Social Learning in a Directed Network

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Abstract

This paper experimentally studies social learning in directed networks. Human subjects make predictions of an uncertain state of the world based on two sources of information, a) their private information and b) social information that can be gathered by waiting in a directed network. Theoretical predictions suggest that human subjects should wait when the benefit from waiting in the network exceeds the cost. Following the predictions, subjects will wait longer in a more connected network with a low waiting cost. Experimental results support that subjects wait longer in a more connected network or when the waiting cost is low, but they don't wait long enough as the equilibrium predicts. The observed deviation can be partly explained by the quantal response equilibrium and partly explained by some subjects adopting a simple heuristic.

Keywords: Social Learning, Waiting Game, Decision-making, Directed Networks, Human Subject experiment

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1 Introduction

Many economic decisions rely on social information obtained through a network. This social information can be transmitted vaguely through others' behaviors or more precisely through costly communication. When a decision is easy to reverse, for example, trying a new brand of yogurt, the vague social information reflected from others' behavior is sufficient for improved decision making; however, when the decision becomes more costly to reverse, such as the purchase of a second-hand vehicle or signing up a one-year rental lease, people may demand more precise information by talking to their direct and indirect friends in their social network. Previous studies on social learning mostly focus on the observational learning (Anderson and Holt, 1997; Hung and Plott, 2001; Çelen and Kariv, 2004; Goeree et al., 2007) and overlook the role of communication in the network. It is important to fill in the gap to understand how people achieve social learning in a communication network.

When a decision is hard to reverse, people may go beyond the observational learning and communicate with others in their network to obtain more information. Often the time, the information flow is directed. Someone who has purchased a second-hand car is more likely to give advises than gather more information about the market. Depending on the network structure and how costly it is to wait before making a decision, a rational decision-maker should only wait when the increase in their expected payoff exceeds the waiting cost as modeled in Acemoglu et al. (2014). Do people make optimal decisions as this theory predicts? Specifically, do people utilize the communication network the way it is modeled?

To test it, I run a laboratory experiment that takes a 2-by-2 between-subject design varying the waiting cost and the directed communication network structure. Both networks are 5-person directed networks with 10 edges and the same degree distribution. The difference lies in how much information can be transmitted through the network. In the not fully connected network (network NC), people are unable to obtain all the information no matter how long they wait in the network. The network structure imposes an upper limit of how much information could be obtained at each position. In comparison, the other network (network C) is fully connected. If people are patient and wait for long enough, they can obtain all information possessed by everyone in the network. In my experiment, observational learning is about whether other subjects have made a decision and stopped gathering more information. Waiting incurs a cost but grants subjects the opportunity to observe the private information of others directly. Communication is enforced to be truthful. To make an optimal decision, a subject needs to 1) be perfect Bayesian updating; 2) understand the structure of the network and the flow of the information. The pure-strategy perfect Bayesian equilibrium predicts that subjects behave the same in network NC regardless of the waiting cost and network C with high waiting cost. They should only wait longer in network C with a low waiting cost.

What I find is that subjects tend to over-wait when 1) the waiting cost is low but the network is not fully connected (over-wait for unobtainable information/redundant information); 2) the waiting cost is high but the network is fully connected (over-judge the value of additional information); 3) they tend to under-wait when both the waiting cost is low and the network is fully connected. The deviation from perfect Bayesian equilibrium could be partly explained by subjects making mistakes and holding wrong beliefs. Heterogeneity among subjects is a second explanation of the observed deviation in the lab. There seems to be a substantial proportion of subjects who use a simple heuristic (always wait for 1 turn) in their decisions making in the directed network environment. Mirroring the naive learning DeGroot's model in an observational learning setting, in a directed network, it is worthwhile to consider some naive stopping rules.

The paper is organized as follows. Section 2 reviews some related literature. Section 3 presents the theoretical background and predictions of the experiment. In section 4, I explain the experimental design, including the treatments, the choice of networks, and different parameters. Section 5 shows the main results.

2 Literature Review

2.1 Social learning and information choice

My experiment is related to the large and growing works of literature on social learning experiments. Compared to the early stage social learning experiments, my experiment places subjects in a more complicated environment where subjects may increase their signals' qualities by waiting and observing others' signals. The classical social learning experiment was first proposed by Anderson and Holt (1997) to test the social learning theories (Bikhchandani et al., 1992; Banerjee, 1992) in a sequential-move structure. Sgroi (2003) modifies the classic social learning experiment by allowing subjects to observe two independent draws of the jar, and finds that people will wait if their signals are not informative, and the guesses are normally initialized by people with highly informative signals.

Only recently people start modeling social learning in networks and paying attention to how the network structure may influence learning. On one hand, some studies focus on how an exogenous communication network would influence subjects' belief formation in a simultaneous-move setting. Although studies in this stream also investigate whether subjects embed the network structures in their decision makings, the environment is fundamentally different from my experiment. In these studies, subjects are first asked to make a guess based on their private information simultaneously. Then they can observe their neighbors' guesses in the network and change their guesses in the next round. The game ends when the network reaches a consensus or by a random termination. Subjects observe their neighbors' guesses with no delay or any waiting cost. Their decisions are not irreversible as they can freely change their decisions for multiple times within the allowed time. For example, Grimm and Mengel (2020) study 3 different types of undirected network structures (star, kite, circle) and whether subjects' decision-makings vary based on their knowledge of the structure of the network. Chandrasekhar et al. (2020) study 3 chosen undirected networks and try to differentiate the agent types between DeGroot naive learning agent and Bayesian learning agent. Choi et al. (2012) study a similar problem in 3-person networks.

On the other hand, other studies focus more on the formation of networks in the social learning experiment. Subjects are given the opportunity to link to their previous subjects. For example, Çelen and Hyndman (2012) studies the endogenous formation of networks in groups of 4 subjects. In their experiment, subjects make sequential decisions by observing a free private signal and paying costs to observe previous subjects' guesses. Consistent with the theoretical prediction, a small cost of linking to previous subjects can increase the average welfare. They also find evidence suggesting that people tend to over-link and conform excessively. My experiment is closer to this stream of studies. When a subject decides to make an irreversible decision, it can be seen as the subject drops all his out-degree links, thus it's a reverse version of the network formation problem. Unlike these studies where subjects freely form links with others in the network, in my experiment, the network links are already formed. This experiment focuses more on whether subjects can utilize a communication network the way it is commonly modeled.

It also contributes to the recent debate on subjects' information choices in social learning. Prior experiments document that subjects tend to over-weight their private information Weizsäcker (2010), Ziegelmeyer et al. (2010) in a sequential move social learning experiment. In more recent and complex environments, subjects also tend to acquire excessive social information or suboptimally overweight the social information. (Goeree and Yariv (2015), Eyster et al. (2015), March and Ziegelmeyer (2018), Duffy et al. (2019), Duffy et al. (2021)). Similar to these studies, subjects in my experiment are given a private signal and can obtain social information from other subjects. Unlike the previous settings, the social information subjects obtain is of higher quality through the communication network: instead of others' choices, subjects will observe others' signals directly; and subjects have some freedom in determining how much social information they want to gather. By imposing the truthful communication assumption, I further simplify the Bayesian updating problem in the inference stage. When the social information contains others' behaviors, a correct inference requires a correct belief about others and more involved statistical inferences. In my experiment, a correct inference is only based on a simple counting of which state has more signals. Conditional on the information a subject gathered, most inferences utilize the private and the social information optimally, with an exception when the signals are not informative, subjects present a slight tendency to rely on their private information.

2.2 Waiting game and information acquisition

My experiment is also related to the studies of waiting games and information acquisition. The theoretical model is an investment game proposed by Chamley and Gale (1994), where firms with different private information decide whether and when to invest in a joint project. In a waiting game, subjects obtain signals with different quality and can delay their decision-makings to observe other subjects' behaviors with more informative signals. Delaying the decision incurs a waiting cost. Previous studies have confirmed that subjects will wait when their signals are not informative in various settings, and subjects are responsive to different waiting costs. (Ziegelmeyer et al., 2005;Çelen and Hyndman, 2012; Ivanov et al. (2013)) The waiting games is conceptually different from my environment. Waiting is more profitable if others make prompt decisions in the waiting games. In contrast, in my experiment, signals are transmitted in the network more smoothly when subjects are patient enough.

In many costly information acquisition experiments (Kübler and Weizsäcker (2004) Kraemer et al. (2006)), subjects are found to either excessively acquire information or behave rationally. For example, Nelson et al. (2010) documents that experience matters for subjects to learn the probability of an event. Çelen and Hyndman (2012) find subjects tend to over-link with others who made a decision before them to over-acquire information. Kraemer et al. (2006) found about 50% subjects acquire information excessively. Eyster et al. (2015) found around 75% subjects behave as the Bayesian Equilibrium predicts, and the other 25% neglect redundancy. Consistent with these findings, I find a large proportion of subjects who are able to behave rationally and there is another share of subjects who adopt some simple heuristic in their decision-makings. Due to the feature of experiment, the most popular strategy, "always wait for 1 turn", means that subjects may over-acquire or under-acquire social information in different treatments. Beyond that, I am able to document some other types of subjects, for example, the lone wolfs and social animals as suggested by Duffy et al. (2019),Duffy et al. (2021).

3 Theoretical Background

The design of this experiment studies how subjects learn through truthful communication with their neighbors in an exogenous directed network. The model is adapted from Acemoglu et al. (2014). In this section, I will describe the social learning problem, the communication environment and discuss the theoretical prediction for Bayesian rational subjects.

3.1 Social Learning Problem

The basic structure of the problem is a variant of the social learning problem Bikhchandani et al., 1992. There are two equally likely states of the world, let θ denote the true state of the world, $\theta \in \{0, 1\}$. Nature chooses one state randomly, $P(\theta = 0) = P(\theta = 1) = \frac{1}{2}$. The state of the world θ is unknown to all subjects.

For a finite set $N^n = \{1, 2, 3, ..., n = 5\}$ of subjects, each subject $i \in N^n$ makes an irreversible guess of the true state of the world $x_i \in \{0, 1\}$. The goal for each subject is to correctly identify the true state of the world.The payoff function can be expressed as $\Psi - \psi(x_i - \theta)^2$ where ψ is a constant. If the guess is correct, the subject will receive a large amount of payoff, denoted as Ψ; if the guess is incorrect, the subject will receive a small amount of payoff, denoted as $\Psi - \psi$. By construction, $\psi < \Psi$. In my experiment, $\Psi = 140$, $\Psi - \psi = 40$.

Before making the guess, each subject i is endowed with an informative private signal, denoted as s_i. The signal will reflect the true state of the world with precision q, where $\frac{1}{2} \leq q \leq 1$. The signals that each subject receives are independently and identically distributed. In my experiment, the precision q is set to be 0.7.

Other than the private signal, each subject also has the opportunity to learn more signals from their neighbors. Unlike the classic social learning experiment where subjects can only observe other subjects' guesses, in this model, subjects can observe other subjects' private signals. How much additional information a subject can obtain is constrained by an exogenous communication network. Subjects are randomly assigned to a node in a directed network. The network predetermines how information is aggregated among subjects in the group. With complete information of the communication network, subjects can wait to acquire more private signals of others before they make the irreversible guess.

To sum up, in this experiment, a subject needs to make two-step decisions. Given the exogenous communication network and their assigned node position, subjects need to decide 1) how much additional information from their neighbors they want to obtain; 2) based on all acquired signal(s), the guess of the true state of the world.

3.2 Communication Environment

3.2.1 General settings and concepts for the communication network

In a directed network, I assume subject i forms beliefs about the state of the world from her private signal s_i and the information she obtains from other subjects through a given communication network G^n. The communication network G^n represents the set of communication constraints imposed on all subjects.

I assume that turn t is discrete by turns, and there is a cost c for waiting in each turn. Communication happens in each turn. At each turn t, subject i decides to "wait" or "guess". Waiting incurs a cost but may allow the subject to obtain more information in the subsequent turn from her neighbors in the communication network. Guessing means that the subject i exits the game, stops gathering more information, and will obtain her payoff based on the guess. In my experiment, I picked two levels of costs: Low cost, $c^L = 1$; High cost, $c^H = 8$.

Each subject obtains information from other subjects through a communication network represented by a directed graph $G^n = (N^n, \epsilon^n)$, where ϵ^n is the set of directed edges with which subjects are linked. We say that subject j can obtain information from subject i if there is an edge from i to j in graph G^n, that is, $(i, j) \in \epsilon^n$. Let $I^n_{i,t}$ denote the information set of subject i at turn t and let $\mathfrak{I}^n_{i,t}$ denote the set of all possible information sets. For every pair of subject i, j, such that $(i, j) \in \epsilon^n$, we say that subject i is subject j's information source and sends a message $m^n_{ij,t}$ to subject j at turn t with the following map:

$$m^n_{ij,t} : I^n_{i,t} \to M^n_{ij,t}, \text{ for } (i, j) \in \epsilon^n$$

I define the information set of subject i at turn $t \geq 1$ as:

$$I^n_{i,t} = \{s_i, m^n_{jt,\tau} \text{ for all } 1 \leq \tau \leq T, \text{ and } j \text{ such that } (j, i) \in \epsilon^n\}$$

and $I^n_{i,0} = s_i$. In particular, the information set of subject i at turn $t > 0$ consists of her private signal, and all the messages her information sources sent to subject i.

