Rivalrous Resource Sharing in Networks can Exacerbate Existing Inequalities

Eaman Jahani[1,2] and Dean Eckles[1,2]

[1]Sloan School of Management, MIT
[2]Institute for Data, Systems and Society, MIT
{eaman,eckles}@mit.edu

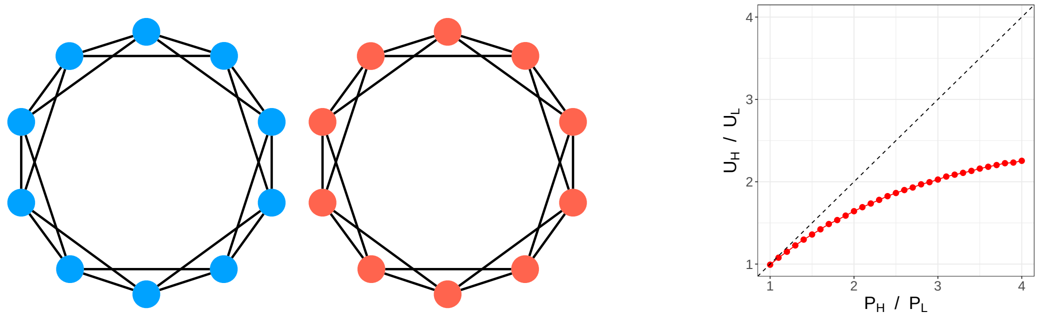
October 1, 2021

1 Introduction

Inequality has been consistently rising over the past 40 years in the US [1]. Its destabilizing forces and negative impact on economic growth have motivated academics and policy makers to address the roots of its persistence [2, 3]. Policy makers and the economics literature has mostly focused on the economic forces behind inequality such as market imperfections, tax policy or monopoly rents. However, there is increasing recognition that the roots of inequality trace back to social structures and how they interact with economic institutions [4]. Segregation or status homophily in network is believed to be main social driver behind inequality [4–8]. The link between social network homophily and inequality is based on unequal access to information. In basic terms, sorting in social networks by status and access to economic information leads to concentration of opportunities in a small part of the society, widening existing gaps over time.

The unequal diffusion of resources or opportunities is the basis of several studies which have provided a theoretical account of how small differences in individual advantage can translate into large and persistent differences over time [5, 6, 9]. The unequal diffusion is an informational account of network effects on inequality and occurs when valuable information is generated by different people at different times and the network exhibits three characteristics 1. Information diffuses across network ties, 2. One group generates the information or opportunities at a higher rate, 3. The network is homophilous in the group attribute. These three conditions make the networks of the advantaged group richer in resources, a phenomenon referred to as "inequality in social capital" [6]. Homophily is the main driver of the differential access to information and it implies that opportunities remain exclusive to one group, exacerbating existing differences over time.

Given the significant implications of networks in exacerbating inequalities, it is important to go beyond the general theoretical framework and determine the process in detail. Only then we can prescribe interventions to combat the forces that regenerate inequality. For example, a simple structural explanation based on information diffusion does not lead to larger than initial levels of inequality. Figure 1 shows the results of a simple simulation that confirms this point in a network with two disconnected circular lattices, the most extreme case of homophily. In each round, each node in the network independently generates valuable information with fixed probability and passes it along to its neighbors. The network has two disconnected components, each representing a group with fixed probabilities P_H and P_L, akin to status. Access to the information increases a node's utility by a unit



(a) (b)

Figure 1: **Diffusion in homophilous networks does not necessarily widen inter-group difference.** Two circular lattices comprising the full (left). Nodes with the same color, a lattice, all have the same probability of generating valuable information in each round. One group has higher probability than the other. Lack of cross-group connections implies extreme homophily. The ratio of group utilities after accounting for one-hop diffusion for various levels of initial differences (right). Estimates are from 20 simulations each with 10,000 rounds. 95% confidence intervals are too small to be visible.

in each round. If we denote the total utility of all nodes in each group after 10000 rounds by U_H and U_L, then the ratio $\frac{U_H}{U_L}$ signifies the level of inter-group difference accounting for the network effects. This ratio is compared against the initial inter-group difference $\frac{P_H}{P_L}$ in figure 1b, which indicate that the diffusion in the network actually reduces the inter-group difference by about 54% from the initial exogenous differences when $\frac{P_H}{P_L} = 4$.

The problem with this simple approach is that it is purely structural and ignores the fact that inequality arises from the incentive structure of processes that occur in the network and that inequality is durable because it's indeed the equilibrium state of that process [10]. In other words, individuals in a social network are not myopic, instead they strategically form links and decide who to cooperate with. Our measures of social capital, in particular those capturing information or favor exchange capital [11], mostly focus on the network structure, and ignore its interaction with strategic behavior and human capital. But in reality, it is possible that the same expansive network structure for the poor does not provide the same informational benefits as it does for the rich, despite predicting similar level of informational social capital. Thus, it is imperative to account for the nuanced processes that occur within the network and lead to unequal access to valuable resources.

Another problem with the simple structural account above is the assumption that the valuable resource is non-rivalrous and individuals don't compete for accessing it. However in reality, many resources shared in social networks, such as employment information or rations or new business innovation opportunities, are rivalrous (their utility goes down as more people share it). This rivalry introduces strategic behavior in resource sharing because sharing will reduce own utility but might encourage anticipated reciprocity with contacts that improves utility in the future. Thus if an individual believes that the future gains it receives from its contacts do not compensate for the losses it incurs currently by sharing the valuable resources, then it might decide to withhold the resource from its contacts. This sort of strategic behavior resembles the conditionally cooperative behavior that has been illustrated in lab experiments [12]: people cooperate if they know others will also cooperate. This is very relevant in the case of inequality in endowments since if high type players anticipate their low type contacts cannot cooperate, they will in turn reduce their cooperation. Beyond the effects of rivalry on individual decision making, its macro effects at the group level outcomes are more intriguing. Does rivalry affect different groups differently? In this paper, we attempt to study information sharing processes in networks pertaining to rival resources and its implications on inequality.

This type of rivalry in resources and its effect on cooperation has been studied before. It is usually introduced by changing the number of individuals who compete for the same fixed resources. For example when the rivalrous resource is employment information, Beaman finds that refugees who get resettled in locations with a larger community tend to have worse employment outcomes and wages because a larger pool of refugees will compete for the same fixed employment opportunities. Similarly in the context of cooperation and information sharing, there is evidence of crowding effects in public good games. Increasing the number of players sharing the same rivalrous common good decreases individual contributions and leads to worse welfare outcomes [14]. Similar patterns have been reported when individuals share valuable information with low-degree contacts fearing that sharing with high-degree contacts might lead to over-crowding on the rivalrous resource [15]. A similar force affects the choice of migration as migrant move to places where their contacts don't have too many friends they have to compete with [16]. Our work was specifically inspired by the derivation of pairwise stability in job contact networks which showed the positive correlation between employment outcome and the number of contacts, due to increasing information sources, but negative correlation with number of two-links-ways contacts, due to increased competition [17]. Similar to [17], we derive the pairwise stable subgame perfect equilibrium in our (rivalrous) information sharing model. But in addition we examine the inequality implications of rivalry by introducing heterogeneous agents which are present simultaneously in the network and adapt different strategies.

The effect of heterogeneity among agents on individual decisions and total welfare has also been studied. There have been mixed results mainly due to different setups. Some evidence suggests that heterogeneity does not affect cooperation rate in public good games and could sometimes even increase it [18–20]. In a context with collective risk such as climate change, Wang et al. show that heterogeneity leads to higher cooperation because the stakes are higher for richer agents and their cooperation incentivizes poorer agents to also cooperate [21]. The main question in all these studies is stated in terms of cooperation rate in non-rivalrous game with heterogeneity and the inequality implications are not considered. Our work examines the effects of agent heterogeneity and rivalry simultaneously in a network game and while our main goal concerns the inequality implications, we also derive how these factors affect the cooperation.

In this paper, we develop a model that introduces a strategic sharing process among agents with heterogeneous levels of initial endowments in a network where the resources are rivalrous. The agents play a repeated game with their neighbors and in each round if they receive the rivalrous resource, they decide whether to share it with their contacts or not. If the heterogeneity is observable, then in equilibrium the agents will follow a conditional cooperation strategy: they will share the resource, if they know their contact will reciprocate in the future. We show that if the initial differences are large enough, the low type has no incentive to share information with their contact whereas the high type will, essentially leading to homophily in type. These micro-scale decisions made by individual have macro-scale implication at the group level, such that they will exacerbate inter-group differences if the initial differences are large enough. In terms of theoretical contributions, this simple model brings to light the importance of network processes involving complex decisions and the interaction of social capital with human capital in the study of inequality.

