# Social Learning through Endogenous Information Acquisition: An Experiment*


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## Abstract

This paper provides an experimental test of a theory of social learning through *endogenous* information acquisition. A group of subjects face a decision problem under uncertainty. The subjects are endowed with private information about the fundamentals of the problem, and make decisions sequentially. The key feature of the experiment is that a subject can observe the decisions of the preceding subjects by forming links at some positive cost. We show that subjects respond to changes in the information structure and the cost of link formation in the expected manner. However, we also show that behavior systematically deviates from the Bayesian benchmark as subjects form more links than theory predicts. Some subjects also exhibit a tendency to conform rather than follow their own information. We also provide a structural econometric model which allows us to estimate the underlying beliefs of subjects about the state of the world and compare them with those obtained through Bayesian updating.



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# 1 Introduction

Evidence that the structure of social interactions (henceforth *social networks*) is important in disseminating information have been found in many contexts. Kelly and Ó Gráda [21] demonstrate the importance of networks in market panics using data from two panics in 1850s New York. Foster and Rosenzweig [13], Conley and Udry [10], and Munshi [26] show that technology diffusion is driven by an underlying social learning process. In particular, Conley and Udry [10] report results of field work in rural areas of Ghana indicating the main channel for the adoption of new technology in an agricultural sector is social learning through networks. Also, it is well-documented in the labor economics literature (see Ioannides and Loury [18]) that social networks are the main source of information about jobs. These are but a few examples exhibiting the significance of such questions as:

**(1)** How does the network structure affect the dissemination of information?
**(2)** How do social networks form as far as information aggregation is concerned.

The answers to these questions are sought in the realm of the theory of the economics of social networks.[1] There are a number of studies concerning the first question (viz. Bala and Goyal [1], and Gale and Kariv [15]). These papers address questions such as how information propagates and how agents learn from each other in exogenously given network structures. This paper is an attempt towards a better understanding of the second question. The model underlying our experiment extends the canonical *social learning* model in order to analyze the role of the information externality on the formation of networks, as well as the impact of the dynamic evolution of networks on the learning dynamics. We carefully design an experiment in order to improve our understanding of endogenous information acquisition—or, link formation—in a social learning environment. We believe the present paper is a first step necessary to understand informational foundations of the works we cite above.

In the canonical social learning model agents receive private signals regarding the state of the world and then make decisions sequentially, after having observed the action choices of all or some of their predecessors. If agents are Bayesian, they infer valuable information from their observations, often leading to herd behavior or informational cascades. A critical assumption of these models is that the interaction between agents is exogenously determined. This paper relaxes this assumption by letting agents choose whom to observe, i.e. form their own network. Put differently, in order to acquire more

[1] For recent and comprehensive surveys of the literature see Jackson [19, 20].

information, an agent can decide to form *links* to other agents to observe their decisions and make his decision thereafter. This is the sense in which we say that the network evolves endogenously.

Our experiment consists of a group of four subjects who sequentially make a decision on the same problem. Each subject is (potentially) endowed with a piece of valuable information regarding the fundamentals of the problem. In addition to his private information, each subject, before making a decision, is allowed to form links to his predecessors. Forming a link is costly, yet it entitles a subject to observe the actions of those with whom he linked. While the subjects cannot observe the actions without a link, they observe the link decisions of those who moved before them. Therefore, the structure itself divulges the degree of network's informativeness, should the subject decide to form any links. We have two different treatments: the full information treatment (FI) and the partial information treatment (PI). The two treatments differ in that in the former treatment, subjects always receive an informative signal, while in the latter they receive a signal with probability less than one. This allows us to analyze how subjects react to changes in the quality of information in this environment.

In a nutshell, each subject first decides whether or not to form any links and then, upon observing the actions through his links, he makes an action decision. This two-step procedure gives us the leverage to pose many interesting questions: how do subjects search for information, how do subjects respond to the cost of link formation, how much information is transmitted by the network, how do subjects aggregate the information obtained from any link decisions?

Section 2 lays out the model that we implement in the laboratory and provides the predictions of the theory. We first describe what we call the network formation game. Then we elaborate more on the specifics of link formation. In particular we explain the details of link formation and the way they collect information through what we call the Bayesian Sequential Link Procedure. Finally we state the theoretical predictions of the model concerning the behavior of the Bayesian agents. Section 3 explains *what* happens in the laboratory, as well as *how* it happens. We also explain some of our choices concerning the experimental design.

In Section 4, we provide a descriptive analysis of the observed link and action decisions of the subjects in our experiment. This is where we show that there are systematic deviations from the Bayes-rational benchmark of Section 2. For example, in both information treatments, informed subjects in the second position link to the first subject approximately 30% of the time, although it is not optimal for any positive cost. Remarkably, however, when the observed action and the signal of the second subject disagree, in the FI treatment there is a strong tendency to conform to the decision of the first subject, while for the PI treatment there is no such tendency. We also show that subjects display herd behavior in link formation: that is, the third subject is much more likely to link if he observes a link between the subjects in the first and second positions; the fourth subject almost always links when the third subject has a link to the second, who also has a link to the first. Finally, we show that subjects do not necessarily form links to the most informative node; instead, they prefer to link to the *larger* sub-network. All of these deviations should not be construed to mean that subjects' behavior is completely erratic. Indeed, subjects respond to changes in the cost of link formation just like the theory predicts. Moreover, by looking across information treatments, we are able to see that subjects do respond to information. For example, herding in link formation is less pronounced in the PI treatment than in the FI treatment. We also show that learning across rounds is largely limited to informed subjects in the second position, and despite theoretical predictions to the contrary, subjects do not appear to make more accurate predictions by forming links.