To further simplify the environment, in my experiment, I enforce truthful communication among subjects. Truthful communication has three implications: (i) communication is restricted to sharing private signals. To avoid information duplication, each subject's private signal will be tagged with his subject ID. (ii) subjects cannot strategically change the message they send in the network, which means that they can't lie or withhold the information they obtain. For example, at turn t, a subject j will send all the private signals he gathered till turn $t-1$ to all subjects who can receive his message. (iii) when a subject has made an irreversible decision, she stops gathering new information from her information sources. This means that she will only be able to share the information she gathered before she made the decision.

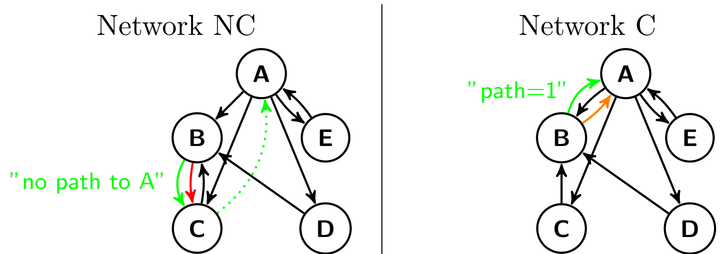
3.2.2 An illustration of the timing of communication

All subjects are placed in a directed communication network with complete information about the network structure (the total number of nodes, their own node's position, complete knowledge of all the directed edges, etc).

- At turn $t = 0$:
  - Each subject i observes a private signal s_i;
  - Each subject's information set contains the private signal she observes.
  - Each subject i chooses $x_{i0} \in \{\text{wait, guess}\}$
- At turn $t = 1, 2, 3...$:
  - If a subject chose to $x_{it-1} =$ "wait" at $t-1$:
    - She observes the information set of her information sources and updates her information set to I_{it}. In this process, the signals in her information source's information set at $t-1$ are transmitted to the subject. The information set will only update any new signals transmitted in each turn t.
    - She chooses $x_{it} \in \{\text{wait, guess}\}$
  - If a subject chose to $x_{it-1} =$ "guess" at t-1:
    - She stops gathering more information from her neighbors. Her information set stops growing.
    - $x_{it} = x_{it-1}$

3.2.3 Two Networks in the experiment

Table 1: Theoretical Predictions for each treatment



Notes: The table shows the two directed networks tested in the experiment. The circles/nodes indicate the positions of each subject in a 5-person directed network. Arrows show how the information is transmitted. An arrow from node A to node B indicates that A's information set gathered at turn $t-1$ will be communicated to node B in turn t. The green arrows show whether the "information maven" can transmit his message to the "information spreader". The left panel shows the network NC's structure, where the red arrow indicates the main difference between network NC and network C. The right panel shows the structure of network C and the orange arrow indicates the main difference from the other network.

Table 2: The difference by Nodes

Position	$InDegree_i$	$OutDegree_i$
A	1(NC) / 2(C)	4
B	3	1
C	2 (NC) / 1 (C)	1
D	1	1
E	1	1

Now, I explain the two networks I tested in the experiment. In a directed network, subject i is connected with subject j through arrows. The arrow indicates the direction of the message transmission process. For example, an arrow from subject i to subject j means that subject i is subject j's information source and will send his message to subject j in each turn. For each subject i, let $InDegree_i$ denote the number of subject i's information source(s) and let $OutDegree_i$ denote the number of subjects who deem subject i as their information source.

This experiment studies two 5-Node directed networks with 8 edges. They have very similar degree distribution. Both networks consist of one node with a high out-degree level ($OutDegree$=4, denoted as A), one node with a high in-degree level ($InDegree$=3, denoted as node B), and three other nodes with limited edges that only connect to the first two nodes. The node with a high out-degree level can be seen as a "social connector" who spreads the information in the network. In the network, node A is designed to be the "social connector" which is the information source for all other nodes in the network. The node with a high in-degree can be seen as an "information maven" that aggregates most of the information communicated in the network. In the network, node B is designed to be the "information maven" which always has node A, C, and D as its information sources. B is an imperfect "information maven" as it can't directly observe E's signal. Node E is designed to be a more "isolated" node in the network that only connects to node A. The signal of E can only be transmitted through A, the "social connector", if A is willing to wait at turn $t = 0$.

The two networks differ by the distance between the "information maven" and the "social connector". In network NC, the "information maven" B is not connected to the "social connector" A. Thus, the network structure is not fully connected(NC). Some subjects in this network can never observe all five signals. In network C, the "information maven" B is an information source of the "social connector" A and can communicate directly to A. This network is fully connected (C) because if everyone is patient enough, all subjects in this network can observe 5 signals. To illustrate the differences better, as shown in Figure. 1, I highlighted the out-edge of B with different colors and mark out the path from B to A with green dashed lines.

Network NC is a weakly connected communication network. The network limits some nodes from obtaining all other nodes' information. For example, node C and D's signals can never be transmitted to A and E. This kind of information segregation limits the highest attainable informativeness of A and E. Moreover, it prompts the "social connector" A to make a decision without waiting, which cuts off the information transmission of E and further reduces the learning efficiency of the network.

Network C can be seen as an "improvement" of the network NC because it breaks the information segregation. In this network, nodes are connected to each other, meaning that the signal observed by one node can potentially be transmitted to any other node. Moreover, since the "information maven" is relatively close to the "social connector", the information is expected to flow quickly in the network.

3.3 Individual Optimization

Subject i's action at turn t is a mapping from her information set to the set of actions, i.e.,

$$\sigma^n_{i,t} : \mathfrak{I}^n_{i,t} \to \{\text{ "wait" }\} \cup \{0, 1\}$$

The tradeoff now becomes: a subject would wait so as to communicate indirectly with a larger set of subjects and choose a better action. However, the future is discounted and delaying is costly. In particular, subject i's value function at turn t when her information set is $I^n_{i,t}$ is given by the expression:

$$U^n_{i,t}(I^n_{i,t}) = max\{ \underbrace{\max_{x_i} \mathbb{E}[\Psi - \psi(x_i - \theta)^2 | I^n_{i,t}]}_{\text{Expected Payoff of the Correct Guess at t}} , \underbrace{\{\mathbb{E}[U_{i,t+\Delta t}(I^n_{i,t+\Delta t}) | I^n_{i,t}] - c * \Delta t, \text{ for } \Delta t = 1, 2, ...\}}_{\text{Discounted Value to Decide Later}} \} \tag{1}$$

This expression involves a double maximization: first, the subject decides whether to wait or to guess, and in the case that she decides to guess, she chooses the one that maximizes her expected instantaneous payoff. If subject i decides to guess at turn t, the optimal action would be

$$x_{i,t}^{n,*} = \underset{x}{\operatorname{argmax}} \mathbb{E}[\Psi - \psi(x-\theta)^2 | I_{i,t}^n]$$

Since "guess" is irreversible, the subject's decision problem reduces to determining the timing of her action. The optimal stopping problem for subject i depends crucially on the actions of the rest of the subjects, since the latter affects subject i's information set.

3.4 Social Planner's problem

A social planner whose objective is to maximize the aggregate expected welfare of the population of n subjects would implement the timing profile that is a solution to the optimization problem:

$$\max_{sp^n} \sum_{i=1}^{n} \mathbb{E}_{sp^n}[U_I^n]$$

where $sp^n = (\tau_1^{n,sp}, \tau_2^{n,sp}, ..., \tau_n^{n,sp})$ and $\tau_i^{n,sp}$ implies that subject i stops exchanging information and takes an action after $\tau_i^{n,sp}$ communication rounds.

3.5 Theoretical Predictions for the Rational Model

Since the time is discrete, it is possible to obtain the Pure-Strategy Perfect Bayesian Equilibrium through backward induction. I provide the optimal stopping rule for each node in all four treatments. The details of how to reach the prediction are provided in appendix Appendix A.1. "For non-equilibrium choices, the model predicts that thresholds are increasing in individual precision choices." (From $szkup_trevino_2020$).

Waiting cost	Network NC (not fully connected)	Network C (fully connected)
$c^h = 8$	(0,1,1,0,0)	(1,1,0,0,0)
	-	-
$c^l = 1$	(0,1,1,0,0)	(2,2,3,3,3)
	P.I. (1,2,2,1,0)	

The prediction shows that in network NC, the optimal choice for nodes with $InDegree = 1$ is to make a prediction at turn 0 (corresponding to nodes A,D,E). The optimal choice for nodes with $InDegree > 1$ is to wait for 1 turn (corresponding to nodes B and C). When the waiting cost is low, there exists a Pareto improvement if the subject at node A is willing to wait for 1 turn and let the signal of E pass down the network, the accuracy of prediction could be improved by increasing the informativeness of 3 other subjects at nodes B,C,D, and the overall network's welfare.

When the network is fully connected (network C), the optimal choice for all positions differ between a high and a low waiting cost. When the waiting cost is high, in the sense that the improved informativeness cannot offset the cost of waiting for one more turn to obtain more signals, the optimal choices for nodes with $InDegree = 1$ is the same as the ones in network NC. When the waiting cost is low, it is optimal for all nodes to wait sufficiently long and observe all 5 signals in the network. It means that the optimal choice for nodes with $InDegree > 1$ is to wait for 2 turns and for nodes with $InDegree = 1$ to wait for 3 turns. There is no Pareto improvement.

Based on the equilibrium predictions, I formulate the following hypotheses for the group and individual behaviors.

Hypothesis 1 *Groups are only responsive to the waiting cost in network C. When the waiting cost is low and the network is fully connected, the average waiting turn is longer. The average waiting turn for the other three treatments will be the same.*

(a) *The average waiting turns can be ranked as: 0.4 = NC_H = NC_L = C_H < C_L = 2.6.*

(b) *At nodes with indegree=1 (node A, D, and E in network NC; node C,D, and E in network C), the ranking is: 0 = NC_H = NC_L = C_H < C_L = 2.*

(c) *At nodes with indegree=2 or 3 (node B,C in network NC; node A,B in network C), the ranking is: 1 = NC_H = NC_L = C_H < C_L = 3.*

Hypothesis 2 *The information transmitted (measured by the number of signals transmitted) in network C with low waiting cost is the highest. In the other three treatments, the information transmitted (signals transferred among subjects) is the same and lower than Network C with low cost.*

Hypothesis 3 *The welfare is the highest in Network C with low waiting cost, followed by Network NC with low waiting cost. The welfare in network NC and network C with high waiting cost is almost the same.*

4 Experimental Design and Administration

To empirically test whether subjects behave in a directed network as the theory predicts, I designed a between-subject experiment that systematically varies (i) the waiting cost; (ii) the network structure. Each session consisted of instructions, an incentivized quiz to ensure that subjects understood the instructions, 10 supergames, and a demographic survey. All payoffs were displayed in Experimental Currency Units (ECUs) and were converted to USD at the end of the experiment at 76 ECUs equals one US dollar. Next, I describe specific parts of the experimental design in more detail.

4.1 Repeated Games with Position Rotation

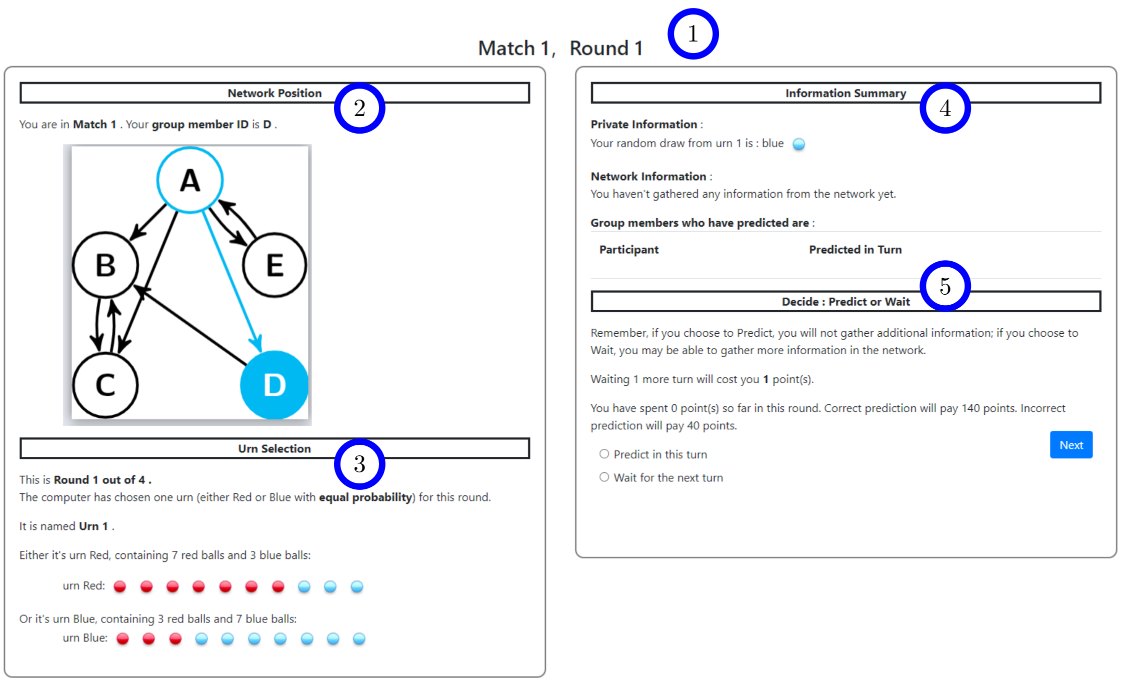
In each session, subjects are randomly matched into groups of five for 10 supergames. In each supergame, they interact with the same group members for 3 rounds. [1] In each round, they face a

[1]In the pilot session (NC-l), subjects interact with the same group members for 4 rounds.

new “main task” and decide to wait for how long before making an irreversible prediction.