Furthermore, we implement a randomized multi-player online lab experiment closely resembling the model to validate its theoretical prediction. The advent of crowd-sourcing platforms such as Amazon Mechanical Turk have enabled researchers to develop and test their hypothesis in large-scale online lab experiment [22–24]. We conducted our experiment similar to these past works by recruiting participants from Amazon Mechanical Turk, and randomly assigning them to a binary type and a position in a homophilous network. Multiple participants played a game simultaneously over multiple rounds and made decisions whether to share rivalrous monetary rewards with each other. We find strong evidence of conditional cooperation as the low type cooperates at a much lower rate than the high type. The adoption of different strategies employed by different groups leads the high type to take a larger share of the rivalrous resources than expected by its initial endowment.

2 Model

We study a network process that exacerbates inter-group differences beyond what's expected by exogenous variation in individual ability. Our setup considers a game in which a rivalrous resource repeatedly diffuses in the network, access to which increases one's utility.

2.1 Game Setup

The game has infinite number of rounds with discount factor c. In each round, there exists a rivalrous resource with total value of 1 and all players that have access to the resource will equally share its utility. There are two types of players: there are n_H agents of high type and n_L agents of low type. There are more low type than high type agents: $n_L > n_H$. In each round, exactly one player of each type receives the resource with uniform within-type probability. A high type player will receive the resource with probability $p_H = \frac{1}{n_H}$ while a low type player will receive it with probability $p_L = \frac{1}{n_L}$. Given that there are more low type than high type agents, a high type agent is more likely to independently receive the resource: $p_H > p_L$. If an agent receives the resource, it has the option to share it with any of its network contacts. Since the resource is rivalrous, sharing it will reduce potential utility from the current round, but the agent still has incentive to share if it believes the contact has a high enough probability to receive the resource in the future and reciprocate. The combined strategy of all players leads to an undirected network structure that is endogenous to the game. A link appears in the network when both players' strategies are to share with each other. In the following we assume that each player can have at most a degree of d.

2.2 Pairwise Nash Stable Network

We will now derive the subgame perfect equilibrium (SPE) based on grim trigger strategies on each agent. The outcome will effectively describe a pairwise Nash stable network [25, 26] where the existence of links indicate sharing by both agents and their absence indicates no sharing by either. For simplicity, we assume only ties within the same type are possible, hence the network will be maximally homophilous. After describing the SPE, we will argue that the same conclusions holds if we were to allow cross-type edges as well. Furthermore, we assume $n_L c$ and $n_H c$ are not integers to avoid a few uninteresting edge cases that are easy to solve for but greatly expand the set of possibilities to enumerate. We will briefly remark how the equilibrium looks like when these conditions are not true. In the following, we denote the equilibrium degree of each player by d^*_H and d^*_L for either type.

Theorem 2.1. *Assuming $n_L c$ and $n_H c$ are not integers, agents employ grim trigger strategies and only within-group sharing is possible, then*

1. *if $n_L > \frac{d+1}{c-1}$ and $n_H < \frac{1}{c-1}$, then $d^*_H = d$ and $d^*_L = 0$ in the pairwise Nash stable network. A circular lattice within each type is such a network.*
2. *if $n_L > \frac{d+1}{c-1}$ and $n_H > \frac{1}{c-1}$, then $d^*_H = d^*_L = 0$ in the pairwise Nash stable network.*
3. *if $\frac{1}{c-1} < n_L < \frac{d+1}{c-1}$ and $n_H > \frac{1}{c-1}$, then either $d^*_H = d^*_L = 0$ or $d^*_H = d^*_L = d$ in the pairwise Nash stable network.*
4. *if $\frac{1}{c-1} < n_L < \frac{d+1}{c-1}$ and $n_H < \frac{1}{c-1}$, then $d^*_H = d^*_L = d$ in the pairwise Nash stable network.*
5. *if $n_L < \frac{1}{c-1}$, then $d^*_H = d^*_L = d$ in the pairwise Nash stable network.*

Proof. The grim trigger strategy of each player is a binary vector corresponding to sharing decisions with all other players if having received the resource. Since players are exchangeable, we can simplify the notation and express the strategy of each player as the number of other players it is sharing with: d_H and d_L for either type. To derive SPE, we express the expected utility of a player from either type starting from the current round if the player has received the resource (the player does not take any action if it does not receive the resource).

$$\begin{aligned}
U_H(d_H, d_L) &= \frac{1}{d_H + d_L + 2} + \sum_{i=1}^{\infty} \frac{1}{c^i} \frac{1}{d_H + d_L + 2} \frac{d_H + 1}{n_H} \qquad (1) \\
&= \frac{1}{d_H + d_L + 2}\left(1 + \frac{d_H + 1}{n_H(c-1)}\right) \\
U_L(d_H, d_L) &= \frac{1}{d_H + d_L + 2}\left(1 + \frac{d_L + 1}{n_L(c-1)}\right)
\end{aligned}$$

The term $\frac{1}{d_H+d_L+2}$ in equation 1 corresponds to utility from the shared resource in a round and the constant 2 refers to the original receivers of the resource, one from either type. The term $\frac{d_H+1}{n_H}$ in equation 1 denotes the probability of receiving the resource in future rounds by either the player itself or one of its neighbors. In SPE, each player maximizes utility starting in each round conditioned on receiving the resource:

$$
\begin{aligned}
d_H^* &= \underset{d_H \in \{0,1,\ldots,d\}}{\arg\max} \ \frac{1}{d_H + d_L^* + 2}\left(1 + \frac{d_H + 1}{n_H(c-1)}\right) \\
d_L^* &= \underset{d_L \in \{0,1,\ldots,d\}}{\arg\max} \ \frac{1}{d_H^* + d_L + 2}\left(1 + \frac{d_L + 1}{n_L(c-1)}\right)
\end{aligned}
$$

The marginal utilities are:

$$
\begin{aligned}
u'_H(d_H) &= \frac{d_L^* - n_H(c-1) + 1}{n_H(c-1)(d_H + d_L^* + 2)^2} \\
u'_L(d_L) &= \frac{d_H^* - n_L(c-1) + 1}{n_L(c-1)(d_H^* + d_L + 2)^2}
\end{aligned}
$$

Depending on the sign of the numerator in the marginal utilities, we characterize the Nash stable network with different cases:

1. if $n_L > \frac{d+1}{c-1}$ then $u'_L(.) < 0$ for any value of d_H^*. Thus, the optimal choice for d_L is the lower corner point: $d_L^* = 0$. If $n_H < \frac{1}{c-1}$, then $u'_H(.) > 0$ and the optimal choice for d_H is the upper corner point: $d_H^* = d$.

2. if $n_L > \frac{d+1}{c-1}$ and $n_H > \frac{1}{c-1}$, we have $d_L^* = 0$ from the previous case. But now $u'_H(.) < 0$, thus the optimal choice for d_H is the lower corner point: $d_H^* = 0$.

3. if $\frac{1}{c-1} < n_L < \frac{d+1}{c-1}$ and $n_H > \frac{1}{c-1}$, then $u'_L(.) < 0$ if $d_H^* = 0$, hence $d_L^* = 0$. Similarly, $u'_H(.) < 0$ if $d_L^* = 0$, hence $d_H^* = 0$. So $d_L^* = d_H^* = 0$

is one SPE, but there is another possible SPE. $u'_L(.) > 0$ if $d^*_H = d$, hence $d^*_L = d$ and similarly $d^*_H = d$ if $d^*_L = d$. So $d^*_L = d^*_H = d$ is another SPE. It is easy to see that mid-values for either d^*_H or d^*_L cannot be SPE, because we have assumed $n_L c$ and $n_H c$ are not integers, so the marginal utilities cannot be zero requiring the optimal choices to be corner points.

4. if $\frac{1}{c-1} < n_L < \frac{d+1}{c-1}$ and $n_H < \frac{1}{c-1}$, then $u'_H(.) > 0$ and the optimal choice for d_H is the upper corner point: $d^*_H = d$. Given $d^*_H = d$, then $u'_L(.) > 0$ and $d^*_L = d$.

