1)	Active
			(2,0,2,0,2,0)	Specialized
Core-periphery	0.75	2	(1,1,1,1,1,1)	Active
			(2,0,2,0,2,0)	Specialized

Table 3: Summary statistics

Treatments	Subjects	Sessions	Earnings		
			avg	max	min
(Turtle,$\delta_{0.35}$)	36	2	\$14.4	\$18.2	\$12.9
(Turtle,$\delta_{0.75}$)	36	2	\$19.3	\$24.4	\$16.9
(Wheel,$\delta_{0.35}$)	36	3	\$14.1	\$19.9	\$12.3
(Wheel,$\delta_{0.75}$)	36	2	\$18.9	\$24.0	\$13.1
(Circle,$\delta_{0.35}$)	36	2	\$12.1	\$14.5	\$11.5
(Circle,$\delta_{0.75}$)	36	3	\$15.7	\$17.2	\$14.0
(Core-periphery,$\delta_{0.75}$)	36	3	\$18.2	\$25.6	\$10.2

Table 4: Equilibrium convergence : $|\lambda_{min}|$

Network	$\lvert\lambda_{min}\rvert$	δ	Equilibrium profile	Characterization	N	Convergence(%)
(Turtle, $\delta_{0.35}$)	2	0.35	(1,1,1,1,1,1)	Unique	240	80(33.3%)
(Wheel, $\delta_{0.35}$)	3	0.35	(1,1,1,1,1,1)		240	72(30%)
			(2,0,2,0,2,0)	Specialized		6(2.5%)

Table 5: Regression for the specialized actions

	(1)	(2)	(3)	(4)
Wheel	0.144***	0.174***	0.174***	0.186***
	(0.0177)	(0.0179)	(0.0179)	(0.0233)
Fixed effect	no	yes	yes	yes
Woman	no	no	yes	yes
Risk Averse	no	no	no	yes
Constant	0.279***	0.601***	0.601***	0.634***
	(0.0156)	(0.0659)	(0.0686)	(0.0700)
Observations	1920	1920	1920	1920
R-squared	0.033	0.200	0.200	0.200

Table 6: Equilibrium Convergence : δ

Network	$\lvert\lambda_{min}\rvert$	δ	Equilibrium profile	Characterization	N	Convergence(%)
Turtle	2	0.35	(1,1,1,1,1,1)	Unique	240	80(33.3%)
Turtle	2	0.75	(1,1,1,1,1,1)		240	48(20%)
			(2,1,0,2,1,0)	Specialized		15(6.6%)
Wheel	3	0.35	(1,1,1,1,1,1)		240	72(30%)
			(2,0,2,0,2,0)	Specialized		6(2.5%)
Wheel	3	0.75	(1,1,1,1,1,1)		240	35(14.5%)
			(2,0,2,0,2,0)	Specialized		14(6.4%)
Circle	2	0.35	(1,1,1,1,1,1)	Unique	240	96(40%)
Circle	2	0.75	(1,1,1,1,1,1)		240	71(29.5%)
			(2,0,2,0,2,0)	Specialized		8(3.3%)

Table 7: Equilibrium Convergence

Network	$\lvert\lambda_{min}\rvert$	δ	Equilibrium profile	Characterization	N	Convergence(%)
Turtle	2	0.75	(1,1,1,1,1,1)		240	48(20%)
			(2,1,0,2,1,0)	Specialized		15(6.6%)
Core-periphery	2	0.75	(1,1,1,1,1,1)		240	0(0%)
			(2,0,2,0,2,0)	Specialized		38(16%)

Table 8: Regression for the specialized equilibrium

	(1)	(2)
Core-periphery	0.0842**	0.0814**
	(0.0380)	(0.0387)
Fixed effect	no	yes
Constant	0.0668***	0.0644
	(0.0156)	(0.0659)
Observations	480	480
R-squared	0.014	0.104

Table 9: Regression for the specialized actions.