To test whether subjects respond to different positions in a directed network and help them understand the network structure better, I rotate subjects’ positions at the beginning of each supergame. Subjects will experience each position twice in the experiment. The program is designed to ensure that everyone has experienced each position once in the first five rounds.[2] Figure 1 presents how the environment is presented to subjects in NC_l treatment. Throughout the experiment, subjects are reminded of their network position in each match as presented in figure 1 (2) network position. Their current position is denoted as a solid blue circle. Their information sources are marked with a blue circle.

Figure 1: Turn 0 Round Beginning Screenshot



Notes: The screenshot shows the turn 0 beginning screen for a subject at node D in network NC with low cost. Subjects at other positions in the network see a similar screen that only differs in the picture of (2). The screenshot shows: (1) match and round information: if subjects wait for future turns, the text will reflect which turn they are at. For example, at turn 1, the text shows“Continue of Round 1, Turn 1:”. (2) network position: subjects’ assigned position in the network is marked out by a solid blue cycle. Their information source is marked out with a blue circle. (3) urn selection: the main task. (4) information summary: subjects’ private information and social information are relected in this section. If subjects wait for future turns, the information in this section will change accordingly. (5) decide to predict or wait: subjects make their decisions in this section. Their payoffs of a correct and an incorrect guess are reminded here alongside with how much cost they have spent so far.

[2]Subjects are not explicitly told about this detail. They only know their positions will change at the beginning of each supergame.

4.2 Main Task Representation

The main task is described as an urn guessing game. At the beginning of each round, the computer randomly chooses one urn which is either a red urn or a blue urn. Subjects' task is to guess which urn is chosen based on their private information and any other information they are willing to acquire from the network. This task is visualized and presented in figure 1 (3) urn selection.

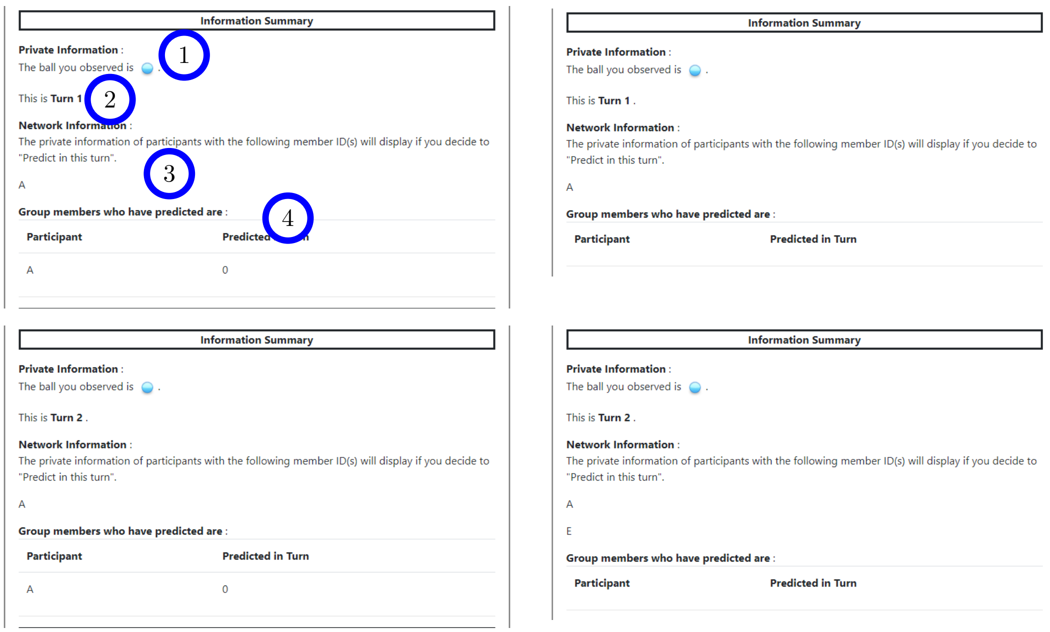
4.3 Dynamic Information Summary

To facilitate their guessing, they can take advantage of two sources of information, which are presented in figure 1 (4) information summary. The first type of information is the private information which is given to them at the beginning of each round. The information is presented as a ball drawn from the randomly chosen urn and the color of the ball (the content of the private information) is directly observable to the subject. The second type of information is social information which can be acquired by waiting in their assigned network. The network information is described as the ball drawn to other subjects in the network. As long as subjects wait in their network, they will have the opportunity to view others' ball colors when they make the prediction. They have access to their information sources' owned information with a one-turn lag. To reduce cognitive burden, in the interface, they are reminded of how much additional information they have acquired so far. Moreover, they will know who in the network has made a prediction as shown in figure 2.

In each round, subjects can decide how many turns they want to wait before making an irreversible decision. In figure 1 (5) Decide: predict or wait, they see the relevant payoff information and choose to decide or wait for each turn.

If subjects decide to wait, their information summary section will change to reflect the additional information in the next turn. See figure 2 for two different situations when a subject at node D in network NC decides to wait for 1 and 2 turns. Although the additional information obtained at turn 1 is always certain, additional information which can be acquired in turn 2 depends on others' decisions.

Figure 2: Different Information Summary from Waiting Screenshots

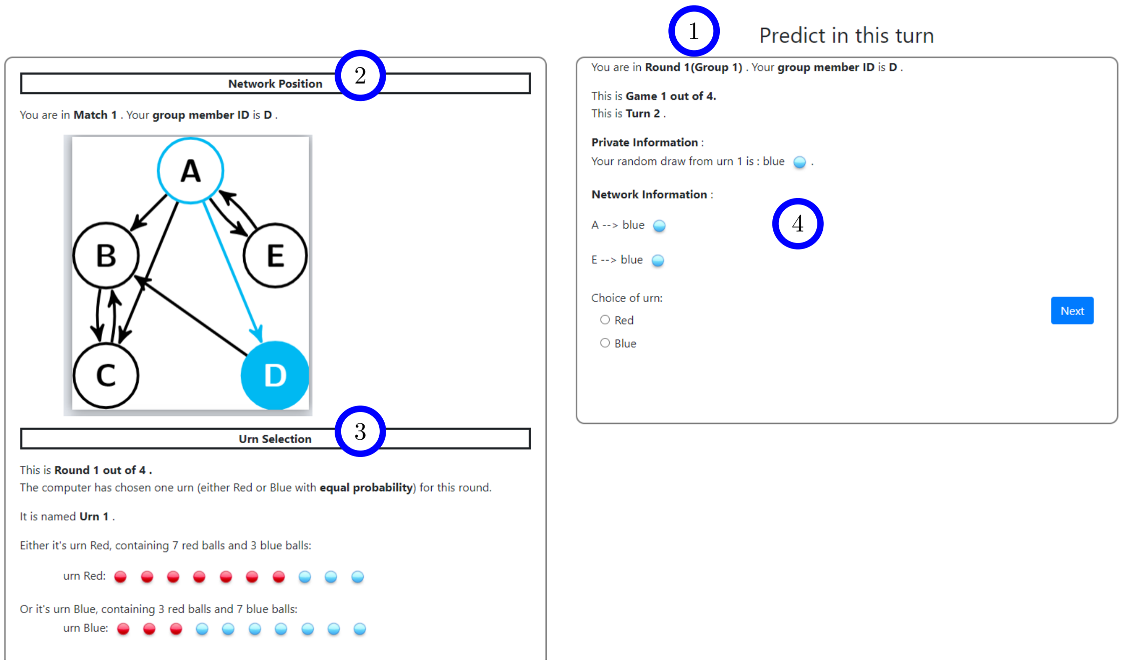


Notes: The screenshot shows the information summary of turn 1 and turn 2 for a subject at node D in network NC with low cost. The left column shows a situation when only the subject at node A makes a perdiction at turn 0. The right column shows another situation when no one in the network makes a prediction at turn 0. The information summary includes: (1) directly observable private information, (2) turn information, (3) network information that is not directly observable, (4) group members who have predicted. Note conditional on when the subject at node A predicts, the information obtainable at turn 2 is different for subject D.

4.4 Prediction Page

Whenever a subject decides to make a prediction, he will see all information content gathered so far and make a decision accordingly. Figure 3 shows a prediction page for subjects at D who predicts at turn 2 and gathered 2 additional signals.

Figure 3: Turn 2 Prediction Page Screenshot



Notes: The screenshot shows the turn 2 prediction screen for a subject at node D in network NC with low cost. Subjects at other positions in the network see a similar screen that only differs in the picture of (2). The screenshot shows: (1) prediction page, (2) network position, (3) urn selection, (4) revealed network information.

4.5 Administration Details

The main treatment of the experiment consisted of 13 sessions run at the Vernon Smith Experimental Economics Laboratory at Purdue University in 2021. Details of each session are provided in Table A-4 in the Appendix. On average, each session takes around 90 minutes. The average payment for each subject is $24.5.

Table 3: Summary of Experiment Administration

	Treatment		Administration		Demographics		
	Network Type	Waiting Cost	Sessions	Earnings	% Male	% STEM	% U.S. Borned
0	C	H	2	23.05	65.0	85.0	40.0
1	C	L	5	24.84	50.0	56.0	70.0
2	NC	H	2	24.55	55.0	55.0	65.0
3	NC	L	4	24.92	50.0	60.0	67.5

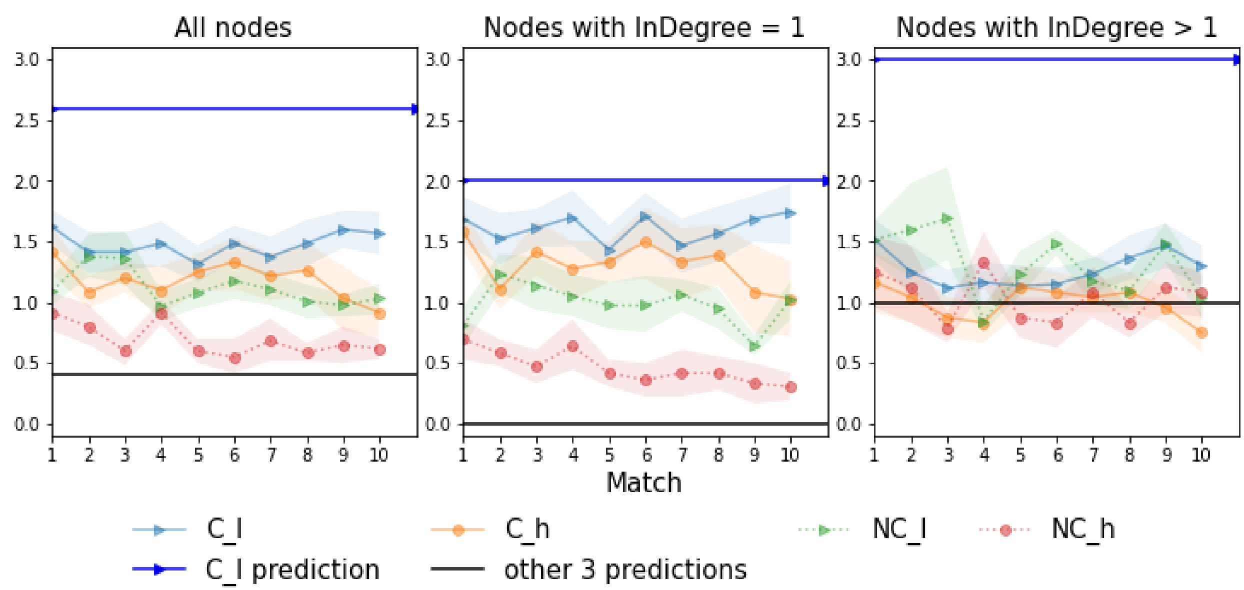
Notes: % STEM denotes the proportion of participants that are in STEM majors. % US HS denotes the proportion of participants that completed high school in the US.

5 Experimental Results

5.1 Do people wait as pure-strategy Bayesian equilibrium predicts?

5.1.1 Between-subject Analysis

Figure 4: Group Average Waiting Turns by Treatment



Notes: From left to right, the sub-figures show the average group waiting turns for all nodes, nodes with 1, and multiple information sources. The solid lines indicate network C while the dashed lines indicate network NC. The triangle markers indicate the low waiting cost treatment while the round markers indicate the high waiting cost treatment. The blue and the black solid lines show the pure strategy perfect Bayesian equilibrium for treatment C_l and the other three treatments. The shades indicate 90% bootstrap confidence intervals.