In Section 5 we derive and estimate a structural model of behavior for the second and third decision makers. Specifically, the richness of our data allows us to identify and estimate the underlying beliefs of the decision makers on the underlying state of the world. For subjects in the second position our results depend on the treatment: in the FI treatment, such subjects tend to under-weight contradictory information received from a link to the first agent, while in the PI treatment the result is reversed. When considering the third agent, matters are substantially more complex because such agents can face one of two networks and must condition their decisions on the observed network. When the third agent observes a link between the first and the second, we are able to modify our structural model and estimate the underlying beliefs of the agent. In this case, our results indicate that when the agents in the third position observe that the actions taken by the first and the second agent are in agreement, they tend to be over-confident that the true state is that which was chosen by the first and second agents. When the action choices of the first and the second agent disagree, in the FI treatment, it appears that subjects in the third position tend to over-weight the action taken by the second agent and underweight the action taken by the first. In contrast, in the PI treatment, when the observed actions disagree, the observed signal is decisive. The aforementioned results for the third decision maker are largely supported by the results of a series of reduced-form logit regressions which make use of the entire data set and not just the subset of the data in which the second agent linked to the first.

Finally, in Section 6 we offer some concluding remarks and directions for future research and two appendices collect the proofs of our theoretical results and the instructions used in the experiments.

## 2 Theoretical Background

The design of our experiment is based on a theory of social learning in which agents can choose whose action to observe. In this section, we introduce the model and carefully discuss its theoretical predictions. These predictions offer the rational benchmark for the analysis of subjects' behavior in the laboratory.

### 2.1 Network Formation Game

The basic structure of the problem—which we call the **network formation game**—is as follows. There are two equally likely states of the world $\theta \in \{-1, 1\}$. The game consists of four agents who are randomly assigned to a position in a decision line indexed by $i = 1, 2, 3, 4$. Agents act sequentially in a predetermined order. The agents' problem involves correctly identifying the true state of the world. Precisely, each agent $i$ is supposed to take an action $a_i \in \{-1, 1\}$, which we call the **action decision**. If an agent's action matches the true state, then he receives a payoff $m > 0$; otherwise his payoff is zero. Thus, we can represent the preferences of agent $i$ by the utility function

$$u_i(a_i; \theta) = \begin{cases} m & \text{if } a_i = \theta, \\ 0 & \text{otherwise.} \end{cases}$$

Before he makes a decision, agent $i$ receives a private signal $\sigma_i \in \{-1, 0, 1\}$. We say that the agent is **informed** when the signal he receives is either $-1$ or 1. The signals $\sigma_i \in \{-1, 1\}$ are informative about the true state because conditional on the true state the probability that the signal matches the state is $p = 2/3$. In contrast, the signal $\sigma_i = 0$ is uninformative because given $\sigma_i = 0$ the probability of state $\theta = -1$ and $\theta = 1$ are both $1/2$. Hence, the agent cannot distinguish the states of the world based on his signal. Therefore, we say that agent $i$ is **uninformed** if he receives the signal $\sigma_i = 0$. Finally, we assume that an agent is informed with probability $q \in (0, 1]$, and uninformed with probability $1 - q$.

The signals that agents receive are independently and identically distributed conditional on the true state. Table 1 summarizes the probabilities with which an agent receives each signal conditional on the state of the world.

After receiving a private signal but before making the action decision, an agent has the option to observe action decisions made by the preceding agents in the decision line. The decision whether to observe any of the preceding agents' actions—and, if so, whose actions to observe—is called the **link decision**. We make two assumptions on the process of information gathering through link formation, both of which simplify the

Table 1: Information Structure

| $\sigma$ | $\theta$ | |
|---|---|---|
| | $-1$ | $1$ |
| $1$ | $q/3$ | $2q/3$ |
| $0$ | $1-q$ | $1-q$ |
| $-1$ | $2q/3$ | $q/3$ |

analysis without changing the results qualitatively.[2]

**(1)** First, link decisions are assumed to be public information: that is, each agent observes all the link decisions made by the preceding agents but not their action decisions.

**(2)** Second, by forming a link to one of the preceding agents, not only does an agent observe the action decision of this agent, but also all the actions that this agent observed through his link decision(s). The cost of each link is assumed to be $c \geq 0$.

The next section provides a detailed description of the process of link formation.

## 2.2 Bayesian Sequential Link Procedure

The process of link formation for each agent is a sequential process. In other words, if an agent can form more than one link, he initially compares the cost and benefits of forming no links versus forming a link. After he forms the first link (if at all), he observes the relevant action choices and then, based on the information gained, weighs the costs and benefits of forming another link, and so on.

Figure 1: Bayesian Sequential Link Procedure: An Example


Let us be more specific and explain what we call the **Bayesian Sequential Link Procedure** (BSLP) by use of an example, which is illustrated in Figure 1. It is the fourth agent's turn to move and he observes the following: The second agent did not form a link to the first, and took his action based on his private information. The third agent formed a link to the second; yet, after observing the action of the second, he did not form

[2] Relaxing either assumption will simply change the equilibrium cost thresholds that we derive below.

a link to the first agent. Therefore, he took his action based on the information deduced from the second agent's action and his private information. There are two links that the fourth can form: a link to the third agent, through which he can observe the action of the third and the second, and a link to the first agent, through which he can observe the action of the first agent.[3]

According to BSLP, the fourth agent evaluates the problem in the following way. Based on his own information, he decides whether it is optimal to incur $c$ and form a link to the third. But in doing so he keeps in mind that he could continue and form a link to the first by incurring the cost $c$ again. More precisely, he considers all possible action profiles that he can observe through his link to the third agent. Also, conditional on his private information, he knows the probability with which he can observe each action profile. Furthermore, for each one of these contingencies, he considers the action profile he can observe by a second link and decides whether he would form the second link or not as if he is at that situation. Finally, with this continuation value in mind, he decides whether to form his first link or not. In what follows, we will explain this procedure more formally. All the results that we will report in the following sections are based on the use of the formula we derive here.

As it is the case in the example, forming a link is equivalent to saying that the agent observes the outcome (the action profile) of an experiment (forming a link). For the purposes of the present paper, it is enough to look at the case where there are two random variables, $X_1, X_2$, which are independent conditional on $\theta$, but not necessarily identical. Let $\mathcal{X}_i$ be the set of all realizations of $X_i$. The realizations of the random variables are denoted by $x_1$ and $x_2$ respectively. Therefore, an agent facing $X_1$ and $X_2$ first decides whether to take an optimal action simply based on his private information, or to experiment $X_1$. If he decides to experiment $X_1$, for any realization $x_1$, he specifies whether to take an optimal action, or to further experiment $X_2$. If he decides to experiment $X_2$, for all realizations $x_2$, he specifies the optimal action he should take.