5. if $n_L < \frac{1}{c-1}$, then $u'_L(.) > 0$ and subsequently $u'_L(.) > 0$ since $n_H < n_L$. Thus, $d^*_H = d^*_L = d$.

All equilibrium choices above have positive or negative marginal utility at the equilibrium depending on the corner point they occur in. Thus adding or severing links only reduce utility, which implies the solutions concepts above are also pairwise stable. Therefore, all equilibrium solutions above correspond to pairwise Nash stable networks. □

Remark 2.1.1. *As mentioned earlier, allowing for $n_L c$ or $n_H c$ to be integers do not lead to interesting predictions, but greatly expand the possible cases. For example, if we allow $n_H c$ to be an integer, then in addition to cases (1) and (2) in theorem 2.1, we will have yet another case as following: if $n_L > \frac{d+1}{c-1}$ and $n_H = \frac{1}{c-1}$, then $d^*_L = 0$ but now $d^*_H \in \{0, 1, ..., d\}$ since the high type player will always have zero marginal utility regardless of its choice. These edge cases are not interesting and we don't explore them further.*

Corollary 2.1.1. *If the game allows for cross-type edges, it is easy to see that the network formation would exactly follow theorem 2.1. Because a high type* *player has more incentive to share with another high type than a low type. Thus when $d_H^* > 0$ in theorem 2.1, the connections will all be to the high type and when $d_H^* = 0$ there won't be any connection to the low type either. Since the high type does not share with the low type, a low type player will not share with the high type either resulting in two disconnected components in equilibrium even if cross-type edges were possible.*

Corollary 2.1.1 states that no sharing will occur from the high type to the low type. The conditional cooperation argument [12], which is supported in lab experiments [27], provides a mechanism behind this result. A high type player anticipates that a low type cannot sufficiently reciprocate in the future, thus it reduces its cooperation with the low type.

Corollary 2.1.2. *If $n_L > \frac{d+1}{c-1}$ and $n_H < \frac{1}{c-1}$, then the expected utility of high type in each round is $E[u_{H,r}^*] = \frac{d+1}{(d+2)n_H}$. The total share of the high type as a group from the rivalrous resource will be $U_H^* = \frac{d+1}{d+2}$.*

If the rivalrous resource was shared equally or there was no network, then we would expect $E[u_{H,r}] = \frac{1}{2n_H}$ and the total share of high type to be $U_H = \frac{1}{2}$. Comparing this equality baseline versus the Nash stable equilibrium outcome from corollary 2.1.2, we conclude that *if there is sufficiently high rivalry among the low type and sufficiently low rivalry among the high type, the intergroup differences will be exacerbated in the network game. The same conclusion would hold even if cross-type edges were possible.*

In summary, the exogenous variation in the level of access to a rivalrous resource leads to different strategies adopted by the low and high types such that information sharing only occurs among the high type. This results from large differences in future prospects of network benefits between the low and high type. The macro implication of the adopted strategies is that the high type as a group will receive a larger share of the common resource than expected simply by the exogenous differences.

3 Experimental Design

We now discuss a randomized experiment we developed using the Empirica platform [28] to test the predictions of our model in a multi-player online game. The goal here is not to exactly replicate the model predictions above as satisfying the assumptions of theorem 2.1 is very challenging (e.g. it will require a large low type population and even if so not all players will be strategic). Rather, our goal is to experimentally verify that high type players cooperate at a higher rate than low type players and as a result collectively receive a larger share of the common resource than expected simply by their exogenous advantage over the low type players.

In this game, players are recruited and randomly assigned to either high or low type and placed into different positions in a fixed network. The network is homophilous by type. The game has multiple rounds and in each round one player from each type receives valuable information about a rivalrous resource, in this case the location of a gold mine on a map, and decides whether they want to share this information with their neighbors in the network. Because there are less high type than low type players, a high type player receives the information about the location of the gold mine more often than a low type player. Players try to maximize their reward by finding and collecting the gold over all rounds as it translates to their final compensation in dollars. The gold mine is a rivalrous resource, as sharing it with others reduces one's reward in the current round, but sharing might still be a good idea for potential reciprocated benefits in the future.

3.1 Status Structure and Randomized Resource Allocation

Each game has 9 players, 3 of which are randomly selected to be of high status (type) and the remaining 6 will become the low status (type). In each round, the game reveals the location of the gold mine to one randomly selected player from each type. The game instruction ensures players are aware of the status structure and states that the high type players receive the location of the gold on average in twice as many rounds as the low type players. The instructions is purposefully vague on the exact process and it could be interpreted as independent gold assignment in each round, but to ensure a level of fairness so that players within each group potentially receive equal payoffs, players within each group receive the location of the gold in equal number of rounds and the game randomly shuffles the order they receive it.

3.2 Reward Structure

The game needs to repeat over many rounds for player strategies to resemble an equilibrium state. However, we are limited by the time each game can take and use 12 rounds since it also ensures high and low type players each receive the gold 4 and 2 times respectively. A gold mine in each round has \$2.4 total value which will be distributed equally among all players digging it. For example, if none of the players to whom the gold is revealed originally share the information with their contacts, each will receive \$1.2 in that round. If each of them shares it with one neighbor, then each of the four players digging will receive \$0.60.

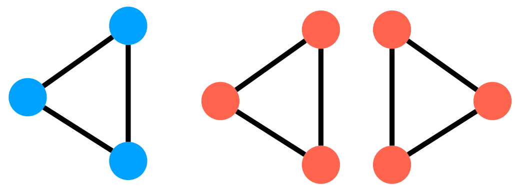


Figure 2: The structure of the network. Red (blue) nodes correspond to low (high) status players. Each player has two neighbors with whom they can share information about the location of the gold mine and is randomly assigned to a node in the network.

3.3 Network Structure

In contrast to our model which treats the network formation as an endogenous process, the experiment simply uses a fixed network structure which corresponds to the model prediction when the maximum degree is $d = 2$. The network will effectively have three disconnected triangles, one with the high status and two with the low status players. Figure 2 illustrates the network structure. The choice of two disconnected triangles among the low status players rather than a single connected hexagon is made intentionally to first avoid leakage or interference between pairs of users not directly connected and second to make comparison with the high status network and inference using resampling easier. Players upon arrival to the experiment platform will be randomly assigned to a node in the network, which will also determine their status.

3.4 Game Setup

The game has 12 rounds, however the instructions on the game does not specify the number of rounds, as such the players do know when the game will end. Each round has the following 3 stages.

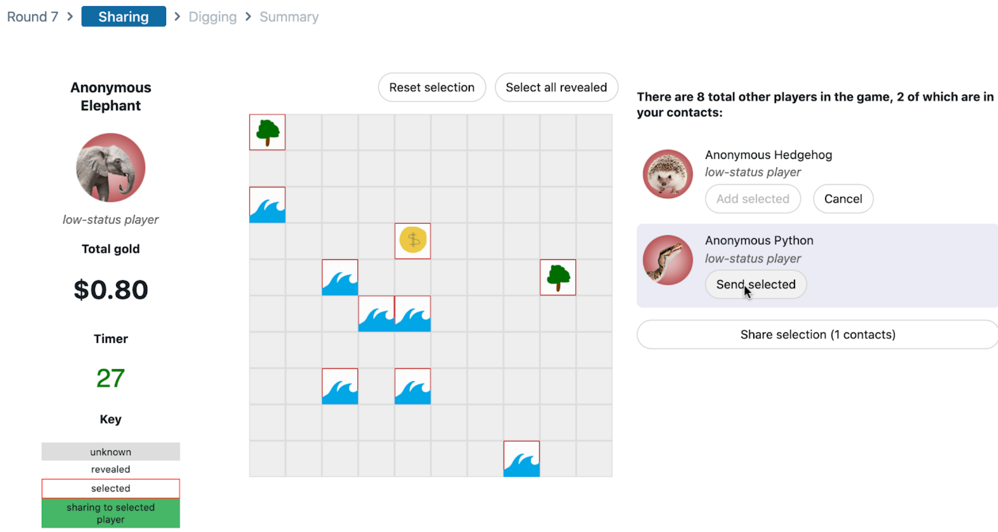


Figure 3: The snapshot of the first (sharing) stage in round 7. The player profile is shown on the left and the neighbors list is on the right. In this case, the player and their neighbors are all from the low status group with a red background. High status profiles have a blue background. In this stage, the player has received the location of the gold and is sharing it with the python.