I start by comparing the group average waiting turns across treatments. In the lab, subjects don't behave exactly as the theoretical predictions as shown in figure 4. The deviation comes from two ends. On one hand, I observe over-waiting in treatments NC_l and C_h. Based on the pure-strategy Bayesian equilibrium, the group average waiting turns should stay around the same for these three treatments. Although the average waiting turns is close to the theoretical predictions in NC_h treatment (average waiting turn is 0.69). Subjects wait significantly longer when the network is fully connected (average waiting turns in C_h is 1.18, p-value=0.029) or the waiting cost is higher (average waiting turns in NC_l is 1.12, p-value=0.023)[3]. On the other hand, subjects tend to under-waiting in treatment C_l. Having both features (a fully connected network and low waiting cost) doesn't increase the average waiting turns significantly higher as the theory predicts (the average waiting turn in C_l is 1.48, higher than NC_l with p-value = 0.023, but not different from C_h with

[3]Unless otherwise noted, throughout the paper, the reported p-value is based on non-parametric permutation test.

p-value = 0.154). The results hold for all matches or only consider the latter 5 rounds. Individual random-effect regression results confirm the findings as presented in table 4.

By InDegrees, it is clear to see that the differences across treatments are mainly driven by subjects' behaviors at nodes with 1 information source(InDegree=1). The average waiting turns are significantly different from 0, the theoretical prediction, even in the treatment closest to the prediction (NC_h=0.46, > 0 with p-value<0.01). Unlike the theoretical predictions, subjects are responsive to the network structure and the waiting cost. With low waiting cost (NC_l), subjects on average wait for 0.96 turns before making a guess (NC_l > NC_h with p-value = 0.017). In a fully connected network (C_h), subjects with 1 information source on average wait for 1.3 turns(C_h > NC_h with p-value = 0.019). Although subjects tend to over-wait in treatments C_h and NC_h, they under-wait in treatment C_l. The average waiting turns in C_l are 1.6, close to the theoretical predictions but significantly lower. This under-waiting is partly driven by the under-waiting of subjects at nodes with multiple information sources.

With multiple information sources, subjects in all four treatments wait for around 1 turn before making a guess. Although subjects tend to wait longer when the waiting cost is low, subjects at nodes with multiple information sources significantly under-wait in treatment C_l, causing the deviation in treatment C_l to be the largest from the theoretical predictions.

Result 1 *Subjects deviate from the pure strategy Bayesian equilibrium. Groups are responsive to the waiting cost in both networks. For a given waiting cost, being in a fully connected network increases the average waiting turn. The average waiting turn is ranked as NC_h < NC_l ≈ C_h < C_l.*

(a) *At nodes with indegree=1, the ranking is 0 < NC_h < NC_l ≈ C_h < C_l < 2.*

(b) *At nodes with indegree>1, the ranking is 1 ≈ NC_h ≈ C_h < NC_l ≈ C_l < 3.*

Table 4: Individual Decision Turns

	All Nodes			Single Information Source			Multiple Information Source		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
network C	0.49***	0.41*	0.44***	0.84***	0.69***	0.75***	-0.04	-0.04	-0.05
	(0.15)	(0.21)	(0.16)	(0.17)	(0.21)	(0.14)	(0.13)	(0.22)	(0.19)
low waiting cost	0.41***	0.27***	0.31***	0.50***	0.30***	0.34***	0.27**	0.18	0.25**
	(0.11)	(0.09)	(0.07)	(0.12)	(0.08)	(0.08)	(0.11)	(0.12)	(0.10)
network C * low waiting cost	-0.11	-0.08	-0.03	-0.19	-0.15	-0.13	0.00	0.03	0.12
	(0.24)	(0.25)	(0.20)	(0.27)	(0.25)	(0.21)	(0.20)	(0.25)	(0.20)
log(round)		-0.06*	-0.06**		-0.06	-0.06		-0.05	-0.06
		(0.03)	(0.03)		(0.04)	(0.04)		(0.04)	(0.04)
Individual waiting time in round 1		0.15***	0.11***		0.15***	0.11***		0.15***	0.10**
		(0.03)	(0.04)		(0.04)	(0.04)		(0.04)	(0.04)
Previous A's average waiting time		-0.04	-0.05		0.06	0.03		-0.14	-0.16
		(0.08)	(0.08)		(0.10)	(0.10)		(0.11)	(0.11)
Previous group average waiting time		0.15	0.14		0.19	0.18		0.11	0.10
		(0.09)	(0.09)		(0.12)	(0.12)		(0.10)	(0.11)
Comprehension Test Score			0.11*			0.09			0.13
			(0.07)			(0.07)			(0.08)
Constant	0.69***	0.47***	-0.07	0.46***	0.12	-0.48	1.03***	0.90***	0.50
	(0.02)	(0.16)	(0.72)	(0.03)	(0.19)	(0.82)	(0.00)	(0.23)	(0.73)
Observations	4,000	3,870	3,870	2,400	2,322	2,322	1,600	1,548	1,548
Number of subjects	130	130	130	130	130	130	130	130	130
Demographics	No	No	Yes	No	No	Yes	No	No	Yes

Notes: The table report random-effects regression results from all four treatments. The dependent variable is the individual's decision turn, ranging between 0 and 5. Demographics include age, gender, major in STEM, US-born or not, subjects' length of staying in US, race, years in college, and experience in participating in economic experiments. Standard errors are clustered at session level. *** p<0.01, ** p<0.05, * p<0.1.

Next, I compare the number of signals transmitted in the network which is measured as the number of signals a subject observes when he makes a guess. It is closely related to the subjects' waiting decisions but may reflect more on the strategic components of how subjects utilize the network. For the same waiting turns, a person with 3 outDegrees will send out more signals than a person with 1 outDegree. Meanwhile, a person who is connected to the information raven and waits for one turn will receive more signals than someone who is more isolated. The number of signals transmitted in the network can thus be seen as a measure of 1) how much the network is utilized; 2) if subjects' utilities increase linearly with the number of signals they gathered, this measure may help me understand people's decision process better.

Since the waiting time deviates from Bayesian equilibrium's prediction, the number of signals transmitted in the network doesn't fully follow the predictions either. I don't observe a difference across treatments, which means that most subjects are unable to utilize the treatment C_l to improve their informativeness. Individual regression results show that the number of signals transmitted is slightly higher in the fully connected network (network NC). However, since subjects don't wait for sufficiently long enough turns to gather all signals from the network, the number of signals transmitted at nodes with multiple information sources is the same across different treatments. In network C, the information spreader is the one with multiple information sources. Their under-waiting behaviors cause most groups in C_l to stay uninformative as the other three treatments.

Table 5: Individual Number of Signals Transmitted

	All Nodes			Single Information Source			Multiple Information Source		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
network C	0.64***	0.47*	0.54**	1.11***	0.91***	1.00***	-0.06	-0.13	-0.09
	(0.21)	(0.26)	(0.23)	(0.21)	(0.24)	(0.19)	(0.21)	(0.31)	(0.30)
low waiting cost	0.31**	0.07	0.15	0.35***	0.11	0.14	0.26	0.09	0.22
	(0.15)	(0.13)	(0.09)	(0.10)	(0.07)	(0.09)	(0.23)	(0.23)	(0.15)
network C * low Waiting cost	0.09	0.13	0.16	0.06	0.11	0.13	0.13	0.14	0.20
	(0.34)	(0.33)	(0.29)	(0.34)	(0.32)	(0.28)	(0.37)	(0.40)	(0.35)
log(round)		-0.01	-0.01		-0.01	-0.01		0.00	0.00
		(0.03)	(0.03)		(0.05)	(0.05)		(0.04)	(0.04)
Individual waiting time in round 1		0.19***	0.14**		0.16***	0.12**		0.25***	0.17**
		(0.05)	(0.06)		(0.05)	(0.05)		(0.06)	(0.08)
Previous A's average waiting time		0.10	0.07		0.14**	0.12*		-0.01	-0.04
		(0.08)	(0.07)		(0.07)	(0.06)		(0.11)	(0.10)
Previous group average waiting time		0.17***	0.16**		0.18**	0.18**		0.09	0.08
		(0.06)	(0.07)		(0.08)	(0.09)		(0.10)	(0.11)
Comprehension Test Score			0.20***			0.18**			0.23**
			(0.07)			(0.08)			(0.10)
Constant	2.21***	1.71***	0.80	1.44***	0.92***	-0.37	3.36***	2.93***	2.62**
	(0.02)	(0.18)	(1.02)	(0.04)	(0.23)	(1.09)	(0.00)	(0.24)	(1.18)
Observations	4,000	3,870	3,870	2,400	2,322	2,322	1,600	1,548	1,548
Number of subject_idnum	130	130	130	130	130	130	130	130	130
Demographics	No	No	Yes	No	No	Yes	No	No	Yes

Notes: The table reports random-effects regression results from all four treatments. The dependent variable is the number of signals observed when a subject makes a guess. Demographics include age, gender, major in STEM, US-born or not, subjects' length of staying in US, race, years in college, and experience in participating in economic experiments. Standard errors are clustered at session level. *** p<0.01, ** p<0.05, * p<0.1.

Although subjects at nodes with a single information source tend to gather more signals, the additional information doesn't help them to make more informed guesses. Consequently, I observe the average correctness of guesses does not differ across treatments. Moreover, I don't observe a difference in the average payoffs across treatments. Although in both networks, having a low waiting cost makes the average payoffs to be higher, the difference is only statistically significant (p-value=0.002) when the network is fully connected as shown in table 6.

Table 6: Average payoff by treatments

		All nodes	In-degree=1	In-degree>1
c	h	104.71	102.89	107.45
		(2.61)	(2.8)	(3.09)
c	l	114.46	113.05	116.56
		(1.71)	(1.78)	(2.03)
nc	h	107.8	104.9	112.15
		(2.53)	(3.15)	(2.98)
nc	l	112.19	110.68	114.45
		(1.72)	(2.03)	(2.46)

Result 2 *The number of signals transmitted and the average payoffs in each treatment can be ranked as follows:*

(a) *For all nodes, both rankings are NC_h ≈ NC_l ≈ C_h ≈ C_l.*

(b) *At nodes with InDegree=1, the number of signals transmitted is ranked as: NC_h < NC_l < C_h ≈ C_l. The average payoff is ranked as: C_h ≈ NC_h < NC_l ≈ C_l.*

(c) *At nodes with indegree>1, both rankings are C_h ≈ NC_h ≈ NC_l ≈ C_l.*

5.1.2 Within-subject Analysis

So far, I have focused more on comparing the group waiting behaviors across treatments. A nice feature of my experiment is that I rotate subjects' positions in the network, which allows me to observe the same individual's waiting choice at different nodes with 1 or multiple information sources.

Table 7 and 8 present the subject's waiting turns distribution across treatments, separated by nodes with 1 or multiple information sources. The highlighted cells indicate the optimal choices predicted by the pure strategy Bayesian equilibrium. The last three columns in the table show how the observed waiting turns compare with the empirically optimal ones. I define an empirically optimal choice as follows: if a choice is not predicted by the theory but fits one of the two criteria. First, a guessing turn that is earlier than the theoretical prediction may be considered empirically optimal if a) this subject can no longer gather more signals from waiting because his information source(s) all made predictions too early than theoretical predictions; b) this subject holds a wrong belief that proves to be true. For example, a subject at nodes with 1 information source in C_l is supposed to wait for 3 turns, but if he observes that both subjects at nodes A and B have guessed at turn 0, then it is only optimal for him to guess at turn 1 since no more additional information could be transmitted in the network. Similarly, if this subject believes that all of his information sources will guess at turn 0 and decides to guess at turn 0, and if this turns out to be true, his behavior is considered empirically optimal too. Second, a guessing turn that is later than the theoretical prediction may be considered empirically optimal if the subject believes that her information source will wait longer than the theory predicts and she responds optimally either a) by making a guess after observing the information source didn't wait or b) by gathering the additional information after waiting for appropriately long enough. An example would be in NC_l where a subject at node D wrongly believes that the subject at node A will wait longer. If A waited longer and she was able to gather more information by waiting for 2 turns, her decision is empirically optimal. In this classification, I hold one criterion as before: since subjects can't see the content of the social information before making a guess, a decision is only optimal if the expected payoff exceeds the total waiting cost. This means that the empirically optimal choices will only deviate from the theory in treatments with a low waiting cost.

Based on table 7, the deviation of nodes with 1 information source mostly comes from over-waiting with one exception in treatment C_l where most deviations come from under-waiting. NC_h has the highest ratio of subjects who make an optimal decision, over half (57%) decided to make a guess at turn 0. This is consistent with the group average finding where NC_h performs the closest to the theoretical prediction. The second well-performed treatment is C_l where 47% of subjects made empirically optimal decisions. Remember C_l deviates from the theoretical prediction the farthest. Yet, after considering that not everyone in the network is as patient as the theory predicts, the empirically optimal decisions stay around half (47%) with another 45% of the time people making a decision too soon (maybe they didn't see the value of a fifth signal or have wrong belief). The other two treatments both have a majority of people who waited for too long. One is due to the network structure and the other is due to the low waiting cost. At nodes with 1 information source, people are more likely to over-wait. Yet in treatment C_l where they are supposed to wait longer, most people make a guess too soon.