	(1)	(2)	(3)	(4)
Core-periphery	0.323***	0.323***	0.322***	0.330****
	(0.0238)	(0.0240)	(0.0226)	(0.0235)
Fixed effect	no	yes	yes	yes
Woman	no	no	yes	yes
Risk Averse	no	no	no	yes
Constant	0.446***	0.505***	0.504***	0.449***
	(0.0164)	(0.0687)	(0.0707)	(0.0845)
Observations	1920	1920	1920	1920
R-squared	0.109	0.151	0.151	0.152

Table 10: Equilibrium Convergence

Network	AvgDegree	$\lvert\lambda_{min}\rvert$	δ	Equilibrium	Character	N	Converge(%)
Circle	2	2	0.35	(1,1,1,1,1,1)	Unique	240	96(40%)
Turtle	3	2	0.35	(1,1,1,1,1,1)	Unique	240	80(33.3%)
Circle	2	2	0.75	(1,1,1,1,1,1)		240	71(29.5%)
				(2,0,2,0,2,0)	Specialized		8(3.3%)
Turtle	3	2	0.75	(1,1,1,1,1,1)		240	48(20%)
				(2,1,0,2,1,0)	Specialized		15(6.6%)

Table 11: Regression for the specialized actions.

	(1)	(2)	(3)	(4)
Turtle	0.323***	0.323***	0.322***	0.330****
	(0.0238)	(0.0240)	(0.0226)	(0.0235)
Fixed effect	no	yes	yes	yes
Woman	no	no	yes	yes
Risk Averse	no	no	no	yes
Constant	0.446***	0.505***	0.504***	0.449***
	(0.0164)	(0.0687)	(0.0707)	(0.0845)
Observations	1920	1920	1920	1920
R-squared	0.109	0.151	0.151	0.152