1. **Sharing Stage:** In the first stage, the experiment platform reveals 10 random squares of the map to each player. If a player is assigned to receive the location of the gold, it will be revealed among these 10 squares. Each player then decides which squares to share or not share with which of the two neighbors. This decision is probably informed by the interactions with the neighbor in the previous rounds. Figure 3 shows a screen snapshot of the sharing stage.

2. **Digging Stage:** In the second stage, the experiment platform reveals the squares that were shared by the neighbors. If the gold mine was originally revealed to the player or one of their neighbors shared its location with them, the player can dig the location and is guaranteed to

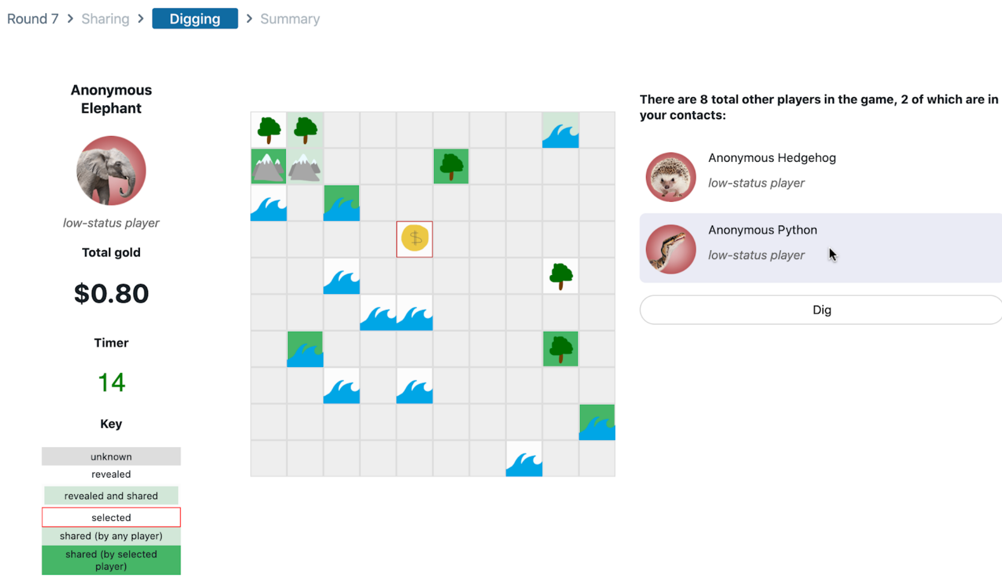


Figure 4: The snapshot of the second (digging) stage in round 7. This stage immediately follows the snapshot shown in Figure 3. The squares that were shared by one of the neighbors (python) are highlighted in green by hovering over the neighbor. The player originally received the location of the mine and has selected its square to dig.

receive some reward. Otherwise, the player can choose another square as a best guess to dig. Figure 4, shows a screen snapshot of the digging stage.

3. **Summary Stage:** In the third stage, the full map is revealed and if the player successfully dug at a gold mine, they will receive information about their reward, which depends on how many other players were also digging. This stage also summarizes the sharing decision of all neighbors. In particular, it shows the player which squares (potentially including the gold mine) the neighbors decided to share and which ones they decided to hide. Figure 5 shows a screen snapshot of the summary

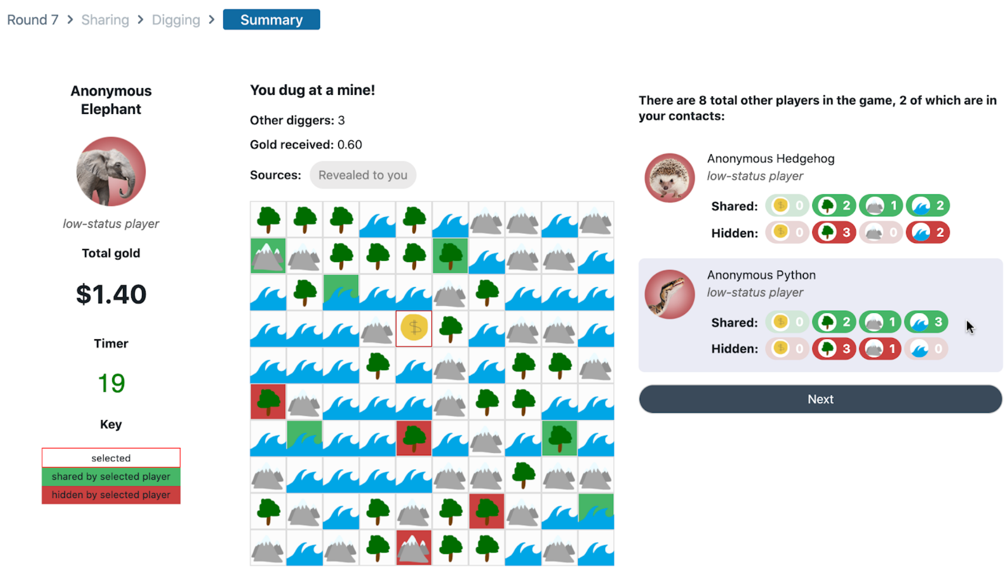


Figure 5: The snapshot of the third (summary) stage in round 7. This stage immediately follows the snapshot shown in figure 4. By hovering over each neighbor, the player can see their sharing decision in this round. The squares that python decided to share are highlighted in green and the squares they decided to hide are highlighted in red. Since the player dug at a mine and there were 3 other players digging too, the player receives $0.6 ($2.4/4).

stage.

4 Data

We collected data for 38 games that successfully finished with all players present. Games were advertised on MTurk in batches of maximum 3 games so that no more than 30 players were connected to the platform at the same time. MTurk workers who signed up for a batch received an email 15 minutes before the game started and those who joined the platform were randomly assigned to a position in the network. Each game took about 15 minutes and

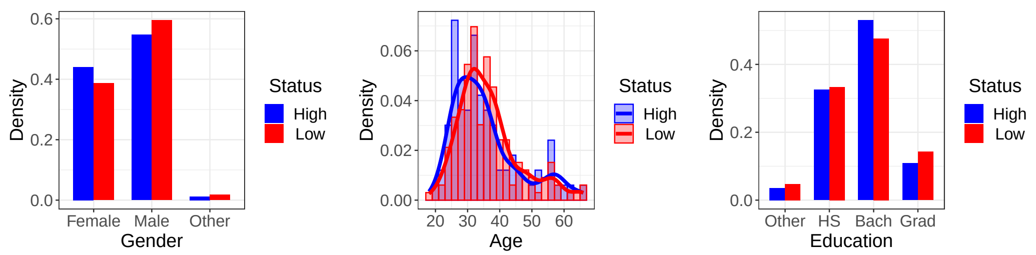


Figure 6: Distribution of player gender, age and education by treatment (status) condition. In the education plot, HS, Bach, Grad refer to High school, Bachelor's degree and post-graduate degree respectively.

MTurk workers were not allowed to play more than once. Data collection took a period of 2 weeks from 2021-03-22 to 2021-04-05.

Out of the 38 games, there were 10 games in which players of a single type missed digging the gold more than once even if they knew its location. This can happen either due to connection problems or player inattentiveness. As we also mentioned in the pre-registration document, analyzing such games and comparing them against a null model is challenging, because not only group level rewards will be lower due to the missed opportunities but also inattentiveness might affect cooperation. As outlined in the exclusion criteria of our pre-registration document, the final data excluded these games and had 28 games with 252 unique players. Comparing the treatment groups (high or low) along three basic demographic variables does not reveal a significant difference. The p-value of the two-sample chi-square test on gender and education level between the high and low treatment groups are 0.69 and 0.79 respectively. Similarly, the p-value of the two-sample Kolmogorov-Smirnov test on age is 0.35. Figure 6 compares the distribution of these variables among participants across the status treatment.

5 Methods

Our main hypothesis is that high status players share the location of gold more frequently than low status players. This leads to high status players as a group receiving a larger share of total available gold than would be expected without network sharing, which would have been about 50% given that exactly one high-status and one low-status player receive the information in each round. Similarly, the mean reward or mean fraction of total rewards that goes to a high type player is larger than the value predicted without network effects. These hypothesis involve quantities at the individual and group levels. Hence, we compare the experimental data against a null model in two ways. In the first analysis, described in section 5.2, the dependent variable is the within-status dyadic sharing rate and the null model indicates no difference in sharing rate by status treatment. In the second analysis in section 5.3, the dependent variable is the fraction of rewards to each status and the null model predicts equal distribution of rewards to the status groups.