Moving to nodes with multiple information sources, people perform more optimally in these positions. When the waiting cost is high, people are equally likely to make a guess too soon or too late, but overall, the proportion of people making an optimal choice is higher (around 65%) than in treatments with a low waiting cost. When the waiting cost is low, people tend to under-wait more frequently, suggesting that they misjudge the values of different numbers of signals.

Table 7: Distribution of Decision Turns for nodes with 1 information source

		Distribution (%)						Empirically Optimal(%)		
network	waiting_cost	0.0	1.0	2.0	3.0	4.0	5.0	Early	Optimal	Late
c	h	**22.22**	28.89	45.28	3.33	0.28			**22.22**	77.78
c	l	19.56	20.22	41.00	**18.00**	1.0	0.22	45.33	**47.00**	7.67
nc	h	**57.50**	38.89	3.33	0.28				**57.50**	42.50
nc	l	**30.26**	46.92	17.82	3.97	1.03		12.69	**39.74**	47.56

Notes: This table presents the subject's waiting turns distribution across treatments at nodes with 1 information source. The highlighted cells indicate the optimal choices predicted by the pure strategy Bayesian equilibrium. The last three columns in the table show how the observed waiting turns compare with the empirically optimal ones.

Table 8: Distribution of Decision Turns for nodes with multiple information source

		Distribution (%)						Empirically Optimal(%)		
network	waiting_cost	0.0	1.0	2.0	3.0	4.0	5.0	Early	Optimal	Late
c	h	17.50	**65.42**	17.08				17.50	**65.42**	17.08
c	l	16.50	44.17	**35.17**	4.17			49.83	**43.67**	6.50
nc	h	15.42	**66.67**	17.08	0.83			15.42	**66.67**	17.92
nc	l	11.35	**56.35**	25.00	5.19	0.96	1.15	46.92	**39.62**	13.46

Notes: This table presents the subject's waiting turns distribution across treatments at nodes with multiple information source. The highlighted cells indicate the optimal choices predicted by the pure strategy Bayesian equilibrium. The last three columns in the table show how the observed waiting turns compare with the empirically optimal ones.

To further understand the individual decision-making process, I run Probit regressions on an individual's probability of making an optimal waiting decision and the two directions of deviation. The results are presented in table 9. The dependent variable is a dummy variable that equals to one if a subject's waiting time in one round is empirically optimal in columns (1)-(3), earlier than the empirical optimal time in columns (4)-(6), or later than the empirically optimal time in columns (7)-(9). The explanatory variables include their treatment variable and their network position in each round, individual characteristics, time trend, and experience gained over time.

Consistent with the previous findings, subjects are less likely to make an optimal decision when the waiting cost is low. They are more likely to make an optimal decision as they play the game for a longer time (positively correlated with log(round)) or understand the environment better (shown as a higher comprehension score). When they observe an equal number of signals in the previous round, they tend to act less optimally by over-waiting more, maybe in the hope to gather more signals to break the tie.

Moving to sub-optimal behaviors, subjects seem to systematically behave sub-optimally in response to the treatment parameters. They tend to under-wait when the waiting cost is low, when they have more information sources (InDegree¿1), and especially so when combining both. However, when they are placed at a node with higher outDegree, such that they will transmit information to more than 1 person, they are more likely to over-wait. Individual characteristics matter in the suboptimal behavior, especially if a subject begins as someone who waits shorter, she is more likely to under-wait and vice versa. A subject who relies more on his private information (reflected as a higher percentage of guesses equal to his private information) is more likely to under-wait. Accumulated past experience has a different impact on individuals' sub-optimal behaviors. If a subject's own private information was wrong in the previous round, he is less likely to under-wait, but not more likely to over-wait. If a subject's social information was helpful in the previous round, he is less likely to under-wait and more likely to over-wait. An equal number of opposite signals observed in the previous round makes subjects more likely to over-wait.

Table 9: Probability of Waiting Optimally, Under-waiting, or Over-waiting

	Optimal Waiting Time			Under-wait			Over-wait		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
low waiting cost	-0.26	-0.26	-0.35**	0.94***	1.35***	1.45***	-0.47*	-0.73***	-0.62***
	(0.17)	(0.17)	(0.16)	(0.08)	(0.16)	(0.19)	(0.24)	(0.24)	(0.19)
InDegree>1	0.23*	0.19	0.18	0.41**	0.54***	0.55***	-0.90***	-0.96***	-0.98***
	(0.13)	(0.12)	(0.11)	(0.19)	(0.18)	(0.11)	(0.15)	(0.14)	(0.16)
InDegree>1 * network C	0.01	0.07	0.10	0.26***	0.35**	0.44**	-0.49*	-0.66**	-0.77***
	(0.15)	(0.15)	(0.17)	(0.08)	(0.16)	(0.18)	(0.28)	(0.28)	(0.23)
out_degree	0.03	0.01	0.00	-0.12***	-0.15***	-0.16***	0.13*	0.18**	0.20***
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)	(0.08)	(0.07)	(0.07)
log(round)		0.10***	0.12***		-0.10*	-0.10		-0.07	-0.11**
		(0.04)	(0.04)		(0.06)	(0.08)		(0.06)	(0.05)
Individual waiting time in round 1		0.05	0.05		-0.28***	-0.23***		0.12***	0.09*
		(0.04)	(0.04)		(0.09)	(0.08)		(0.04)	(0.05)
A's average waiting time in m-1		-0.03	-0.02		-0.05	-0.00		0.06	0.01
		(0.04)	(0.03)		(0.09)	(0.08)		(0.05)	(0.05)
Group average waiting time in m-1		-0.10*	-0.09		-0.02	-0.03		0.20**	0.16**
		(0.06)	(0.06)		(0.08)	(0.10)		(0.08)	(0.07)
Private infor was wrong in r-1		0.05	0.04		-0.13***	-0.10**		0.02	0.00
		(0.05)	(0.04)		(0.04)	(0.04)		(0.05)	(0.05)
Social infor was helpful in r-1		-0.05	-0.07		-0.61***	-0.53***		0.51***	0.46***
		(0.11)	(0.10)		(0.14)	(0.15)		(0.08)	(0.08)
Equal number of signals in r-1		-0.33***	-0.32***		-0.27	-0.23*		0.59***	0.57***
		(0.10)	(0.10)		(0.17)	(0.14)		(0.09)	(0.08)
% of guesses = private infor			-0.79			3.93***			-2.04***
			(0.74)			(0.99)			(0.78)
Comprehension test score			0.12**			-0.29***			0.01
			(0.06)			(0.11)			(0.08)
Constant	-0.14	-0.16	-0.77	-1.31***	-0.52**	-0.88	0.03	-0.70***	1.13
	(0.21)	(0.24)	(1.00)	(0.19)	(0.26)	(1.31)	(0.27)	(0.26)	(1.38)
Observations	4,000	3,600	3,600	2,344	2,097	2,097	4,000	3,600	3,600
Demographics	No	No	Yes	No	No	Yes	No	No	Yes

Notes: The table report Probit regression results from all four treatments. In column (1) - (3), the dependent variable is a dummy variable indicating whether the subject's waiting time is empirically optimal. In column (4)- (6), the dependent variable is a dummy variable that equals to 1 if the subject doesn't wait as long as the empirically optimal time. If the optimal waiting turn is 0, then this variable is equal to null. In column (7)-(9), the dependent variable is equal to 1 if the subject waits longer than the optimal decision turns. Control variables include: 1) treatment-related: the waiting cost, the network structure, and the positions a subject takes at the decision round; 2) experience gained in the experiment: how many rounds a subject has played, a subject's first round waiting time which may indicate his tendency of preferring to over-wait or under-wait, the previous round waiting time, and the information experienced in the previous round; 3) individual characteristics such as how many times the subject will make a guess coinciding with his private information, the comprehension test score and other demographic variables. Demographics include age, gender, major in STEM, US-born or not, subjects' length of staying in US, race, years in college, and experience in participating in economic experiments. Standard errors are clustered at session level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

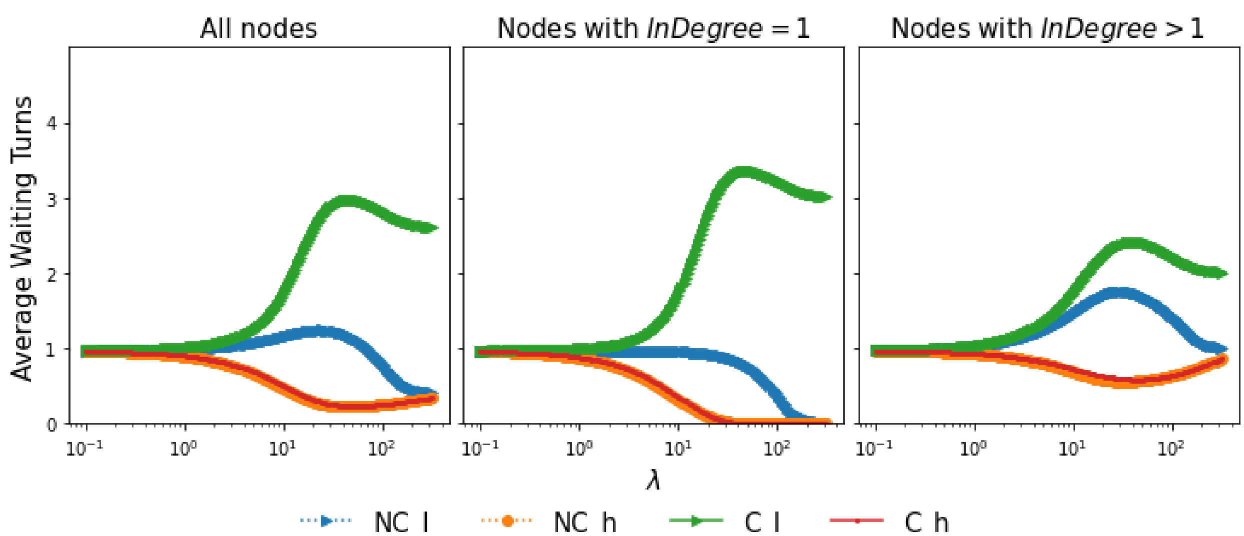
5.2 Possible explanations for the observed deviations

So far, I have shown that subjects don't behave as the pure-strategy Bayesian equilibrium predicts. What can explain the observed deviations? In this section, I attempt to use a Quantal response equilibrium model and the strategy frequency estimation methods to better explain the observed behaviors.

5.2.1 Quantal Response Equilibrium Model Prediction (QRE)

In a somewhat complicated environment like this, subjects may make various mistakes that cause a deviation from the theoretical prediction. If I assume that the observed deviations come from subjects' idiosyncratic preference shocks, it is possible to calculate the quantal response equilibrium (QRE), proposed by McKelvey and Palfrey (1995, 1998), for my treatments. Instead of always choosing the best strategies, subjects are assumed to choose strategies with higher expected payoffs with high probability that follows a logistic distribution. More details about how to derive the QREs can be found in appendix Appendix A.2. The average waiting turns by treatments and for nodes with one or multiple information sources can be illustrated in the following figure:

Figure 5: QRE Prediction of Average Waiting Turns by Treatment



Notes: Panel shows the group average of waiting turns by treatment predicted by Quantal Response Equilibrium when the game is represented in the extensive form. The expected payoffs use proper Bayesian updating rule and are standardized to be 1 when a subject makes a guess at turn 0.

Although the QRE converges to the pure strategy Bayesian perfect equilibrium, the path it takes is quite different. When the rationality parameter λ is small enough (less than 10), subjects are not going to differentiate their guessing times at different nodes. As the rationality parameter becomes larger, the average waiting time may be ranked as: NC_h = C_h < NC_l < C_l. The ranking is the same for nodes with one or multiple information sources. When the rationality parameter is sufficiently large (over 100), the QRE predictions meet the pure strategy Bayesian perfect equilibrium.

To estimate the rationality parameter in the experiment, I follow the equilibrium correspondence approach. It takes two steps: first, I calculate the logit QRE correspondence for each treatment. Then I search for the value of λ for which the observed distribution of choices is the closest to the logit QRE. let $p_{nt}(\lambda)$ denote the probability of a subject at node n decide at turn t, let f_{nt} denote the empirical choice frequencies, for each given λ, the log likelihood function can be expressed as:

$$Logl(\lambda, f_{nt}) = \sum_{n \in \{\mathrm{A,B,C,D,E}\}} \sum_{t=0}^{5} f_{nt} log(p_{nt}(\lambda))$$

The maximum-likelihood estimate is given by $\hat{\lambda} = argmax_{\lambda} logL(\lambda, f_{nt})$. I conduct the same exercise on three sets of logit QRE correspondences, namely, 1) QRE derived from the normal form representation of my environment, 2) QRE derived from the extensive form representation; 3) QRE derived from the extensive form representation and assume an incorrect linear probability updating rule.