Let $s_0 = (\sigma), s_1 = (\sigma, x_1), s_2 = (\sigma, x_1, x_2)$ denote the information nodes where the agent observes only his private information, his private information and the realization of $X_1$, and his private information, the realization of $X_1$ and of $X_2$, respectively. Note that the set of all realizations at node $s_0$ is $S_0 := \{-1, 0, 1\}$, at node $s_1$ is $S_1 := S_0 \times \mathcal{X}_1$, and at node $s_2$ is $S_2 := S_1 \times \mathcal{X}_2$. We denote the maximum expected utility an agent can get at a node $s \in \{s_0, s_1, s_2\}$ without further experimentation by

$$\underline{v}(s) := \max\left\{ \Pr(\theta = 1|s), \Pr(\theta = -1|s) \right\} m. \tag{1}$$

[3] By Blackwell's [6] celebrated theorem, it is straightforward to see that it is not optimal to form a link to the second, rather than the third. Similarly, it is not optimal to form a link to the first and then to the third agent.

Also, at node $s_j$, where $j \in \{0,1\}$ the ex ante maximum expected utility from further experimentation is

$$\begin{aligned} \bar{v}(s_j) &:= \sum_{s_{j+1} \in S_{j+1}} \Pr(s_{j+1}|s_j) \max\left\{\underline{v}(s_{j+1}), \bar{v}(s_{j+1}) - c\right\}, \text{ and} \\ v(s_2) &:= \bar{v}(s_2). \end{aligned} \tag{2}$$

since at each $s_j$ an agent compares $\underline{v}(s_j)$ against $\bar{v}(s_j) - c$ to decide whether to experiment $X_{j+1}$ or to take the optimal action at $s_j$. To capture this, finally we define what we refer to as the **value of information** from further experimentation by

$$v(s_j) := \bar{v}(s_j) - \underline{v}(s_j) - c \quad \text{for } j \in \{0,1\}. \tag{3}$$

Therefore at $s_j$, an agent decides to further experiment if $v(s_j) > 0$, otherwise he takes the optimal action at $s_j$ without experimenting $X_{j+1}$.

By using the equations (1), (2), (3) and backward induction, we can fully describe the optimal strategy of an agent. The following proposition formally states the complete characterization of BSLP that we illustrated.

PROPOSITION 1. *The optimal policy of Bayesian sequential link procedure for an agent is characterized by a pair $(\tau, a^*)$ such that*

$$\tau \quad = \min\left\{j \in \{0,1,2\} : v(s_j) \leq 0\right\}, \tag{4}$$

$$a^* \quad \in \arg\max_a \left\{ \textstyle\sum_\theta \Pr(\theta|s_\tau) u(a,\theta) \right\}. \tag{5}$$

Proposition 1, and the value of information, as defined by (3), provide us with the full characterization of the decision problem. In words, an agent stops at the first node at which the value of information is negative; otherwise he keeps forming links. If the agent stops at the node $s_\tau$, then he takes the action that maximizes his expected utility given his information. The equilibrium results that we present in the following section are derived by use of this characterization.

## 2.3 THEORETICAL PREDICTIONS

In this section we provide an intuitive discussion of the equilibrium behavior of agents $i \in \{1,2,3,4\}$, and also enumerate the equilibrium networks that can be observed in the network game. In Appendix A we formally derive these results as corollaries to Proposition 1

First Agent. The decision problem of the first agent is easy because there is no preceding agent and thus he takes an action based only on his private signal. If the first agent is informed, then he follows his signal. Whereas, if he is uninformed he randomizes between the two possible actions. Therefore, unless $q = 1$, the second agent cannot determine the status of the first agent as either informed or uninformed. Figure 2 depicts this situation. We reserve the diamond to refer to an agent whose status cannot be determined.

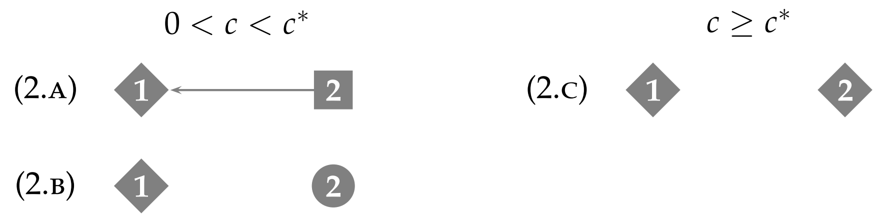
Figure 2: After the First Agent

(1.a) 


Second Agent. The second agent faces a more interesting problem because he has the option to observe the first agent's action. Here, optimal behavior depends on whether or not the agent is informed. If the second agent is informed, by applying Proposition 1, we find that he does not form a link for any positive cost. Intuitively, this is easy to see: if the second agent incurs the cost $c$ and forms a link to the first, either he will observe an action that is the same as his own private information, or he will observe the opposite action. For $q < 1$, he will favor the action that is in line with his signal, while when $q = 1$, he will become indifferent between the two actions. This suggests that forming a link does not provide any value to an informed second agent since he can always save the link cost and follow his own signal.

On the other hand, if he is uninformed, then it is optimal to form a link to the first agent if the cost is low enough, because there is a positive probability that the first is informed. If the cost is high, an uninformed second agent does not form a link. That is, there is a threshold cost of link formation, $c^*$, such that the uninformed second agent forms a link if and only if $c \leq c^*$. It is also shown that the threshold value $c^*$ increases linearly in the probability of being informed, $q$, and in the payoff from a correct action, $m$. Intuitively, when $q$ is higher, the first agent is more likely to be informed and thus, from the perspective of an uninformed second agent, it becomes more valuable to form a link to the first agent. In a similar vein, when the payoff from a correct decision is larger, the same amount of information increases the potential benefit from that information. Figure 3 depicts the networks that can emerge in the equilibrium for $0 < c < c^*$, and $c \geq c^*$. The square indicates the event in which it can be deduced that the agent is uninformed, while the circle indicates that he is informed.