5.1 Notation

In what follows, we let $I_{gold}(g, r, i)$ represent an indicator variable which takes the value of 1 when the gold is revealed to player i in round r of game g. Similarly, $I_{shared}(g, r, i, j)$ is a binary indicator that takes the value of 1 when player i shares the gold with player j in round r of game g. $U_{g,i}$ is the utility or total reward of player i at the end of game g. G corresponds to the set of all games, H_g is a set that contains the 6 directional edges in the form of (i, j) between high status players game g and L_g contains the set of 12 directional edges between low status players. Given the notations above, we can express the average sharing rate from player i to player j in game g as followed.

$$S_{g,i,j} = \frac{\sum_{r\in\{1,\ldots,12\}} I_{shared}(g,r,i,j)}{\sum_{r\in\{1,\ldots,12\}} I_{gold}(g,r,i)} \tag{2}$$

Similarly, we can define the average sharing rate within each status group as followed.

$$S_{g,H} = \frac{\sum_{(i,j)\in H_g} S_{g,i,j}}{|H_g|} \tag{3}$$

$$S_{g,L} = \frac{\sum_{(i,j)\in L_g} S_{g,i,j}}{|L_g|} \tag{4}$$

5.2 Dyadic Sharing Rate

Our main hypothesis examines the difference in sharing rate, or *P(sharing / gold is revealed)*, at the level of each dyad across status groups. In this analysis, a unit of observation is the sharing rate on a single directed edge over all 12 rounds or $S_{g,i,j}$. Since sharing is directional, there will be two observations for each dyad corresponding to each direction. We compare the sharing-rate of high-status and low-status players in two ways.

Fisher Exact Test: The sharp null here implies that status has no effect at all on sharing decisions of a player. Since a unit of observation involves each directed edge, we can use the difference in the mean sharing rate of high status group and low status group as the test statistic.

$$t = \frac{\sum_{g\in G} S_{g,H}}{|G|} - \frac{\sum_{g\in G} S_{g,L}}{|G|} \tag{5}$$

The test statistic is effectively the estimated average treatment effect on the sharing rate along a dyad where the treatment is the assignment of the dyad to high or low status. Given the sharp null, we can conduct the usual

Fisher randomization technique to compute the exact p-value of our observed statistic. However, it is important to note that not all randomizations are valid. A valid randomization should generate three disconnected components with one as a high status clique similar to figure 2. But more importantly, the randomization must maintain the same neighbors for each player because the sharing rate of each player is dependent on sharing decisions of their neighbors. If we had allowed randomizations that create different pairings of players than the actual realized network, each player would be exposed to a different neighbor history which could have changed their sharing rate. In other words, the sharp null does not imply the sharing rate is independent of neighbor actions, rather it only assumes independence from status labeling. Hence, we are comparing against a *conditional sharp null: conditioned on the realized assignment of players to network positions, the status has no effect on sharing rate.*

There are only 3 randomizations per game that keep positions and neighbors in the network fixed but flip the status. In each randomization, the status of one of the three triads in figure 2 is set to be high and the remaining two triads are low status. Given 28 collected games, there are 3^{28} possible permutations, so we use sampling from these permutations to generate the distribution of the statistic under the sharp null.

Average Treatment Effect: We could also test the effect of status against the Neyman null of zero average treatment effect or ATE. The challenge is that the Stable Unit Treatment Value Assumption or SUTVA is violated: the outcome of an edge not only depends on the status assignment of the players on each side of the edge but also on the assignment of their neighbors in the triad. This implies that there is potential spillover from one dyad to another. However, we are not interested in the effect of individual status assignments, rather the status assignment in groups. We can denote the potential outcome of a dyad as $S(t_1, t_2, t_3)$ where t_1, t_2 and t_3 correspond to the status or type assignment of the three players in the triad that contains the dyad and $S(t_1, t_2, t_3)$ is the sharing rate from player with status t_1 to player with status t_2. We are not interested in causal quantities such as $E[S(H, L, L) - S(L, L, L)]$, instead we are after a causal quantity such as $E[S(H, H, H) - S(L, L, L)]$. This is because our theory is about how groups of high status cooperate differently than low status and not about the effect of individual status changes.

Using $E[S(H, H, H) - S(L, L, L)]$ as the estimand addresses the SUTVA violation within each triad as the treatment now explicitly accounts for the full triad assignment. Nevertheless, there is still the possibility of spillovers from disconnected triads since there is information flow between triads when sharing the common resource. Therefore, we expand the potential outcome function on a dyad to $S(t_1, t_2, t_3, t_4, t_5, t_6, t_7, t_8, t_9)$ where the first 3 arguments correspond to the status assignment in the triad that contains the dyad, the remaining 6 arguments correspond to assignment of players in other triads and $S(.)$ is the sharing rate from player with status t_1 to player with status t_2. With this definition, the main estimand incorporates the status assignment of players in other triads as shown below.

$$ATE = E[S(H, H, H, L, L, L, L, L, L) - S(L, L, L, L, L, L, H, H, H)] \quad (6)$$

One could use a difference-in-means estimator similar to the one shown in equation 2 for the ATE above. If we were to assume sharing decisions of players are independent of each other, we could conduct inference using a two independent sample t-test with unequal variances. However, one might expect that the potential outcomes in triads might be correlated. For example, it is possible that players engage in tit-for-tat or grim trigger strategies, in which case their sharing rates might be correlated. In the terminology of linear regression, we would say that the error terms are correlated in triads. Therefore, we need to account for this clustering in our inference. We could account for this clustering by defining each triad in each game as a cluster (75 total clusters) and use cluster-robust standard errors. But since there is information flow from one cluster to another during the game summary stages, one needs to be conservative and use the games or the coarsest level possible as the clusters. The only concern with this choice is the small number of clusters (28) which might adversely affect our standard error estimate. However simulations with 28 games that use a probabilistic grim trigger strategy among players of each triad suggest that the inference with cluster robust standard errors and the game as the clustering unit has a correct type I error (type I error = 0.03 when α=0.05) whereas the regular standard error without clustering greatly over-rejects when the null is true (type I error = 0.12 when α=0.05).

In summary to conduct inference on the ATE in equation 6, we use the following regression model with cluster robust standard errors and each game as a cluster.

$$S_{g,i,j} = \beta_0 + \beta_1 t_{g,i,j} + \gamma \mathbf{X_g} + \epsilon_{g,i,j} \tag{7}$$

where $S_{g,i,j}$ as defined in equation 2 is the sharing rate in the dyad from player i to player j in game g, $t_{g,i,j} \in \{H, L\}$ is the randomized status treatment on the tiad that includes i and j and $\mathbf{X_g}$'s are the game fixed effects.

5.3 Fraction of Group Rewards

Any difference in sharing rates will directly lead to unequal shares of total rewards collected by the status groups. We conduct tests to evaluate whether the high status group receives a larger fraction of the total gold than would be expected under the null model. This analysis alleviates any concerns of dependence within games when using sharing rates as the dependent variable since the unit of analysis is a game which is clearly independent of other units.

Null Model: We refer to the model of each player acting individually without any network effects as the null model. Under the null model, utility solely derives from the exogenous individual ability, captured by status in our experiment, and does not have a network component. Without network effects, each group will receive about half of the total gold available, but not exactly 50% since players can still guess the location of the gold if it is not revealed to them. In particular, the low type will receive slightly more than 50% since there are 5 players guessing the location in each round as opposed to 2 in the case of high type. If we denote a binomial process by $Binom(n, p)$ where n corresponds to the number of trials and p is the success probability, then the expected fraction of total gold earned by each group and their ratio under the null model, denoted by μ_H, μ_L and ρ, take the binomial forms below.

$$\mu_H = E\Big[\frac{1 + Binom(2, 1/90)}{2 + Binom(2, 1/90) + Binom(5, 1/90)}\Big] = 0.498 \tag{8}$$

$$\mu_L = E\Big[\frac{1 + Binom(5, 1/90)}{2 + Binom(2, 1/90) + Binom(5, 1/90)}\Big] = 0.514 \tag{9}$$

$$\rho = E\Big[\frac{1 + Binom(2, 1/90)}{1 + Binom(5, 1/90)}\Big] = 0.994 \tag{10}$$

where $Binom(2, 1/90)$ corresponds to a binomial process in which 2 high type players without the gold guess its location among the 90 unrevealed squares and similarly $Binom(5, 1/90)$ corresponds to the same process for the 5 low type players without the gold.