The estimated results are presented in table 10. Assuming all agents have the same rationality parameters, the λ rationality parameter is higher when I derive the QRE predictions using the extensive form instead of a normal form. It suggests that subjects incorporate the additional information updated in each turn dynamically. Furthermore, when I change the expected payoff from the Bayesian updating rule (the statistically correct rule) to an incorrect updating rule (simply assuming that subjects assign a linear relationship such that more signals mean a higher probability to make a correct guessing), the QRE estimation yields a higher λ. If I assume the same rationality parameter within a treatment, as reported in the last 8 columns of table 10, the estimated rationality parameter differs largely across treatments. The normal form representation seems to fit the data better when the waiting cost is high. In comparison, the extensive form representation fits the observed behaviors better when the waiting cost is low. This seems to suggest that subjects are more likely to consider the dynamic information transmissions within a network when the waiting cost is low.

Table 10: QRE Estimation

	Pooled		NC_l		NC_h		C_l		C_h	
Models	λ	$logL$	λ	$logL$	λ	$logL$	λ	$logL$	λ	$logL$
Normal-form	6.48	-6583.4	27.84	-2142.1	7.93	-746.3	3.39	-2663	5.98	-907.9
Normal-form (linear)	7.32	-6522	32.74	-2028.2	10.12	-698.5	3.53	-2664.2	5.98	-908.8
Extensive-form	10.97	-6405	20.138	-2016.5	4.15	-790.7	13.99	-2232.9	0.1	-1039.9
Extensive-form (linear)	12.90	-6157.2	30.19	-1796.6	8.26	-750.9	14.57	-2250.8	0.93	-1038.7

5.2.2 Strategy Frequency Estimation

Regardless of which form the game is represented, the quantal response equilibrium predicts almost no difference between treatment NC_h and C_h, which doesn't fit the experimental results. Alternatively, I consider subjects adopting different stopping strategies other than the optimal Bayesian pure strategy. Based on previous literature, I summarize several possible strategies that have been identified in previous social learning literature. The rules I consider in the estimations are:

1. Empirically optimal(Empirical_Optimal): the decisions follow the pure strategy Bayesian equilibrium predictions and are responsive to others' decisions.

2. Empirical optimal without cost (EmpiricalOptimal_Nocost): the decisions follow the pure strategy Bayesian equilibrium predictions and are not responsive to others' decisions. Although subjects understand the value brought by the additional signals, they focus on increasing the probability of guessing correctly without considering the cost incurred.

3. More is better (More_Better): Corresponding to the excessive information acquisition found in many waiting games (Kübler and Weizsäcker, 2004; Kraemer et al., 2006; Nelson et al., 2010; Çelen and Hyndman, 2012; Eyster et al., 2015), this rule says that subjects will try to gather as many signals as possible. Subjects are responsive to their (direct and indirect) information sources' decisions, namely, if they observe someone has made a prediction, they will adjust by reducing their waiting turns.

4. More is better naive (More_Better_Naive): Similar to the strategy of more is better heuristic. The difference is that subjects are not responsive to their (direct and indirect) information sources' decisions.

5. Lone wolfs (Lone_Wolf): Corresponding to the "Follow your own signal" or overconfidence heuristics uncovered in Huck and Oechssler (2000); Duffy et al. (2019, 2021), this rule represents subjects who never wait and always decide at turn 0.

6. Always Wait for one turn (Always_1Turn): It is a rule of thumb heuristic that seems to be especially relevant in my environment. Corresponding to subjects' over-weighting of social information (March and Ziegelmeyer, 2018; Goeree and Yariv, 2015; Eyster et al., 2015; Çelen and Hyndman, 2012, this rule represents subjects who always wait at turn 1, regardless of their positions and the number of signals they will gather.

More details about how subjects following different strategy rules should behave at different nodes in each treatment are shown in appendix Appendix A.5, since I rotate subjects' positions in the network, these rules predict different behaviors at different nodes in the network, combined with the history each node is facing.

The strategy frequency method follows the approach proposed by Dal Bó and Fréchette (2011) and widely used in many literature, Romero and Rosokha (2018, 2019); Rosokha and Wei (2020).

It is a finite-mixture estimation approach that helps estimate the proportion of strategies used in the experiment. More technical details can be found in Romero and Rosokha (2018). If I restrict the strategies to the above-mentioned six rules, the estimated results are presented below:

Table 11: SFEM results

	All	NC-l	NC-h	C-l	C-h
β	0.7381	0.7905	0.8264	0.6849	0.644
Always_1Turn	**0.2621**	**0.3184**	0.2475	0.1182	**0.4575**
Empirical_Optimal	0.1946	0	**0.4263**	**0.3098**	0.0862
Lone_Wolf	0.1732	0.1827	0.1296	0.1946	0.1418
More_Better	0.1643	0.1839	0.1019	0.2645	0.0498
EmpiricalOptimal_Nocost	0.1052	0.0488	0.0946	0.054	0.2647
More_Better_Naive	0.1007	0.2661	0	0.0588	0
$log(L)$	-2473.06	-700.608	-303.383	-996.307	-410.871

Notes: The bold cell in each column indicates the strategy that is the most commonly used. β indicates the probability of a subject adopting a certain strategy.

In most treatments, the most common strategy is "Always wait for 1 turn" or "Empirically optimal". Consistent with other findings in the network related experiments, although some subjects are able to make optimal choices, there are a substaintial proportion of subjects may adopt some kind of heuristics in decision makings. Incorporating these heuristics in the theory buildings may help increase the predictive power of the models. In sequential environments, the first turn of waiting is crucial to subjects. Having some kind of social information, regardless of how useful it may be, gives subjects a higher utility.

5.3 Do people utilizes the information correctly?

Overall, subjects utilize the information they gathered well, probably because this is a rather simple decision problem. As long as subjects understand that they observe the signals of others, a correct prediction rule is to follow the majority of the signals. A mistake is to make a guess against the majority of the signals. As shown in table 12, the compliance rate of following the private information is close to 100% when both the private and the social information suggest the same state. When the social information is in the opposite direction of the private information but over-powers the private information, the more signals the counter-evidence has, the less likely a subject will continue following his private information. However, when the number of opposite signals is equal, subjects are slightly more likely to follow their own private information. This finding coincides with what Duffy et al. (2019) found where subjects are able to comply with the information they gathered most of the time.

Table 12: Private Information Compliance Rate

Number of Signals Collected	Social Same	Social Opposite and More	Social Opposite and Equal
1	92.1% (936)	-	-
2	99.5% (548)	-	63.5% (384)
3	97.7% (515)	4.4% (135)	-
4	97.8% (579)	3.5% (113)	59.2% (240)
5	98.5% (404)	3.4% (146)	-
Total	96.4% (2982)	3.8% (394)	61.9% (624)

Notes: The table shows the percentage of guesses following subjects' private information. The first column shows the compliance rate when the collected social information indicates the same state as the private information. The second and third columns show when the social information indicates the opposite state as the private information. The second column is when the social information contains more signals of the opposite state than the private information. The third column is when there is an equal number of signals of both states. The numbers in the bracelet show the frequency of each cell.

6 Discussion

The goal of this paper is to test whether subjects can make optimal decisions in a directed network as pure strategy Bayesian equilibrium predicts. Consistent with previous findings, I observe some deviations from the theories. Individual analysis suggests that the deviations cannot be fully explained by the trembling hand effect or mistakes or a failure to apply proper Bayesian updating rules. It seems that although some subjects can make optimal decisions, many others tend to adopt very naive decision rules, such as always-wait-for-1-turn in my environment. Documenting the heuristics and less sophisticated decision rules and incorporating the heterogeneity among subjects may help theorists develop better models. More importantly, when people who use less sophisticated decision rules occupy an important position in the communication network, complete social learning may be impeded. Further research may pay attention to whether people with different decision rules could self-sort into different positions in the network, for example, how the endogeneity of network position and subject's heterogeneity may correlate with each other. In a self-forming or constantly evolving network, if people with more sophisticated decision rules can choose their positions and place themselves in the information maven or information spreader positions, the learning process may speed up.

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Appendix A Online Appendix

Appendix A.1 More details about the model

Pure-Strategy Perfect Bayesian Equilibrium An action strategy profile $\sigma^{n,*}$ is a pure-strategy perfect Bayesian equilibrium of the information exchange game $\Gamma_{info}(G^n)$ if for every $i \in N^n$ and turn t, and given the strategies of other subjects $\sigma_{-i}^{n,*}$, subject i's action $\sigma_{i,t}^{n,*}$ obtains expected payoff equal to the value function of subject i at turn t, $U_{i,t}^n(I_{i,t}^n)$. We denote the set of equilibria of this game by $INFO(G^n)$.

In this section, I provide the optimal stopping rule for each node in the network and define the Nash Equilibrium for different waiting costs.

For a subject who is randomly assigned to a node i in a directed network, the maximum number of additional signals that can be observed in each period equals to the $InDegree_{i,k}^n$ of node i.For signals that can be observed in period 2 or more, whether the signal can be transmitted or not also depends on the behaviors of the middle nodes.

In a 5-node network, the number of possible incoming signals has a maximum limit equal to 4. In my environment, the optimal decision rule is a stopping rule that balances the waiting cost and the expected payoff. The expected payoff depends on the probability of making a correct guess given a certain number of signals. Thus, it will be helpful to calculate the probability of making a correct guess given different numbers of signals.

Let $q > \frac{1}{2}$ denote the informativeness of the signals.

$$P(\text{correct guess}|1\text{ signal}) = q$$

We assume a rational subject will randomly pick one state if the two signals are contradictory.

$$P(\text{correct guess}|2\text{ signals}) = \binom{2}{2}q^2 + \binom{2}{1}q * (1-q) * \frac{1}{2} = q$$

$$P(\text{correct guess}|3\text{ signals}) = \binom{3}{3}q^3 + \binom{3}{2}q^2 * (1-q) = q^2(3-2q)$$

$$P(\text{correct guess}|4\text{ signals}) = \binom{4}{4}q^4 + \binom{4}{3}q^3(1-q) + \binom{4}{2}q^2(1-q)^2 * \frac{1}{2} = q^2(3-2q)$$

$$P(\text{correct guess}|5\text{ signals}) = \binom{5}{5}q^5 + \binom{5}{4}q^4(1-q) + \binom{5}{3}q^3(1-q)^2 = q^3(6q^2+10-15q) \text{ For } q > \frac{1}{2},$$

$$q < q^2(3-2q) < q^3(6q^2+10-15q).$$

From the calculation, we can see that there are three levels of expected payoff, separately conditional on 1 or 2; 3 or 4; and 5 independent private signals. The signal threshold thus is in the set 1,3,5 for a 5-Node fully connected directed network.

Appendix A.1.1 Network (a)

Firstly, start from the "social connector", node A: its length-1 neighbor is E, $B^n_{A,1} = \{E\}$. Since E is relatively isolated, A doesn't have neighbors with higher length. The maximum number of signals E can observe by waiting is 2, which doesn't increase the probability of making a correct guess. Waiting doesn't increase the expected payoff. When the waiting cost is positive, A should always decide at period 0. The optimal signal threshold can be expressed as: $k^n_{A,t} = 1(t = 0)$ if cost $c \geq 0$Secondly, consider the "information maven", node B: its length-1 neighbors are A, C, and D, $B^n_{B,1} = \{A, C, D\}$; its length-2 neighbor is E, $B^n_{B,2} = \{E\}$. If node B waits for 1 period, he will obtain 3 more additional private signals, which can increase the expected payoff. Waiting for 2 periods can increase B's expected payoff if A waits at least 1 period, in which case B can observe all five private signals. The optimal signal threshold is thus:

$$k^n_{B,t} = \begin{cases} 1 & \text{if cost } c \geq P(3sig - 1sig)\psi \\ 3 & \text{if cost } c < P(3sig - 1sig)\psi \\ 5 & \text{if cost } c < \frac{1}{2}P(5sig - 3sig)\psi \text{ and A waits at least 1 periods} \end{cases} \tag{2}$$

, where $P(3sig - 1sig) = 3q^2 - 2q^3 - q, P(5sig - 3sig) = 6q^5 + 10q^3 - 15q^4 - 3q^2 - 2q^3 - q$.
However, based on the above analysis, a rational subject at B should expect that a rational subject at A will guess at period 0. Thus the maximum number of private signals can be observed in this network is only 4, and the optimal signal threshold is adjusted to:

$$k^n_{B,t} = \begin{cases} 1(t = 0) & \text{if cost } c \geq P(3sig - 1sig)\psi \\ 3(t = 1) & \text{if cost } c < P(3sig - 1sig)\psi \end{cases} \tag{3}$$

, where $P(3sig - 1sig) = 3q^2 - 2q^3 - q, P(5sig - 3sig) = 6q^5 + 10q^3 - 15q^4 - 3q^2 - 2q^3 - q$.
Next, for node C: its length-1 neighbors are A and B, $B^n_{C,1} = \{A, B\}$; its length-2 neighbors are D and E, $B^n_{C,2} = \{D, E\}$. If A waits for 1 period, E's private signals will be communicated to node C. If B waits for 1 period, D's private signals will be communicated to node C. The maximum number of private signals C can observe is 5. The signal threshold for node C can be expressed as

$$k^n_{C,t} = \begin{cases} 1 & \text{if cost } c \geq P(3sig - 1sig)\psi \\ 3 & \text{if cost } c < P(3sig - 1sig)\psi \\ 5 & \text{if cost } c < \frac{1}{2}P(5sig - 3sig)\psi \text{ and both A and B wait at least 1 period} \end{cases} \tag{4}$$

, where $P(3sig - 1sig) = 3q^2 - 2q^3 - q, P(5sig - 3sig) = 6q^5 + 10q^3 - 15q^4 - 3q^2 - 2q^3 - q$.
Again, a rational subject at C should know that A will guess at period 0 and B's optimal decision

rule. Thus the rational decision rule for C is adjusted to:

$$k_{C,t}^{n} = \begin{cases} 1(t=0) & \text{if cost } c \geq P(3sig - 1sig)\psi \\ 3(t=1) & \text{if cost } c < P(3sig - 1sig)\psi \text{ (as B will wait 1 period)} \end{cases} \tag{5}$$

, where $P(3sig - 1sig) = 3q^2 - 2q^3 - q$.