Figure 3: After the Second Agent




Third Agent. Note that when $c < c^*$, the third (and fourth) agent(s) can discern whether the second agent is uninformed ((2.a) in Figure 3) or informed ((2.b) in Figure 3) simply by observing the network structure emerging from his link decision. As such, the network structure itself contains valuable information and affects significantly the behavior of all agents coming after the second agent.

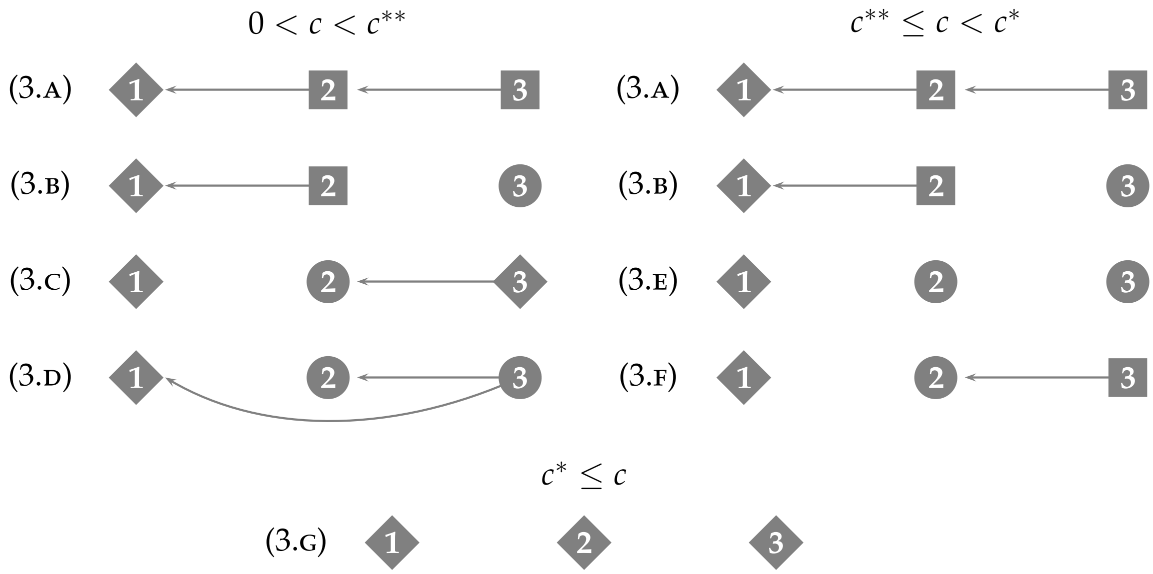
The decision problem for the third agent becomes interesting because the network structure becomes more significant in determining the optimal behavior. When the third agent observes a link between the second and the first agents, he rationally infers that the second agent is uninformed and his action conveys no information. In this case, his problem is equivalent to the second agent's problem: if he is informed, he does not form a link for any positive cost, whereas if he is uninformed, he forms a link to the second agent for $c < c^*$.[4] The networks (3.a) and (3.b) in Figure 4 exhibit these situations.

Suppose that $0 < c < c^*$ and the third agent faces the network (2.b) in Figure 3. When the third agent observes that there is no link between the first and the second agents, he knows that the second agent is informed. However, he knows that the first is informed only with probability $q \in (0, 1]$. Therefore, an uninformed third agent forms a link to the second and imitates his action ((3.c) and (3.f) in Figure 4). Note that after observing the second agent, the uninformed third agent is exactly the same as an informed second agent. Hence a link to the first agent is worthless.

On the other hand, if the third agent is informed, we find that the value of information is positive only when the cost is low enough (i.e. $c < c^{**} = 2qm/39$.) Suppose that $c < c^{**}$. An informed third agent starts forming a link to the second. If he finds out that the action of the second agent is the same as his signal, he imitates the second's action without forming a link to the first ((3.c) in Figure 4.) Otherwise he proceeds with a link to the first agent ((3.d) in Figure 4.) Since there is a chance an informed third agent does not form a link to the third, the fourth agent facing the network (3.c) in Figure 4 cannot tell whether the third is informed or not. On the other hand, when $c^{**} \leq c < c^*$, an

[4] Note that it is also optimal to form a link to the first agent and the third observes only the first agent's action. In order to get around an unnecessary multiplicity of equilibria, we assume that an agent starts to form a link to the closest agent in a line.

Figure 4: After the Third Agent



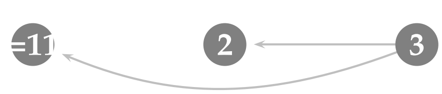

informed third agent does not form a link to the second agent ((3.e) in Figure 4.)

Finally, when the cost is high enough (i.e., $c > c^*$), the third agent observes the empty network where the second did not form a link. Because the third agent cannot distinguish whether the second agent is informed or not, he faces two opportunities of linking with equal amounts of information ((3.g) in Figure 4.) However, due to the high cost, it is never optimal for him to form any link regardless of whether he is informed or not.

We summarize this discussion in the following Corollary.

Fourth Agent. Since most of our attention will be focused on the first three agents in the analysis of the experimental data, we will not provide a full characterization of optimal behavior for agents in the fourth position. We can point out, however, that often the problem of the fourth agent will be strategically equivalent to either the second or the third agent. For example, consider the case where the cost of link formation is low enough, and the fourth agent observes the network displayed in Figure 5.

Figure 5: The Fourth Agent's Problem: An Example



Given this network, the fourth agent can infer that both the second and third agents were informed. He can also infer that the signals of the second and third must have disagreed (since the third agent also formed a link to the first). Therefore, the signals of the second and third essentially cancel, leaving the only relevant signal that of the first agent—exactly as it is for the second agent. Therefore, if the fourth agent is informed, he should not link for any positive cost, while if he is uninformed, he should link provided that $c$ is small enough. To be sure, there are situations in which the fourth agent's problem is not equivalent to one of his predecessors. However, since this is not our main focus, and the intuition is relatively straightforward, we will omit such details.