Non-Parametric Test: This is be our primary analysis at the game-level. The analysis involves the following two measures.

1. Mean fraction of total reward collected by the high status group.

$$\widehat{\mu}_H = \sum_{g \in G} [\frac{\sum_{i \in H_g} U_{g,i}}{\sum_{i \in H_g \cup L_g} U_{g,i}}]/|G| \tag{11}$$

2. Mean ratio of total reward collected by the high status group over the low status group.

$$\widehat{\rho} = \sum_{g \in G} [\frac{\sum_{i \in H_g} U_{g,i}}{\sum_{i \in L_g} U_{g,i}}]/|G| \tag{12}$$

We compare the above measures against their corresponding values from the null model in equations 8 and 10 using the one-sample Wilcoxon signed rank test. With 28 games, we have $\binom{56}{28}$ possible permutations so we need to appeal to its normal approximation to compute the p-value. The null hypothesis in Wilcoxon signed rank test assumes symmetry around the median of paired differences. Since this might not be appropriate, we also report the results from the weaker sign test whose null hypothesis simply assumes the median is a given value.

Parametric Test: We compare the above measures, $\widehat{\mu}_H$ and $\widehat{\rho}$, against the null model predictions using the one-sample t-test. This will be a secondary game-level analysis since we don't expect that the distribution of $\widehat{\mu}_H$ and

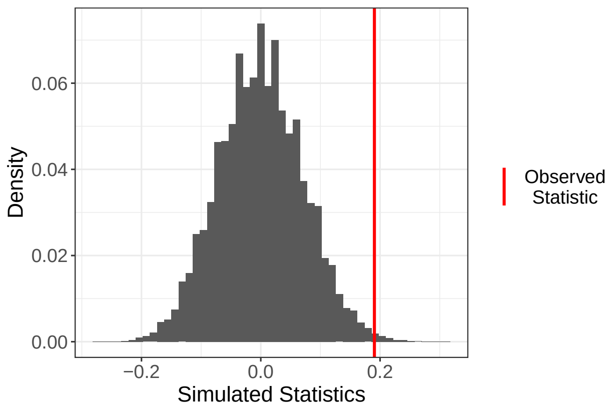


Figure 7: The distribution of the test statistic with the randomization inference versus the observed statistic.

$\widehat{\rho}$ would be close to their asymptotic normal under the null given only 28 games. In fact, our simulations suggest that this test has a higher type I error rate than the significance level with $n = 28$ (e.g. type I error=0.018 when α=0.01).

6 Results

We present the results of different analysis methods in the same order as described in section 5.

6.1 Dyadic Sharing Rate

Fisher Exact Test: Figure 7 shows the result of this analysis. The test statistic, in equation 5, is effectively the average treatment effect at the dyad level. The statistic is positive and significant (two-tailed $p = 0.0067$ with 50000 simulated random assignments) indicating that the high status treatment has a higher sharing rate than the low status treatment.

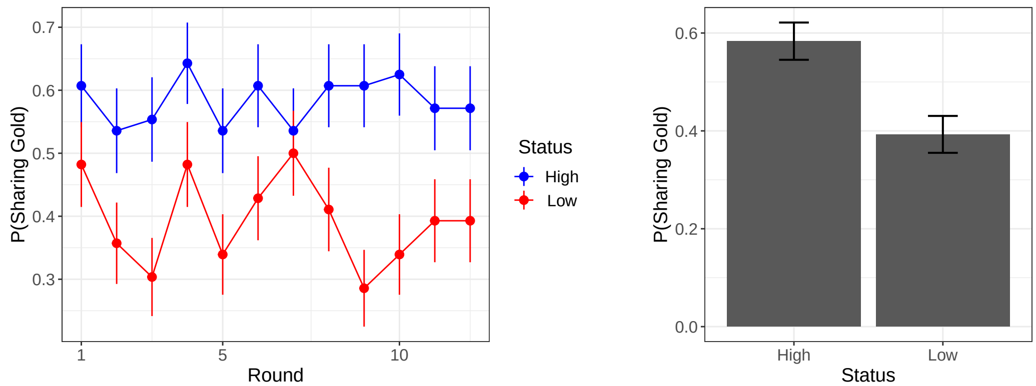


Figure 8: Probability of sharing conditioned on receiving the gold per round (left) and over all rounds (right) by status of players. Bars in the left plot correspond to standard error while they correspond to 95% confidence interval on the right

Average Treatment Effect: Figure 8 compares the mean sharing rate along high status and low status dyads as defined in equations 3 and 4. The results clearly indicate that the high status players share the rivalrous resource with each other at a significantly higher rate in all rounds and overall. This suggests that the rivalry in resource sharing promotes strategic behavior, especially among the low status players. This can be further validated by examining the number of non-gold squares shared by low status players. The game revealed 10 squares to each player in each round, one of which could be a gold mine, and the players could share any number of these squares with any of their neighbors. Sharing non-gold squares might still be a form of cooperation since it helps the other players to find the gold mine through the process of elimination. Figure 9 compares the mean number of non-gold squares shared along high status and low status dyads. As opposed to the results for sharing the gold mine itself, we observe that low status players share more squares on average than high status players. This finding suggests that

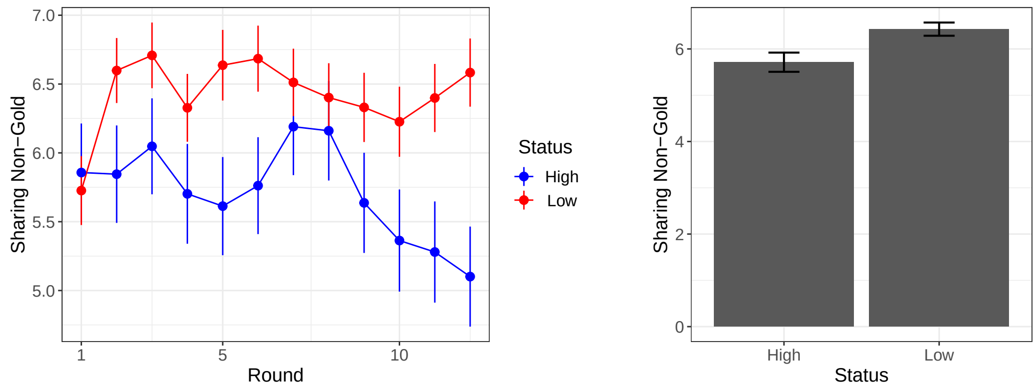


Figure 9: Mean number of non-gold squared shared per round (left) and over all rounds (right) by status of players. Bars in the left plot correspond to standard error while they correspond to 95% confidence interval on the right

low status players act very strategically as they tend to keep the rivalrous resource exclusively, but nevertheless share other valuable information with their neighbors hoping to keep a cooperative relationship in the future.

Table 1 shows the formal inference results on the average treatment effect. The model explained in section 5.2 with cluster robust standard errors at the game level is included in the second column. According to this model, random assignment to a high status triad causes the sharing rate to increase by about 19%. The cluster robust p-values from models with and without game fixed effects (columns 2 and 3) are $p = 0.011$ and $p = 0.009$ respectively.

6.2 Fraction of Group Rewards

In this section, we present the results of hypothesis tests that compare the observed fraction of rewards earned at the end of the game by the high status group ($\widehat{\mu}_H$ from equation 11) and the ratio of high and low status rewards ($\widehat{\rho}$ from equation 12) versus their respective null model predictions in equations

Table 1: Estimated Average Treatment Effect under different models. First column includes the game fixed effects but uses regular standard errors. Second column includes game fixed effects along with cluster robust standard errors. Third column does not include the fixed effects but uses cluster robust standard errors. Fixed effect estimates are not shown.