For node D: its length-1 neighbor is A, $B_{D,1}^{n} = \{A\}$; its length-2 neighbor is node E, $B_{D,2}^{n} = \{E\}$. If A waits for 1 period, the private signal of E will be communicated to D. The maximum number of private signals D can observe is 3. The optimal signal threshold depends on the trade-off between the increased expected payoff and the waiting cost.

$$k_{D,t}^{n} = \begin{cases} 1 & \text{if cost } c \geq \frac{1}{2}P(3sig - 1sig)\psi \\ 3 & \text{if cost } c < \frac{1}{2}P(3sig - 1sig)\psi \text{ and A waits at least 1 period} \end{cases} \tag{6}$$

, where $P(3sig - 1sig) = 3q^2 - 2q^3 - q$.

However, as stated above, a rational subject at A will guess at period 0, thus the only rational decision for D is to guess at period 0 as well. The threshold is adjusted to:

$$k_{D,t}^{n} = 1(t=0) \text{ if cost } c \geq 0 \tag{7}$$

, where $P(3sig - 1sig) = 3q^2 - 2q^3 - q$.

Lastly, for node E: its length-1 neighbor is node A, $B_{E,1}^{n} = \{A\}$. Since A has only one incoming edge from E, E doesn't have higher length incoming neighbors. Thus, the maximum number of signals E can observe by waiting is 2, which doesn't increase the probability of making a correct guess. Waiting doesn't increase the expected payoff. When the waiting cost is positive, E should always decide at period 0. Thus, the signal threshold can be expressed as:

$$k_{E,t}^{n} = 1(t=0) \text{ if cost } c \geq 0 \tag{8}$$

Appendix A.1.2 Network (b)

Firstly, start from the "social connector", node A: its length-1 neighbors are B and E, $B_{A,1}^{n} = \{B, E\}$; its length-2 neighbors are C and D, $B_{A,2}^{n} = \{C, D\}$. If B waits for 1 period, A will obtain 2 more additional private signals, which can increase the expected payoff. The optimal signal threshold is thus:

$$k_{A,t}^{n} = \begin{cases} 1 & \text{if cost } c \geq P(3sig - 1sig)\psi \\ 3 & \text{if cost } c < P(3sig - 1sig)\psi \\ 5 & \text{if cost } c < P(5sig - 3sig)\psi \text{ and B waits at least 1 period} \end{cases} \tag{9}$$

For now, I can't adjust the optimal rules without knowing B's decision rule, so will come back later.

Secondly, consider the "information maven", node B: its length-1 neighbors are A, C, and D, $B^n_{B,1} = \{A, C, D\}$; its length-2 neighbor is E, $B^n_{B,2} = \{E\}$. If node B waits for 1 period, he will obtain 3 more additional private signals, which can increase the expected payoff. Waiting for 2 periods can increase B's expected payoff if A waits at least 1 period, in which case B can observe all five private signals. The optimal signal threshold is thus:

$$k^n_{B,t} = \begin{cases} 1 & \text{if cost } c \geq P(3sig - 1sig)\psi \\ 3 & \text{if cost } c < P(3sig - 1sig)\psi \\ 5 & \text{if cost } c < P(5sig - 3sig)\psi \text{ and A waits at least 1 periods} \end{cases} \tag{10}$$

, where $P(3sig - 1sig) = 3q^2 - 2q^3 - q, P(5sig - 3sig) = 6q^5 + 10q^3 - 15q^4 - 3q^2 - 2q^3 - q$.

Since A and B make decisions interdependently, I can now adjust their rational decision rule by the level of waiting cost. When the waiting cost is very large ($c \geq P(3sig - 1sig)\psi$), neither nodes will wait. When the waiting cost is relatively small($c < P(3sig - 1sig)\psi$),both A and B will wait at least 1 period. Knowing that, their optimal signal thresholds can be adjusted into:

$$k^n_{A,t} = \begin{cases} 1(t=0) & \text{if cost } c \geq P(3sig - 1sig)\psi \\ 3(t=1) & \text{if cost } P(5sig - 3sig) \leq c < P(3sig - 1sig)\psi \\ 5(t=2) & \text{if cost } c < P(5sig - 3sig)\psi \text{ (as B will wait at least 1 period)} \end{cases} \tag{11}$$

$$k^n_{B,t} = \begin{cases} 1(t=0) & \text{if cost } c \geq P(3sig - 1sig)\psi \\ 3(t=1) & \text{if } P(5sig - 3sig)\psi \leq c < P(3sig - 1sig)\psi \\ 5(t=2) & \text{if cost } c < P(5sig - 3sig)\psi \text{ (as A will wait at least 1 periods)} \end{cases} \tag{12}$$

Next, for node E: its length-1 neighbor is node A, $B^n_{E,1} = \{A\}$; its length-2 neighbor is B, $B^n_{E,2} = \{B\}$; its length-3 neighbors are C and D, $B^n_{E,3} = \{C, D\}$. Waiting for 1 period does not increase the expected payoff, but waiting for 2 periods or 3 periods will increase the expected payoff. Since node A is only directed to node D, for node E to obtain A's signal, node D needs to wait for at least 1 period. Thus, the signal threshold can be expressed as:

$$k^n_{E,t} = \begin{cases} 1 & \text{if cost } c \geq \frac{1}{2}P(3sig - 1sig)\psi \\ 3 & \text{if cost } c < \frac{1}{2}P(3sig - 1sig)\psi \text{ and A waits at least 1 period} \\ 5 & \text{if cost } c < P(5sig - 3sig)\psi \text{ and B waits at least 1 period; A waits at least 2 periods} \end{cases} \tag{13}$$

Based on A and B's optimal decision rules, I can now adjust E's optimal decision rule to:

$$k^n_{E,t} = \begin{cases} 1(t=0) & \text{if cost } c \geq \frac{1}{2}P(3sig - 1sig)\psi \\ 5(t=3) & \text{if cost } c < \frac{1}{2}P(3sig - 1sig)\psi \text{ (as B will wait at least 1 period and A will wait at least 2 periods} \end{cases} \quad (b'_E)$$

In my experiment, the parameters chosen ensure that $\frac{1}{2}P(3sig - 1sig) < P(5sig - 3sig)$ [4]. Thus a rational subject at node E will only have two optimal thresholds:

$$k^n_{E,t} = \begin{cases} 1(t=0) & \text{if cost } c \geq \frac{1}{2}P(3sig - 1sig)\psi \\ 5(t=3) & \text{if cost } c < \frac{1}{2}P(3sig - 1sig)\psi \text{ (as B will wait at least 1 period and A will wait at least 2 periods} \end{cases} \quad (14)$$

Lastly, consider node C and D: These two nodes are identical in the sense they are both connected to B and have one incoming edge from A. Looking at C for instance. Its length-1 neighbor is node A, $B^n_{C,1} = \{A\}$; length-2 neighbors are nodes B and E, $B^n_{C,2} = \{B, E\}$; its length-3 neighbor is node D, $B^n_{C,3} = \{D\}$. Waiting for 1 period does not increase the expected payoff, but waiting for 2 periods or 3 periods will increase the expected payoff. If A waits at least 1 period, waiting for 2 periods will allow C to observe 2 additional private signals from B and E. If A waits for 2 periods, and B waits for 1 period, then waiting for 3 periods will let C observe all private signals. The optimal thresholds for C (also D are:

$$k^n_{C(D),t} = \begin{cases} 1 & \text{if cost } c \geq \frac{1}{2}P(3sig - 1sig)\psi \\ 3 & \text{if cost } c < \frac{1}{2}P(3sig - 1sig)\psi \\ 5 & \text{if cost } c < P(5sig - 3sig)\psi \text{ , A waits at least 2 periods and B waits at least 1 period} \end{cases} \quad (15)$$

Combining the optimal decision rules for A and B, a rational subject at node C or D should behave with the following thresholds:

$$k^n_{C(D),t}(k^n_{D,t}) = \begin{cases} 1(t=0) & \text{if cost } c \geq \frac{1}{2}P(3sig - 1sig)\psi \\ 5(t=3) & \text{if cost } c < \frac{1}{2}P(3sig - 1sig)\psi \text{ (as A will wait at least 2 periods and B will wait at least} \end{cases} \quad (16)$$

It turns out a rational subject will behave the same at C, D, and E for different level of waiting costs in network (b).

[4]In my experiment, $q = 0.7$, $\psi = 100$, $\frac{1}{2}P(3sig - 1sig)\psi = \frac{1}{2}(3q^2 - 2q^3 - q)(\psi) = 4.2$, P(5 sig-3sig)$\psi = (6q^5 + 10q^3 - 15q^4 - 3q^2 - 2q^3)(\psi) = 5.292$

Appendix A.2 More Details about the QRE Prediction and Estimation

For the Quantal response equilibrium, the main assumption is that agents have idiosyncratic preference shocks. Following a similar approach adopted by Choi et al. (2012), at each turn $t = \{0, 1, 2, 3, 4, 5\}$, subjects at node n have two actions $x^n_{i,t} \in$ {wait, guess} and the corresponding utility function is defined as $U^n_{it}(x^n_{i,t}) = \lambda_{it}\pi^n_{it} + \epsilon_{it}$, where π^n_{it} represents the expected payoff of taking action $x^n_{i,t}$ at turn t at node n and coefficient λ_{it} shows the sensitivity of subject i to choose action $x^n_{i,t}$ with the expected payoff. The random variable ϵ_{it} stands for subject i's preference shock for action $x^n_{i,t}$, which is assumed to be i.i.d. across turns and at different nodes. When the action $x^n_{i,t}$ is {guess}, the expected payoff is equal to the expected payoff of making a guess given the number of signals collected at turn t. When the action $x^n_{i,t}$ is {wait}, the expected payoff is assumed to be the maximal amount of expected payoff among all future turns. See table A-1 to denote the expected payoff of each turn at different nodes in the network.

In the experiment, subjects can wait for up to 5 turns. I calculate the QRE based on the extensive form of the game. Let $p^n_{i,t}$ denote the probability of subject i at node $n \in \{A, B, C, D, E\}$ guess at turn t. Let $\pi^n_{i,t}$(guess) denote the expected payoff of guessing at turn t. The expected payoff of waiting at turn t becomes $\pi^n_{i,t}(\text{wait}) = \max\{\pi^n_{i,t+1}(\text{guess}), \pi^n_{i,t+2}c, ..., \pi^n_{i,T=5}(\text{guess})\}$. At each turn, a subject i at node n assign the probability between waiting and guessing by applying logit rules to the expected payoffs :

$$p^n_{i,t}(\lambda) = \frac{e^{\lambda\pi^n_{i,t}}(\text{wait})}{e^{\lambda\pi^n_{i,t}}(\text{wait}) + e^{\lambda\pi^n_{i,t}}(\text{guess})}$$

Further let $p_{n,t}$ denote a representative subject's probability of guess at turn t at node n, where $p_{n,t} = \prod_{\tau=0}^{t-1}(1 - p^n_\tau)p^n_t$. The probability of a representative subject guessing at turn t at node n depends on the λ parameter.