### 2.3.1 The Effect of Cost on Welfare

One noticeable feature of these predictions is the amount of information revealed at different cost levels. Indeed, starting from the third agent, the structure of previous links reveal valuable information vis-à-vis 0-cost level. In fact, for arbitrarily small cost, when the probability of being an uninformed agent is large enough, the ex ante welfare of the third agent is larger than 0-cost level. The intuition is simple. Recall that, if the cost is positive, an informed second agent never forms a link to the first agent. This situation, in turn, reveals whether the second agent is informed or not. However, in the 0-cost case, since there is always a link between agents, succeeding agents are not able to make a similar deduction. When $1 - q$ is high enough, the benefit of an uninformed third agent from this extra information dominates the loss of an informed second agent by not observing the first agent.

To demonstrate this claim, we compute the ex ante value of information $v(\cdot)$ conditional on the state of the world both when $c = 0$ and $c > 0$ for the third and the fourth agents. That is we compute

$$v_i^c := \sum_{s \in S_i} v(s) \Pr(s|\theta = 1),$$

where the subscript $i$ denotes the agent (third or the fourth), $S_i$ is the set of all possible information nodes for agent $i$, and the superscript $c$ is the cost. We state this observation in what follows.[5]

Observation 1. *There exists $\bar{q} < 1$ such that for all $q \leq \bar{q}$ and small enough $c > 0$ we have $v_i^c > v_i^0$ for $i \in \{3, 4\}$.*

[5]The computations are simulated by Matlab. The source file is available upon request

# 3 Experimental Design

The experiment was run at the Experimental Economics Laboratory of the Center for Experimental Social Sciences (C.E.S.S.) at New York University. The 72 subjects in this experiment were recruited from undergraduate classes at New York University and had no previous experience in social learning experiments. In each session, after subjects read the instructions they were also read aloud by an experimental administrator.[6] Each session lasted for about one hour and fifteen minutes and each subject participated in only one session. An $8.00 participation fee and subsequent earnings, which averaged about $13.60, were paid in private at the end of the session. Throughout the experiment, we ensured anonymity and effective isolation of subjects in order to minimize any interpersonal influences that could stimulate uniformity of behavior.[7]

In each session, subjects played the network formation game described in section 2.1, for forty independent rounds. At the beginning of each session, subjects' positions were randomly assigned to either 1, 2, 3 or 4. Moreover, their positions were held fixed for the duration of the experiment. In each round, the cost of link formation, in experimental points, was randomly drawn by the computer uniformly from the set $\{0, 2, \ldots, 18, 20\}$. In each round, all members of a group faced the same cost of link formation and this was common knowledge.

In our experiment, we conducted two treatments, which we call (*i*) the full information treatment (FI), and (*ii*) the partial information treatment (PI). In treatment FI, all the subjects received an informative signal (i.e., $q = 1$), while in treatment PI we set $q = 2/3$ so there was a chance a subject receives an uninformative signal. In all treatments, the informativeness of the signal was held fixed at $p = 2/3$, and the cost of each link was determined as described above. Table 2 summarizes the details of our experiment.

In each round, subjects earned $m = 100$ points for correctly guessing the state and 0 points otherwise. Their net point total was determined by subtracting the appropriate number of points for each link that a subject made from the points they collected in that round for guessing the state. At the end of the experiment, the computer randomly selected three rounds for which subjects would be paid. The total number of points was then converted back to dollars at the rate of $1.00 = 15 points.

[6] At the end of the first round, subjects were asked if there were any misunderstandings. No subject reported any problems with understanding the procedures or using the computer program.

[7] Participants' workstations were isolated by cubicles making it impossible for participants to observe other's screens or to communicate. We also made sure that all remained silent throughout the session. At the end of a session, participants were paid in private according to the number on their work-station.

Table 2: Summary of Experiments

| | Number of Subjects | $c$ | $q$ | $p$ | Number of Rounds |
|---|---|---|---|---|---|
| Session 1 (FI) | 20 | Random | 1 | 2/3 | 40 |
| Session 2 (FI) | 16 | Random | 1 | 2/3 | 40 |
| Session 3 (PI) | 20 | Random | 2/3 | 2/3 | 40 |
| Session 4 (PI) | 16 | Random | 2/3 | 2/3 | 40 |

## 3.1 Some Remarks on The Design

Subjects' Positions. In the experiment the subjects engage in a two-step decision process. Our decision to fix the subjects' position throughout the session aims to allow them to develop a *strategy* and play accordingly. Therefore, for fixed $p$ and $q$ subjects decide whom to link at different levels of cost. Critically, it is important to note that in a given session there are either 16 or 20 subjects, and the groups (of four subjects) are reshuffled at each round. Therefore, a subject knows that at each round he is a member of a (possibly) different group.

Random Cost. As section 2.3 discussed in detail, the cost of link formation is one of the critical parameters that affects rational behavior according to BSLP. Therefore, having a subject play at different cost levels, randomly drawn for each of 40 rounds, allows us to observe how his behavior responds to the cost of link formation. The costs were chosen so that subjects in each (non-trivial) position would experience link formation costs such that, according to BSLP, the optimal action is to form a link (if $c$ is low) or not form a link (if $c$ is high). In each decision round, the cost of link formation was the same for all members of a group and each member was told the cost before making any decision. This design feature was made common knowledge to all subjects.

Treatments FI & PI. Similar to the level of cost, different values of $q$ generates different behaviors according to BSLP.[8] The two treatments FI and PI give us the opportunity to compare, across treatments, the effect of varying the probability with which subjects receive a private signal and determine whether the predicted comparative statics hold true.

[8] The exact behavioral differences are evidenced in the threshold costs of link formation. In general, the higher the probability that subjects receive signals, the higher the threshold cost.

Payoffs. We employ a random lottery incentive system in our experiment as we randomly choose three rounds to determine the payoffs of the subjects. Cubitt et al. [11] demonstrates that this incentive scheme generates reliable data. Furthermore, it has many advantages. First, it helps us to generate a large data set while economizing on cost. Second, and more importantly, it assures homogenous behavior during the experiment by mitigating any wealth effects. For instance, had a subject earned many points in earlier decision rounds, his or her behavior might be distorted in the final rounds of the session. Instead, the random lottery incentive scheme makes each round equally important and so behavior should be less history dependent.[9]

# 4 Descriptive Analysis

We start our analysis with a basic description of the experimental data. We organize our presentation by focusing separately on the behavior of the subjects at each decision turn. Our goal is to have a first look at the subjects' behavior and develop the hypotheses that we thoroughly test in Section 5. In particular, we question how subjects use the information available to them, and how/why they deviate from the predictions of the theory.