	Dependent variable:		
	Sharing Rate		
	(1)	(2)	(3)
High Status	0.190***	0.190**	0.190***
	(0.038)	(0.074)	(0.072)
Constant	0.187**	0.187***	0.393***
	(0.095)	(0.025)	(0.040)
Cluster Robust SE	No	Yes	Yes
Game Fixed Effects	Yes	Yes	No
Observations	504	504	504
R^2	0.216	0.216	0.042
Adjusted R^2	0.170	0.170	0.040
Residual Std. Error	0.400 (df = 475)	0.400 (df = 475)	0.430 (df = 502)
Note:			*p<0.1; **p<0.05; ***p<0.01

8 and 10.

Non-Parametric Test: Given the small sample size ($n = 28$), non-parametric tests that don't make any assumption on the distribution of the test statistic seem to be more appropriate. The null model in the following non-parametric tests assumes that the median of the distribution, from which we observe $\widehat{\mu}_H$ values, is equal to μ_H. The one-sample Wilcoxon signed rank test rejects the

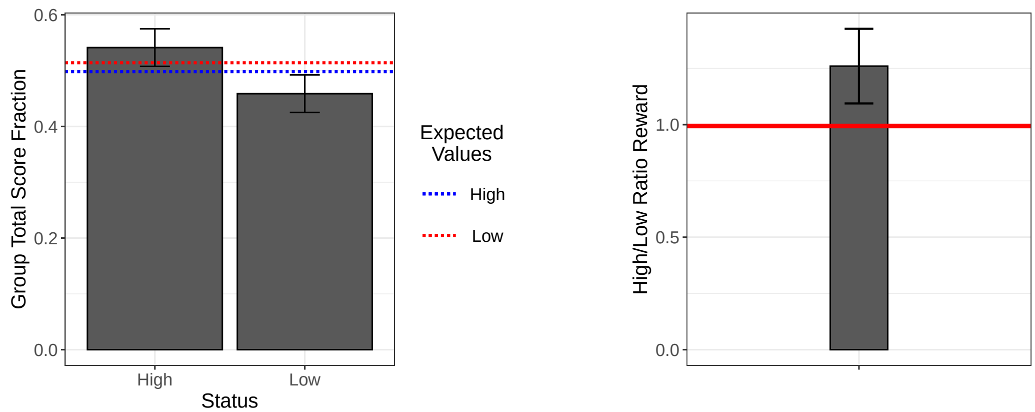


Figure 10: Share of each group from total gold distributed over the game versus their expected share (left). The ratio of high status group versus low status group total gold distributed over the game compared with the expected ratio (right). Bars correspond to 95% confidence interval.

null model with $p = 0.021$ and $(0.507, 0.580)$ as the 95% confidence interval for the fraction of rewards collected by the high group. The weaker sign test also rejects the null model with $p = 0.013$.

We could conduct the same tests using a different statistic and compare the observed ratio of rewards $\widehat{\rho}$ against its null model prediction ρ. The one-sample Wilcoxon signed rank test rejects this null model with $p = 0.010$ and $(1.064, 1.426)$ as the 95% confidence interval on the true ratio of rewards ρ. The sign test also rejects the null with $p = 0.012$. The direction of the observed statistic relative to the null in all the tests above indicate that the high status group collects a larger share of the rivalrous resource than expected under the null model without network effects.

Parametric Test: Figure 10 compares the mean fraction of total rewards collected by each group and their ratio against the null model predictions in equations 8, 9 and 10. The results indicate that the high status assignment has a positive and statistically significant impact on the share of rewards collected by the group. The one sample t-test on the fraction of rewards by the high group rejects the null with $p = 0.016$ and $(0.507, 0.576)$ as the 95% confidence interval. Similarly, the t-test rejects the null on the ratio of rewards with $p = 0.003$ and $(1.090, 1.430)$ as the 95% confidence interval. However, as we mentioned in section 5.3, our simulations suggest that the type I error rate of the parametric t-test with $n = 28$ is slightly higher than the α, so the results above might not fully satisfy the asymptotic assumptions. Nevertheless, our non-parametric tests provide clear evidence rejecting the null, offering more credibility to the findings from these parametric tests.

7 Conclusion

The persistence of inequality has been linked to social networks [4]. The most common account of network effects on inequality takes a purely structural perspective since it considers homophily and network segregation as the drivers of unequal access to opportunities. While this is largely true, a purely structural view misses the nuanced processes that occur in networks [10]. With a simple example of diffusion in networks, we showed that network structure and homophily does not explain how one group can take a "larger share of the pie" than expected solely based on heterogeneity in individual ability. In this paper, we go beyond the simple structural perspective and examine one potential process that affects the unequal distribution of resources. In particular, we assume that agents in a network share information about a common rivalrous resource, and are heterogeneous in terms of their individual ability in accessing the resource. As opposed to the structural perspective which treats agents as myopic, we assume they are strategic and forward-looking. This makes sense since the rivalry in a valuable resource necessitate competition and strategic cooperation. Our experimental results further validate that individuals engage in strategic behavior.

We develop this process into a repeated game of information sharing in networks where network formation is endogenous to the model. There are two types of agents, one with a higher probability of accessing the resource in each round than the other, and each agent decides whether to share information about the rivalrous resource with any other agent. If the differences between agents type are sufficiently large, the model predicts that information sharing or cooperation in the pairwise Nash stable network exists only among the high type. As a result, the high type as a group will receive a larger share of the rivalrous resource than expected solely based on the exogenous probabilities which can be thought of individual ability without network sharing. Furthermore, a randomized multi-player lab experiment that closely mimics the game validates the model predictions. We observe that players who have a higher probability of accessing a valuable resource, which directly translates to monetary reward, are about 19% more likely to share it with their other high status neighbors. Both the theoretical and experimental results indicate the importance of network processes other than simple diffusion in generation of inequality. One can think of the status differences among players in terms of accessing the valuable resource as differences in human capital and the number of neighbors with reciprocal cooperation as social capital. Thus, our results suggest that the interaction of human capital and social capital play an important role in unequal access to opportunities. It also invites further experimental and modeling studies to fully characterize how differences in human capital lead to inequality in social capital [29, 30].

We hope our study of network effects on group-level outcomes contributes to the larger discussion around why a small minority can take an exceptionally large share of common resources. The model predictions demonstrate how the differences among agents and the relative scarcity of the resource in each group lead to cooperation among the high status but competition among the low status to benefit from the limited stock of valuable resource. The extreme scarcity in the low status group prohibits the formation of social capital and promotes a form of elite capture. The model also implies that the low status type is stuck in a durable poverty trap because inequality is the equilibrium of the incentive structure in the network, an argument that is inline with views of inequality as a process [10]. The formation of inequality in this process is an example on how micromotives (e.g. cooperation) lead to macrobehavior (e.g. larger share of the pie by one exclusive group) [31].

Many recent studies have looked at urban segregation, status homophily and lack of mixing in networks and have reported a link, albeit correlational, between inequality and the extent of clustering and homophily [8, 32]. These findings have been the basis of a policy recommendation to promote cross-group linking in social structures as a means of combating inequality. While interventions that bring diverse people together and facilitate inter-group linking could be helpful, without changing the underlying incentive structure of inter-group linking, their impact would not be as large as one hopes. Our model suggests that, at least when it comes to sharing limited common resources, inter-group links are difficult to create and persist and even if they were to form due to policies that encourage mixing, valuable information would rarely be shared across them. This happens due to the incentive structure of cooperation between low and high status groups in social networks which reduces the extent of possible reciprocity and consequently the motivation for high status individuals to share valuable information with the disadvantaged group. A potential remedy to this problem is to limit the visibility of individual endowments, as recent studies have shown that visibility of advantage increases inequality [33] and negatively impacts cooperation [22]. In the context of our model, if it is not easy to observe the agent type, we would expect more inter-group linking and cooperation. However, the efficacy of this approach over long-term might not be stable as agent types can eventually be inferred.

The lack of cooperation in the low status group originates from the rare ability of accessing valuable resources by the group. Thus, it might be helpful to target individuals in the low status group by investing in their human capital. While this will improve the chances of accessing resources and opportunities by those individuals, it does not make them more likely to cooperate with the rest of the low status group because this interventions does not change the underlying incentive structure among the disadvantaged population. The barrier to cooperation in the low status group is a group phenomena and thus requires an intervention at the group level rather than individuals. The ideal intervention is one that empowers the whole group by investing in their human capital just enough to tip the balance in favor of cooperation rather than competition. This intervention not only helps the individuals to access valuable resources independently (e.g. find jobs and be productive), but also increases the incentives for others in both high and low status group to share valuable information with them. A broad investment in the disadvantaged population just enough to overcome the barriers to cooperation has multiplicative effect on their outcome as it also enables the formation of social capital, improves the outcome of the whole group and reduces inter-group differences even beyond what's expected by individual differences. When information sharing becomes the dominant strategy of the low status group, network effects in fact alleviate inequality in a manner similar to what we described at the beginning of the paper and illustrated in figure 1b.