Table A-1: Expected Payoffs by Nodes

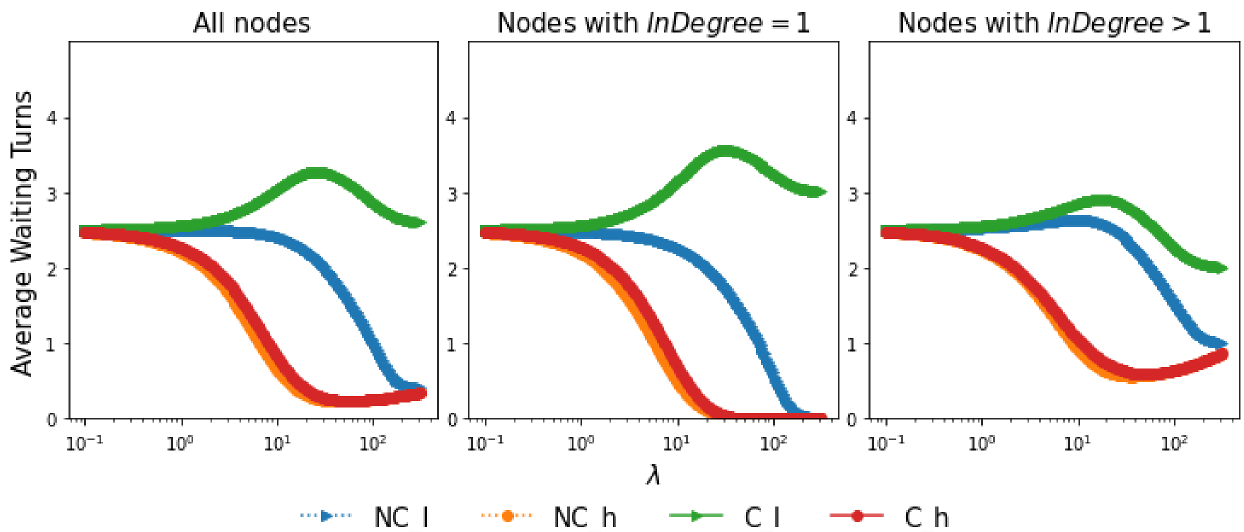
Waiting Turns	network NC				network C		
	A/E	B	C	D	A	B	C/D/E
0	$\pi(1)$						
1	$\pi(2) - c$	$\pi(4) - c$	$\pi(3) - c$	$\pi(2) - c$	$\pi(3) - c$	$\pi(4) - c$	$\pi(2) - c$
2	$\pi(2) - 2c$	$\pi^B - 2c$	$\pi^C - 2c$	$\pi^D - 2c$	$\pi^A - 2c$	$\pi^B - 2c$	$\pi^E - 2c$
3	$\pi(2) - 3c$	$\pi^B - 3c$	$\pi^C - 3c$	$\pi^D - 3c$	$\pi^A - 3c$	$\pi^B - 3c$	$\pi^{E'} - 3c$
4	$\pi(2) - 4c$	$\pi^B - 4c$	$\pi^C - 4c$	$\pi^D - 4c$	$\pi^A - 4c$	$\pi^B - 4c$	$\pi^{E'} - 4c$
5	$\pi(2) - 5c$	$\pi^B - 5c$	$\pi^C - 5c$	$\pi^D - 5c$	$\pi^A - 5c$	$\pi^B - 5c$	$\pi^{E'} - 5c$

where $\pi^B = p_{A0}\pi(4) + (1 - p_{A0})\pi(5)$, $\pi^C = p_{A0}p_{B0}\pi(3) + [(1 - p_{A0})p_{B0} + (1 - p_{B0})p_{A0})]\pi(4) + (1 - p_{A0})(1 - p_{B0})\pi(5)$, $\pi^D = p_{A0}\pi(2) + (1 - p_{A0})\pi(3)$, $\pi^A = p_{B0}\pi(3) + (1 - p_{B0})\pi(5)$, $\pi^E = p_{A0}\pi(2) + (1 - p_{A0})\pi(3)$, $\pi^{E'} = p_{A0}\pi(2) + [(p_{A1} + (1 - p_{A0} - p_{A1})p_{B0}]\pi(3) + (1 - p_{A0} - p_{A1})(1 - p_{B0})\pi(5)$.

Appendix A.2.1 Normal Form Predictions and Estimation

The result of QRE in normal form assumes that subjects pre-assign a probability of guessing at each turn $t \in [0, 5]$ and doesn't change the probability across turns even though the information set may be updated. The path shows a very similar pattern as in the extensive form. When λ is very small, the average waiting turns is higher than the ones in the extensive form because I assume a representative subject assigns equal probability to guessing from turn $t = 0$ to turn $t = 5$.

Figure A-1: QRE Prediction of Average Waiting Turns by Treatment



Notes: Panel shows the group average of waiting turns by treatment predicted by Quantal Response Equilibrium when the game is represented in the normal form.

Table A-2: QRE Estimation by Treatment

		NC-l	NC-h	C-l	C-h
All 30 rounds	λ	15.167	8.262	3.390	5.976
	$logL$	-2261.5	-751.0	-2663.0	-908.0
Later 15 rounds	λ	67.867	8.959	3.390	5.976
	$logL$	-1250.7	-383.8	-1419.7	-483.7

Table A-3: QRE Estimation

		NC-l	NC-h	C-l	C-h
multiple information sources	λ	8.959	6.748	8.959	9.329
	$logL$	-913.1	-327.4	-1026.5	-324.8
single information sources	λ	11.895	8.959	4.322	6.223
	$logL$	-1352.1	-442.2	-1589.6	-542.4

Appendix A.3 Administration

Table A-4: Summary of Experiment Administration

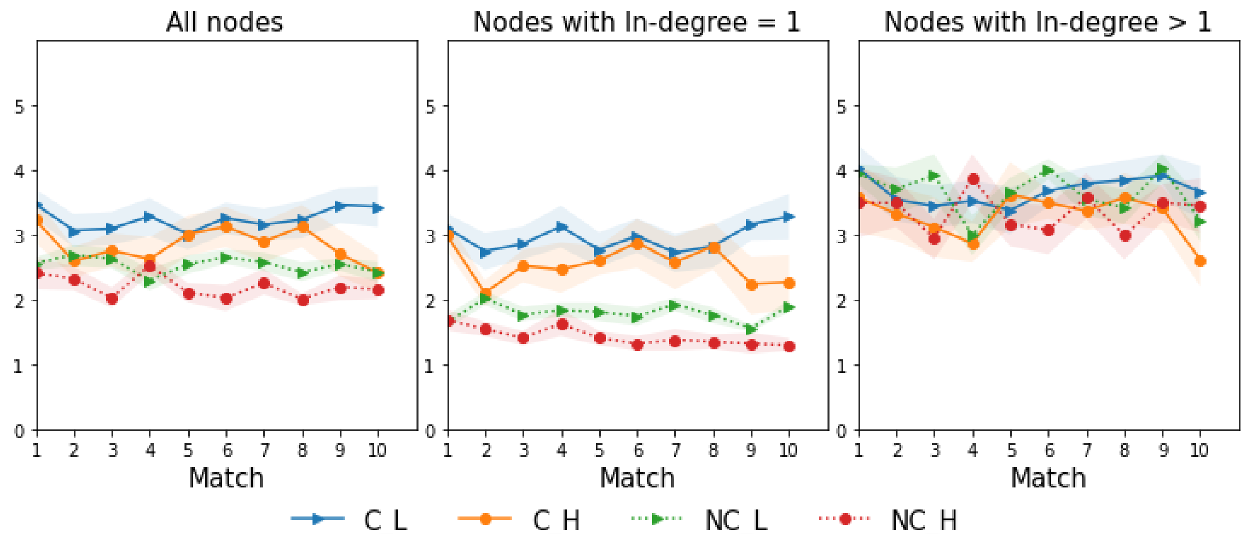
	Treatment			Demographics			
Session	Date	Network Type	Waiting Cost	Earnings	% Male	% STEM	% U.S. Borned
0	03/19/2021	NC	L	24.3	70.0	70.0	60.0
1	04/09/2021	NC	L	25.5	50.0	60.0	60.0
2	04/09/2021	NC	L	24.5	50.0	60.0	90.0
3	04/09/2021	NC	L	25.4	30.0	50.0	60.0
4	04/13/2021	NC	H	24.1	40.0	50.0	60.0
5	04/13/2021	NC	H	25.0	70.0	60.0	70.0
6	04/28/2021	C	H	24.4	60.0	80.0	60.0
7	04/28/2021	C	H	21.7	70.0	90.0	20.0
8	04/29/2021	C	L	23.8	20.0	60.0	70.0
9	04/29/2021	C	L	24.8	60.0	40.0	70.0
10	04/29/2021	C	L	25.0	40.0	60.0	70.0
11	12/03/2021	C	L	25.0	60.0	50.0	70.0
12	12/03/2021	C	L	25.6	70.0	70.0	70.0

Notes: % STEM denotes proportion of participants that are in STEM majors. % US HS denotes the proportion of participants that completed high-school in the US.

Appendix A.4 Additional Results

Appendix A.4.1 Number of Signals Transmitted

Figure A-2: Number of Signals Gathered by Treatment



Notes: Panel shows the group average of waiting turns by treatment, the shades indicate 90% bootstrap confidence interval.

Appendix A.4.2 Accuracy

Table A-5: Average accuracy by treatments

		All nodes	In-degree=1	In-degree>1
c	h	0.74	0.73	0.75
		(0.03)	(0.03)	(0.03)
c	l	0.76	0.75	0.78
		(0.02)	(0.02)	(0.02)
nc	h	0.73	0.69	0.8
		(0.03)	(0.03)	(0.03)
nc	l	0.73	0.72	0.76
		(0.02)	(0.02)	(0.02)

Notes:

Appendix A.5 Details about Decisions Rules

Appendix A.5.1 Empirically optimal turns

I define a subject's empirically optimal behaviors as: 1) they behave as the pure-strategy Beyesian Nash equilibrium predicts; 2) they respond to their information sources' decisions, namely, if they observe that their information sources stop gathering information early, they will early too; 3) they may hold incorrect belief at turn 0 and stop gathering information early or late, but the decision is only optimal when they correctly predict node A's behavior. The following decision turns are classified as empirically optimal. Let x_i^{e*} denote the empirical optimal decision turns at node i and $\hat{x_i}$ denote the realized decision turns in the group at node i:

Table A-6: Empirical Optimal Decisions

Network	Single information source	Multiple information source
NC	$x_{A/E}^{e*} = 0$ for c^L and c^H $x_D^{e*} = \begin{cases} 0 & \text{for } c^L \text{ and } c^H \\ 1 & \text{if } c^L \text{ and } \hat{x_A} = 0 \\ 2 & \text{if } c^L \text{ and } \hat{x_A} \geq 1 \end{cases}$	$x_C^{e*} = \begin{cases} 1 & \text{if } c^H \text{ or } (\ c^L \text{ and } (\hat{x_A} = 0 \text{ or } \hat{x_B} = 0)) \\ 2 & \text{if } c^L \text{ and } \hat{x_A} \geq 1 \text{ and } \hat{x_B} \geq 1 \end{cases}$ (17) $x_B^{e*} = \begin{cases} 1 & \text{if } c^H \text{ or } (\ c^L \text{ and } \hat{x_A} = 0) \\ 2 & \text{if } c^L \text{ and } \hat{x_A} \geq 1 \end{cases}$
C	$x_{C/D/E}^{e*} = \begin{cases} 0 & \text{if } c^H \text{ or } (c^L \text{ and } \hat{x_A} = 0) \\ 1 & \text{if } c^L \text{ and } \hat{x_A} = 0 \\ 2 & \text{if } c^L \text{ and } (\hat{x_A} = 1 \text{ or } \hat{x_B} = 0) \\ 3 & \text{if } c^L \text{ and } \hat{x_A} \geq 2 \text{ and } \hat{x_B} \geq 1 \end{cases}$	$x_A^{e*} = \begin{cases} 1 & \text{if } c^H \text{ or } c^L \text{ and } \hat{x_B} = 0 \\ 2 & \text{if } c^L \text{ and } \hat{x_B} \geq 1 \end{cases}$ $x_B^{e*} = \begin{cases} 1 & \text{if } c^H \text{ or } c^L \text{ and } \hat{x_A} = 0 \\ 2 & \text{if } c^L \text{ and } \hat{x_A} \geq 1 \end{cases}$

Appendix A.5.2 The more the better

This heuristic means that subjects are trying to obtain as many signals as possible before making a decision, regardless of the waiting cost. They only stop when they know there will be no more signals to be gathered.

Table A-7: More is Better Heuristics

Network	Single information source	Multiple information source
NC	$x_D^{e*} = \begin{cases} 1 & \text{if } \hat{x_A} = 0 \\ 2 & \text{if } \hat{x_A} \geq 1 \end{cases}$ $x_{A/E}^{e*} = 1$	$x_C^{e*} = \begin{cases} 1 & \text{if } \hat{x_A} = 0 \text{ and } \hat{x_B} = 0 \\ 2 & \text{otherwise} \end{cases}$ $x_B^{e*} = \begin{cases} 1 & \text{if } \hat{x_A} = 0 \\ 2 & \text{otherwise} \end{cases}$
C	$x_{C/D/E}^{e*} = \begin{cases} 1 & \text{if } \hat{x_A} = 0 \\ 2 & \text{if } \hat{x_A} = 1 \text{ and } \hat{x_B} = 0 \\ 3 & \text{if } \hat{x_A} \geq 2 \text{ or } \hat{x_B} \geq 1 \end{cases}$	$x_A^{e*} = \begin{cases} 1 & \text{if } \hat{x_B} = 0 \\ 2 & \text{otherwise} \end{cases}$ $x_B^{e*} = \begin{cases} 1 & \text{if } \hat{x_A} = 0 \\ 2 & \text{otherwise} \end{cases}$

Additional naive one: don't care about the information source's decision, wait until no more signals coming in:

Table A-8: More is Better (Naive) Heuristics

Network	Single information source	Multiple information source
NC	$x^{e*}_{D} \geq 2$	$x^{e*}_{B/C} \geq 2$
	$x^{e*}_{A/E} \geq 1$	
C	$x^{e*}_{C/D/E} \geq 3$	$x^{e*}_{A/B} \geq 2$