## 4.1 The First Subject

The decision problem of the subjects in the first position is simple: if a subject is informed with signal $\sigma_1 \in \{-1, 1\}$, he should optimally follow his own signal and choose $a_1 = \sigma_1$; if his signal is uninformative, i.e., $\sigma = 0$ (in the PI treatment) then randomization seems to be a natural way to determine the action.

Table 3: The Behavior of the Informed First Subject

| | FI | PI $\sigma_1 \in \{-1, 1\}$ |
|---|---|---|
| Number of errors | 9 | 51 |
| Number of decisions | 360 | 236 |
| Frequency | 2.5% | 21.6% |

[9] While negative payoffs are possible in a decision round, outright bankruptcy was only possible for the fourth decision maker and is an exceedingly unlikely event requiring both extreme irrationality and extreme bad luck. In fact, no subject came close to going bankrupt in our experiment.

Table 3 summarizes the behavior of the informed subjects in the first round. One striking observation is the difference in the number of errors between the FI and PI treatments. In the FI treatment there are nine cases in which the subjects take an action that conflicts with their signals. Whereas, in the PI treatment this number goes up to 51 out of 236 cases in which subjects were informative. We are at a loss to explain the high error rate in the PI treatment, especially when compared to the FI treatment. However, when compared to the overall error rate of 11.2% for informed subjects who do not form any links, the difference is less dramatic. It is also worth noting that two subjects are responsible for 25 of the 51 errors.

## 4.2 The Second Subject

A subject in the second position must make two decisions: a link decision and an action decision. In order to explore our data, we summarize them in three tables. Tables 4 and 5 fully describe the decomposition of link decisions and action decisions in the FI treatment and the PI treatment when subjects are informed, respectively.

### 4.2.1 FI Treatment

In the FI treatment, the theory predicts that a subject should not form a link unless the cost is zero. Out of 360 decisions, we observe 239 cases (66.4%) in which subjects do not form a link and make their decisions based on their signals. Among these 239 cases, in 214 instances (89.5%) subjects take the action that is the same as their signal, while in 25 cases (10.5%), they take the action that is opposite to their signal. Table 4 displays this data.

There is a total of 121 cases (33.6%) in which subjects decide to form a link to the first subject. However, in 25 of these cases the cost is zero, hence they are (weakly) optimal link decisions.[10] When there exists a link between the first and the second subject there are four different possibilities; here we report the empirical frequency conditional on a link, while Table 4 reports the unconditional frequencies.

**(1)** In 61 cases (50.4%), the subjects observe the same action as their signal, and take exactly the same action. In this situation, even though the link decision is a deviation from the theory, the resulting action decision is backed up with two matching pieces of information.

**(2)** There are 21 cases (17.4%) where the subjects observe an action that is

[10] While it is formally not an error to form a link when the cost is zero, that is not to say that the information *should not* be ignored—this is especially true if subjects believe that their predecessors are prone to make mistakes.

different than their signal. Facing two conflicting pieces of information, they decide to follow their signal. This is a curious case since the action choice of the subject makes it even harder to justify their link decision.

**(3)** There are 35 instances (28.9%) where the subjects observe an action different than their signals, but they prefer to follow the first subject's decision. This is just opposite of the second situation: while they disregard the action of the first subject in the previous case, they disregard their private signal here.

**(4)** Finally, there are 4 cases (3.3%) in which the subjects observe the same action as their signal but they ignore both the action they observe and their signals by choosing an opposite action. Such behavior is extremely irrational but, fortunately, it is also quite rare.

TABLE 4: THE BEHAVIOR OF THE SECOND SUBJECT IN FI TREATMENT (IN %)

| | | *Fraction of Observations* | |
|---|---|---|---|
| | | No Link | Link |
| $a_2 = \sigma_2$ | $a_2 = a_1$ | 59.44 | 16.94 |
| | $a_2 \neq a_1$ | | 5.83 |
| $a_2 \neq \sigma_2$ | $a_2 = a_1$ | 6.94 | 9.72 |
| | $a_2 \neq a_1$ | | 1.11 |
| N | | 239 | 121 |

$N = 360$, percentages sum to 100, modulo rounding

#### 4.2.2 PI Treatment—Informed Subjects

In the PI treatment, there are 244 cases in which the subjects are informed. Out of these 244 cases, in 169 of them (69.3%) subjects do not form a link. This behavior is consistent with the predictions of the theory, while in 61 instances (30.7%) subjects decide to form a link even though the cost is strictly positive.

Table 5 is the repetition of Table 4 for informed subjects in PI treatment. The second column shows the number of subjects in each of the four possibilities that we discussed earlier. However, we elaborate more on this in the next subsection as we compare the behavior of informed subjects in the PI and FI treatments.

Table 5: The Behavior of the Second Subject in PI Treatment: Informed Subjects (in %)

| | | Fraction of Observations | |
|---|---|---|---|
| | | No Link | Link |
| $a_2 = \sigma_2$ | $a_2 = a_1$ | 64.34 | 14.34 |
| | $a_2 \neq a_1$ | | 13.52 |
| $a_2 \neq \sigma_2$ | $a_2 = a_1$ | 4.92 | 2.05 |
| | $a_2 \neq a_1$ | | 0.82 |
| N | | 169 | 75 |

$N = 244$, percentages sum to 100, modulo rounding

#### 4.2.3 Comparison of Informed Subjects in PI and FI Treatments

To compare the two treatments refer back to Tables 4 and 5. Although subjects tend to form links slightly less frequently in the PI treatment (30.7%) than in the FI treatment (33.61%), the difference is not statistically distinguishable.

However, there is one notable compositional difference between the two treatments, which can be seen in the highlighted cells in the above tables, that is statistically significant. Specifically, we observe that subjects tend to give more weight to their own signal in the PI treatment as compared to the FI treatment. In the FI treatment, 5.83 percent of the time subjects form a link, observe an action different than their signal and take an action consistent with their signal. This percentage goes up to 13.52 in the PI treatment. Similarly, in the FI treatment 9.72 percent of the time subjects form a link, observe an action different than their signal but take an action consistent with the action they observe, while the same percentage goes down to 2.05 in the PI treatment.