8 Acknowledgements

The authors would like to thank Matthew Jackson for his thoughtful feedback, references and help in developing this study. The authors also appreciate the comments provided by participants at the 2022 Network Science and Economics Conference.

References

[1] Thomas Piketty. Capital in the 21st century. In *Inequality in the 21st Century*, pages 43–48. Routledge, 2018.

[2] Matthew Jackson. Policy cocktails: Attacking the roots of persistent inequality. *Policy*, 2021.

[3] United Nations. Transforming our world: The 2030 agenda for sustainable development, 2020. URL https://sdgs.un.org/goals/goal10.

[4] Matthew O Jackson. Inequality's economic and social roots: The role of social networks and homophily. *Available at SSRN 3795626*, 2021.

[5] Paul DiMaggio and Filiz Garip. How network externalities can exacerbate intergroup inequality. *American Journal of Sociology*, 116(6): 1887–1933, 2011. ISSN 00029602, 15375390. URL http://www.jstor.org/stable/10.1086/659653.

[6] Nan Lin. Inequality in social capital. *Contemporary Sociology*, 29(6):

785–795, 2000. ISSN 00943061, 19398638. URL http://www.jstor.org/stable/2654086.

[7] Gwen Van Eijk. *Unequal networks: Spatial segregation, relationships and inequality in the city*, volume 32. Gwen van Eijk, 2010.

[8] Gergő Tóth, Johannes Wachs, Riccardo Di Clemente, Ákos Jakobi, Bence Ságvári, János Kertész, and Balázs Lengyel. Inequality is rising where social network segregation interacts with urban topology. *Nature communications*, 12(1):1–9, 2021.

[9] Antoni Calvó-Armengol and Matthew O. Jackson. The effects of social networks on employment and inequality. *American Economic Review*, 94 (3):426–454, June 2004. doi: 10.1257/0002828041464542. URL https://www.aeaweb.org/articles?id=10.1257/0002828041464542.

[10] Charles Tilly. *Durable inequality*. University of California Press, 1998.

[11] Matthew O Jackson. A typology of social capital and associated network measures. *Social Choice and Welfare*, 54(2):311–336, 2020.

[12] Urs Fischbacher, Simon Gächter, and Ernst Fehr. Are people conditionally cooperative? evidence from a public goods experiment. *Economics Letters*, 71(3):397–404, 2001. ISSN 0165-1765. doi: https://doi.org/10.1016/S0165-1765(01)00394-9. URL https://www.sciencedirect.com/science/article/pii/S0165176501003949.

[13] Lori A. Beaman. Social Networks and the Dynamics of Labour Market Outcomes: Evidence from Refugees Resettled in the U.S. *The Review of Economic Studies*, 79(1):128–161, 08 2011. ISSN 0034-6527. doi: 10.1093/restud/rdr017. URL https://doi.org/10.1093/restud/rdr017.

[14] R. Mark Isaac and James M. Walker. Group size effects in public goods provision: The voluntary contributions mechanism. *The Quarterly Jour-*

nal of Economics, 103(1):179–199, 1988. ISSN 00335533, 15314650. URL http://www.jstor.org/stable/1882648.

[15] Abhijit Banerjee, Emily Breza, Arun G Chandrasekhar, Esther Duflo, and Matthew O Jackson. Come play with me: Experimental evidence of information diffusion about rival goods. *Work in Progress*, 2012.

[16] Joshua Evan Blumenstock, Guanghua Chi, and Xu Tan. Migration and the value of social networks. 2019.

[17] Antoni Calvó-Armengol. Job contact networks. *Journal of Economic Theory*, 115(1):191–206, 2004. ISSN 0022-0531. doi: https://doi.org/10.1016/S0022-0531(03)00250-3. URL https://www.sciencedirect.com/science/article/pii/S0022053103002503.

[18] Kenneth S Chan, Stuart Mestelman, Robert Moir, and R Andrew Muller. Heterogeneity and the voluntary provision of public goods. *Experimental Economics*, 2(1):5–30, 1999.

[19] Edward Buckley and Rachel Croson. Income and wealth heterogeneity in the voluntary provision of linear public goods. *Journal of Public Economics*, 90(4-5):935–955, 2006.

[20] Abdolkarim Sadrieh and Harrie A.A. Verbon. Inequality, cooperation, and growth: An experimental study. *European Economic Review*, 50(5):1197–1222, 2006. ISSN 0014-2921. doi: https://doi.org/10.1016/j.euroecorev.2005.01.009. URL https://www.sciencedirect.com/science/article/pii/S0014292105000528.

[21] Jing Wang, Feng Fu, and Long Wang. Effects of heterogeneous wealth distribution on public cooperation with collective risk. *Physical Review E*, 82(1):016102, 2010.

[22] Akihiro Nishi, Hirokazu Shirado, David G Rand, and Nicholas A Chris-

takis. Inequality and visibility of wealth in experimental social networks. *Nature*, 526(7573):426–429, 2015.

[23] Hirokazu Shirado, George Iosifidis, and Nicholas A. Christakis. Assortative mixing and resource inequality enhance collective welfare in sharing networks. *Proceedings of the National Academy of Sciences*, 116(45): 22442–22444, 2019. ISSN 0027-8424. doi: 10.1073/pnas.1911606116. URL https://www.pnas.org/content/116/45/22442.

[24] Winter Mason and Duncan J. Watts. Collaborative learning in networks. *Proceedings of the National Academy of Sciences*, 109(3):764–769, 2012. ISSN 0027-8424. doi: 10.1073/pnas.1110069108. URL https://www.pnas.org/content/109/3/764.

[25] Matthew O. Jackson and Asher Wolinsky. A strategic model of social and economic networks. *Journal of Economic Theory*, 71(1):44–74, 1996. ISSN 0022-0531. doi: https://doi.org/10.1006/jeth.1996.0108. URL https://www.sciencedirect.com/science/article/pii/S0022053196901088.

[26] Francis Bloch and Matthew O Jackson. Definitions of equilibrium in network formation games. *International Journal of Game Theory*, 34 (3):305–318, 2006.

[27] Todd L. Cherry, Stephan Kroll, and Jason F. Shogren. The impact of endowment heterogeneity and origin on public good contributions: evidence from the lab. *Journal of Economic Behavior & Organization*, 57(3):357–365, 2005. ISSN 0167-2681. doi: https://doi.org/10.1016/j.jebo.2003.11.010. URL https://www.sciencedirect.com/science/article/pii/S0167268104001167.

[28] Abdullah Almaatouq, Joshua Becker, James P Houghton, Nicolas Paton, Duncan J Watts, and Mark E Whiting. Empirica: a virtual lab for high-

throughput macro-level experiments. *Behavior Research Methods*, pages 1–14, 2021.

[29] Claudia Goldin and Lawrence F. Katz. Human capital and social capital: The rise of secondary schooling in america, 1910-1940. *The Journal of Interdisciplinary History*, 29(4):683–723, 1999. ISSN 00221953, 15309169. URL http://www.jstor.org/stable/206979.

[30] James S. Coleman. Social capital in the creation of human capital. *American Journal of Sociology*, 94:S95–S120, 1988. ISSN 00029602, 15375390. URL http://www.jstor.org/stable/2780243.

[31] Thomas C Schelling. *Micromotives and macrobehavior*. WW Norton & Company, 2006.

[32] Milena Tsvetkova, Claudia Wagner, and Andrew Mao. The emergence of inequality in social groups: Network structure and institutions affect the distribution of earnings in cooperation games. *PLOS ONE*, 13(7): 1–16, 07 2018. doi: 10.1371/journal.pone.0200965. URL https://doi.org/10.1371/journal.pone.0200965.

[33] Matthew J. Salganik, Peter Sheridan Dodds, and Duncan J. Watts. Experimental study of inequality and unpredictability in an artificial cultural market. *Science*, 311(5762):854–856, 2006. ISSN 0036-8075. doi: 10.1126/science.1121066. URL https://science.sciencemag.org/content/311/5762/854.