Figure 1: Treatments

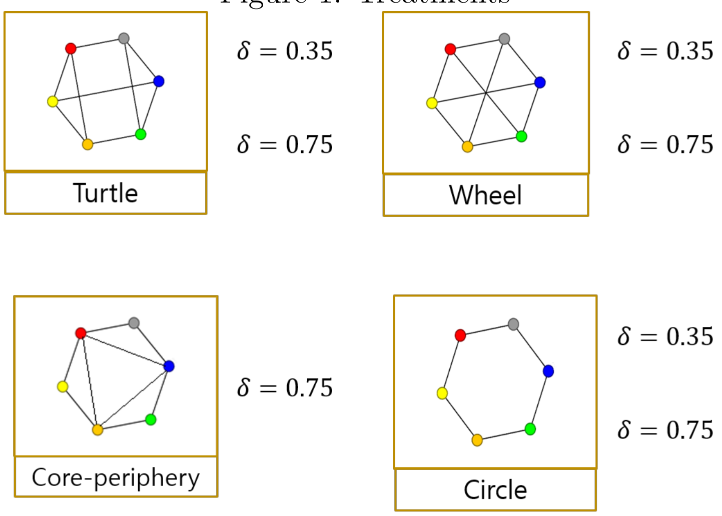

Figure 2: Equilibrium convergence : across periods

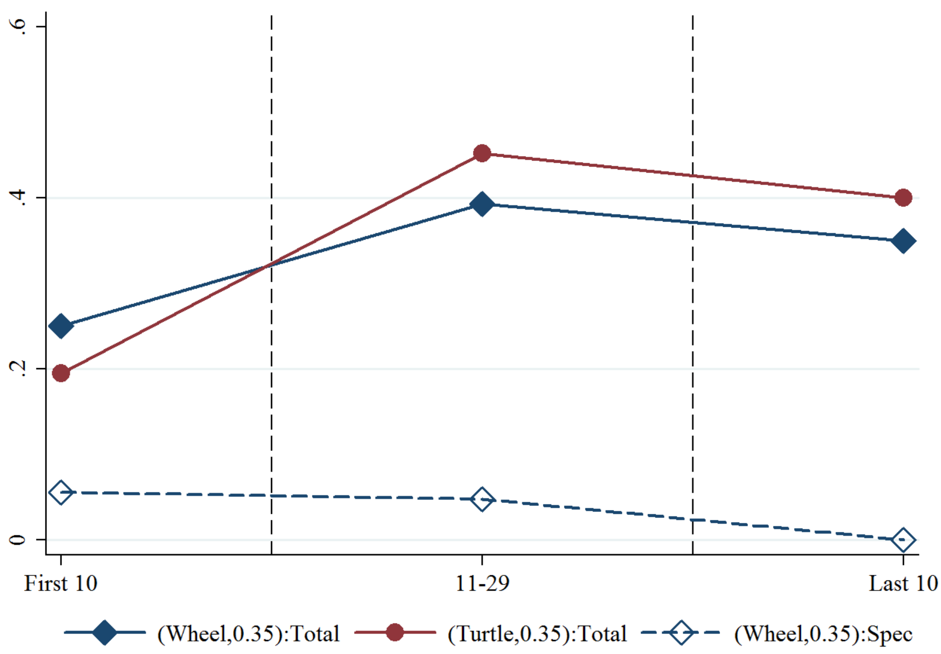

Figure 3: Contribution across treatments

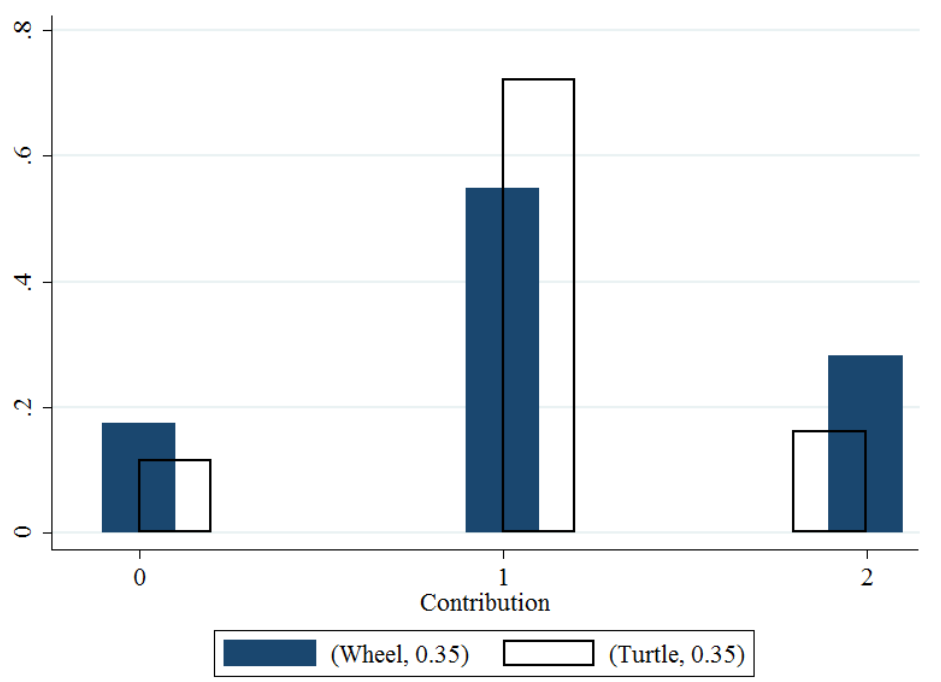

Figure 4: Contribution across treatments

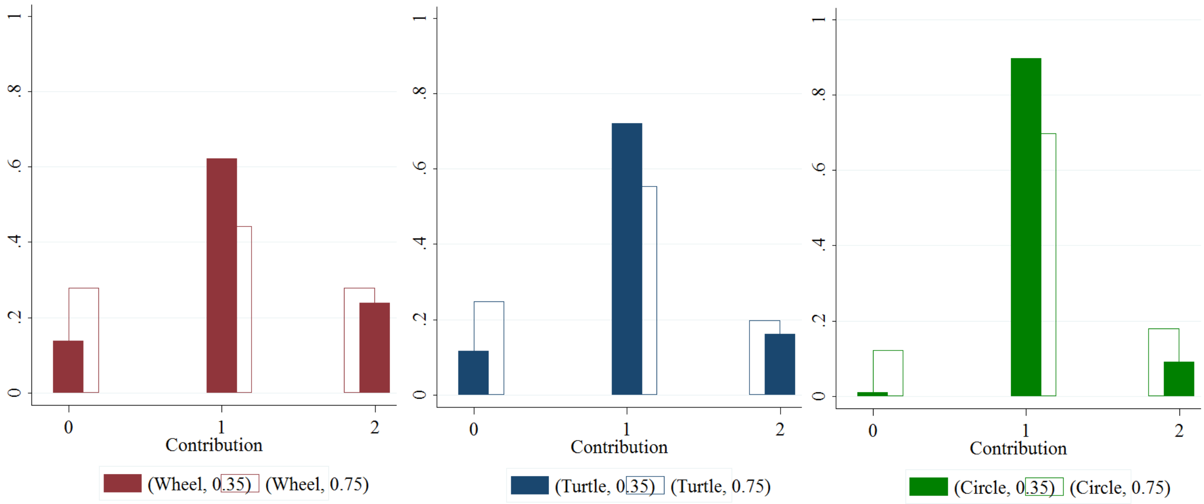