Observation 2. *Linking behavior is not substantially different across treatments; however, it deviates from the rational benchmark. In contrast, action decisions do differ across treatments. Whereas in the* PI *treatment subjects who observe an action that conflicts with their own signal almost always follow their own signal, in the* FI *treatment there is a noticeable tendency to conform to the observed action.*

Formally, since informed agents should never form links for any positive cost, the fact that they do should be seen as evidence against the null hypothesis that subjects conform to the rational benchmark. Statistically, for both the FI and PI treatments we conduct a one-sample proportions test with null hypothesis $H_0 : \mu = 0.01$ and alternative hypothesis $H_1 : \mu > 0.01$. We find, respectively, $Z_{\text{FI}} = 48.9$ ($p < 0.01$) and $Z_{\text{PI}} = 37.7$ ($p < 0.01$). To show that linking behavior is not different across treatments, we test the null hypothesis $H_0: \mu_{\text{FI}} = \mu_{\text{PI}}$. We are unable to reject this hypothesis, finding $Z = 0.7401$ ($p = 0.46$). Finally, to show the greater tendency to conform in the FI treatment than in the PI treatment, we look at the proportion of times informed subjects conform to the first agent despite conflicting information in both treatments. In particular, we test $H_0: \mu^c_{\text{FI}} = \mu^c_{\text{PI}}$ vs. $H_1: \mu^c_{\text{FI}} > \mu^c_{\text{PI}}$. We find $Z = 4.7$ ($p < 0.01$) and, therefore, reject the null hypothesis in favor of our alternative.

#### 4.2.4 PI Treatment—Uninformed Subjects

Recall from the discussion of Section 2.3 (and in particular Figure 3) that the optimal behavior of the second subject depends on the level of cost. It turns out that with the parameters of the experiment, an uninformed subject should always form a link when the cost is less than 11, and should avoid forming a link when it is above 11. This is generally the case: in 49 of 66 instances (74.2%) in which $c < 11$ subjects correctly formed a link, while in only 16 of the 50 instances (32%) in which $c > 11$ did subjects form a link. A two sample proportions test easily rejects the null hypothesis that the frequencies are the same ($Z = 4.54$, $p < 0.01$).

#### 4.2.5 Responsiveness to Cost

While it is formally a mistake for the informed second subject to form a link to the first at any positive cost, it is a more costly mistake when the cost is higher. Therefore, one would expect that there is a decrease in the number of links as the cost of forming link increases. This is exactly what we find in Table 6, which reports a series of estimations. The variable `informed` is a dummy variable which takes value 1 if the subject is informed and zero otherwise, while the variable `link cost` is simply the cost of link formation. The dependent variable is a dummy variable which takes a value of 1 if the subject formed a link and a value of zero otherwise. We use a random-effects logit estimation procedure to control for subject-specific heterogeneity. For each information treatment, the first column provides the basic estimation result, while the second column contains the variable `period` to capture possible learning effects. For continuous variables the table reports marginal effects at the mean of the independent variables and assuming that the random effect is zero, while for discrete variables it reports the discrete change in the probability of a link when the variable goes from zero to 1.

Notice that in each estimation the coefficient on the variable `link cost` is negative and statistically significant. Therefore, the higher is the cost, the less likely are subjects to form links. This leads us to the following observation:[11]

[11] Further evidence in support of this observation can be found in Section 4.4.

Observation 3. *While subjects' linking behavior deviates from the Bayesian benchmark, the frequency with which links are formed is decreasing with the cost of link formation, as would be predicted by a relaxed model which allows for stochastic best response. In particular, for each unit increase in the cost of link formation, the probability that a link is formed declines by between 5 and 7 percentage points.*

Table 6: Random Effects Logit Regressions: Second Subject

| | FI | FI | PI | PI |
|---|---|---|---|---|
| `informed` | NA | NA | -0.434 | -0.407 |
| | NA | NA | (0.100) | (0.109) |
| `link cost` | -0.053** | -0.069** | -0.066 | -0.066 |
| | (0.027) | (0.028) | (0.021) | (0.023) |
| `period` | NA | -0.016** | NA | -0.011** |
| | NA | (0.007) | NA | (0.005) |
| `LL` | -98.74 | -80.81 | -133.93 | -127.81 |
| `N` | 360 | 360 | 360 | 360 |

Estimated standard errors are in parentheses.
Highlighted cells significant at 1%; ** significant at 5%.
Marginal effects at mean of independent variables and assuming R.E. is zero.

We will comment in much greater detail on learning in Section 4.5, but simply note here that there is a significantly negative learning effect in both treatments. In particular, the probability of linking declines by between 1 and 1.6 percentage points each period. Thus, it would appear that subjects' behavior got closer to the rational benchmark as the experiment progressed.

## 4.3 The Third Subject

The subjects in the third position face a more complicated problem since there are two possible networks that they can observe. The first network is the one in which there is a link between the first and the second subjects, while the second is the one with no link between the first and the second subjects.

We start our analysis with the link formation behavior of the subjects in the FI treatment. Table 7 provides these data. Note that when $q = 1$, as in the FI treatment, the network of the first type (the second is linked to first subject) is not an equilibrium network for any $c > 0$. Nevertheless, we observe this off-the-equilibrium path network in the experiment. The first two rows in Table 7 show the behavior of the third subject facing such networks. There are 121 networks of this type. Note that in 24 of them the cost is zero, which rationally justifies the existence of the link. In all the cases in which $c > 0$, the third decides to form a link 56 percent of the time. It is worth analyzing the action behavior of the third in these situations. Table 8 summarizes the decomposition of action decisions of the third subject.