Figure 5: Specialized equilibrium selection across period

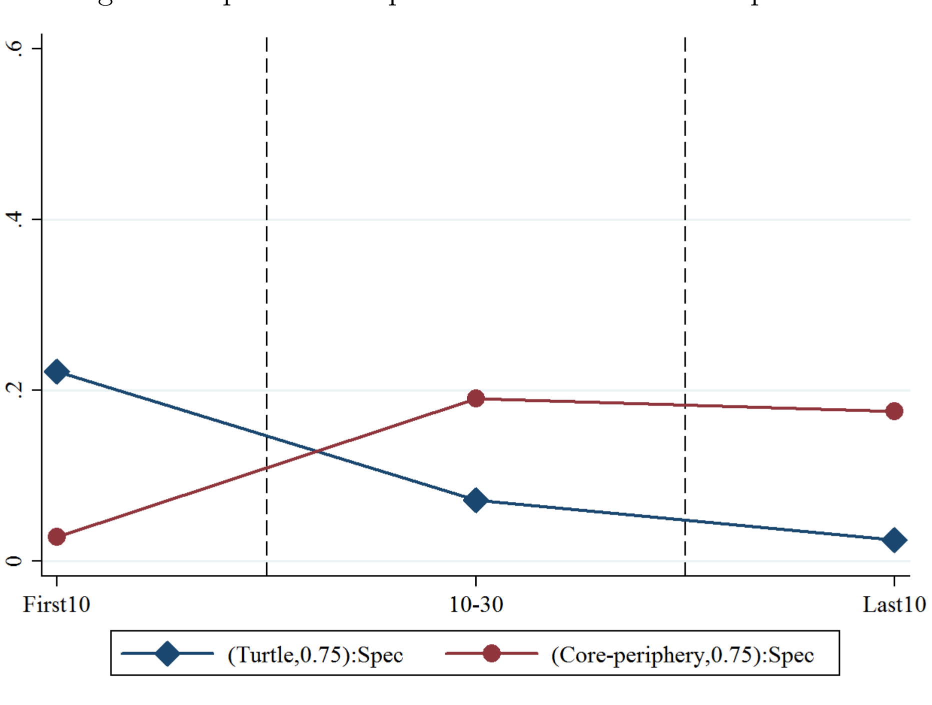

Figure 6: Contribution across treatments

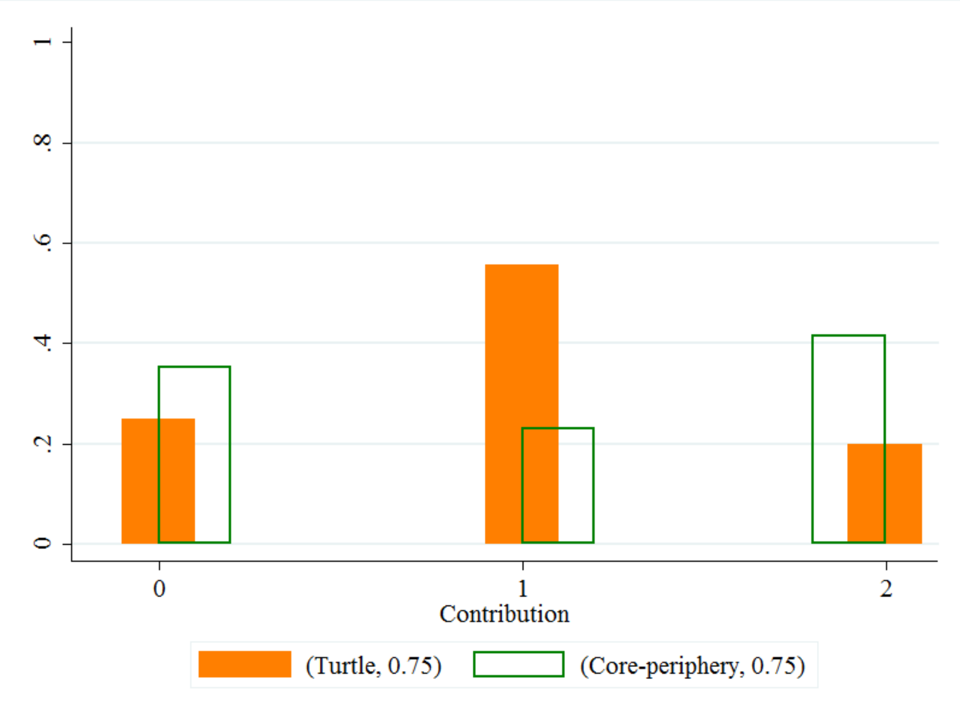

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Figure 7: Contribution across core and periphery position