Table 7: The Distribution of Networks in the FI Treatment (in %)

| Networks | $c < 5$ | $c > 5$ | N |
|---|---|---|---|
| (3.A) $1 \leftarrow 2 \leftarrow 3$ | 13.06 | 10.28 | 84 |
| (3.B) $1 \leftarrow 2 \quad 3$ | 2.50 | 7.78 | 37 |
| (3.G) $1 \quad 2 \quad 3$ | 5.28 | 48.33 | 193 |
| (3.C) $1 \quad 2 \leftarrow 3$ | 4.44 | 2.50 | 25 |
| (3.D) $1 \leftarrow 3$, $2 \leftarrow 3$ | 3.89 | 1.94 | 21 |

The exact threshold cost is $c^{**} \simeq 5.13$.
$N = 360$, percentages sum to 100, modulo rounding.

Let us first look at the case where the third forms a link to the second. If the two actions that the third observes are the same as his signal, then he always chooses the action that matches this information (39 instances versus 0.) If, however, the actions of the second and third subjects are the same but different than the signal of his, the third subject tends to follow the actions that he observes more often than his signal (20 instances versus 6 instances.) Finally, if the actions of the first and the second are different, then his private signal becomes more decisive. In fact, in 16 cases out of 19, the third subject observes two different actions and finally takes the same action as his signal.

The other network that the third subject observes is when the second subject does not form a link to the first (the last three rows in Table 7). In this case, there are three possibilities for the third subject: either he does not form any links, he forms only one link, or he forms two links. There are 239 such instances. Among those cases, 81 percent of the time he does not form any links, 10 percent of the time he forms a link to the second and stops, and 9 percent of the time he forms two links. Note that, according to the predictions of the theory if the cost is greater than 5 the third subject should not form any links. This happens in 90 percent of those situations in which the cost of link formation is greater than 5. In terms of the action decisions, as Table 8 indicates, we do not observe a substantial number of mistakes.

We also make the same analysis for the PI treatment. Tables 9 and 10 provide a sum-

Table 8: The Decomposition of Action Decisions in the fi Treatment (in %)

| Networks | | $a_3 = \sigma_3$ | $a_3 \neq \sigma_3$ | N |
|---|---|---|---|---|
| (3.a) | $a_1 = a_2 = \sigma_3$ | 46.43 | 0 | 84 |
| | $a_1 = a_2 \neq \sigma_3$ | 7.14 | 23.81 | |
| | $a_1 \neq a_2$ | 19.05 | 3.57 | |
| (3.b) | | 78.38 | 21.62 | 37 |
| (3.g) | | 86.53 | 13.47 | 193 |
| (3.c) | $a_1 = \sigma_3$ | 80.00 | 4.00 | 25 |
| | $a_1 \neq \sigma_3$ | 8.00 | 8.00 | |
| (3.d) | $a_1 = a_2 = \sigma_3$ | 19.05 | 19.05 | 21 |
| | $a_1 = a_2 \neq \sigma_3$ | 0 | 0 | |
| | $a_1 \neq a_2$ | 52.38 | 9.52 | |

Percentages sum to 100, modulo rounding, for each network.
N is number of observations for each network.

mary of the data for the pi treatment. The left panel of Table 9 details the networks formed by informed subjects, whereas the right hand side panel details the networks formed by uninformed subjects. Also, Table 10 is the decomposition of informed subjects' action decisions in the pi treatment.

Table 9: The Distribution of Networks in pi Treatment (in %)

| Networks | $\sigma_3 \in \{-1, 1\}$ | | | $\sigma_3 = 0$ | | |
|---|---|---|---|---|---|---|
| | $c < 3$ | $c > 3$ | N | $c < 11$ | $c > 11$ | N |
| (3.a) | 10.59 | 7.26 | 42 | 26.61 | 4.03 | 38 |
| (3.b) | 3.81 | 14.41 | 43 | 9.68 | 4.03 | 17 |
| (3.g) | 2.97 | 43.64 | 110 | 13.71 | 20.97 | 43 |
| (3.f) | 0 | 5.93 | 14 | 5.65 | 4.84 | 13 |
| (3.d) | 0.42 | 11.02 | 27 | 5.65 | 4.84 | 13 |

$c^* \simeq 11.11$ and $c^{**} \simeq 3.41$.
For both informed and uninformed, percentages sum to 100.
N is number of observations for each network.

Observation 4. *There is a substantial difference in linking behavior when the third subject faces network (2.A) or (2.B). In particular, when the third subject observes a link between the first and the second (network (2.A)), he is very likely to form a link, whereas when the third subject observes that no link has been formed (network (2.B)), he is very unlikely to form a link.*

Table 10: The Decomposition of Action Decisions in pi Treatment—Informed Subjects (in %)

| Networks | | $a_3 = \sigma_3$ | $a_3 \neq \sigma_3$ | N |
|---|---|---|---|---|
| (3.A) 1 ← 2 ← 3 | $a_1 = a_2 = \sigma_3$ | 40.48 | 0 | 42 |
| | $a_1 = a_2 \neq \sigma_3$ | 11.90 | 21.43 | |
| | $a_1 \neq a_2$ | 22.92 | 0 | |
| (3.B) 1 ← 2   3 | | 95.35 | 4.65 | 43 |
| (3.G) 1   2   3 | | 93.64 | 6.36 | 110 |
| (3.C) 1   2 ← 3 | $a_1 = \sigma_3$ | 85.71 | 7.14 | 14 |
| | $a_1 \neq \sigma_3$ | 0 | 7.14 | |
| (3.D) 1 ← 3, 2 ← 3 | $a_1 = a_2 = \sigma_3$ | 14.81 | 0 | 27 |
| | $a_1 = a_2 \neq \sigma_3$ | 3.70 | 22.22 | |
| | $a_1 \neq a_2$ | 51.85 | 7.41 | |

Percentages sum to 100, modulo rounding, for each network.
N is number of observations for each network.

Formally, let $\mu^i(j)$ denote the probability that an informed third agent forms a link in information treatment $i \in \{\text{PI}, \text{FI}\}$ when facing network structure $j \in \{L, NL\}$ (*i.e.*, either a link between the first and second agent or not). For both the fulFI and PI information treatments, we conduct a two-sample proportions test of $H_0: \ \mu^i(L) = \mu^i(NL)$ against $H_1: \ \mu^i(L) > \mu^i(NL)$. For the FI treatment we find $Z = 9.4$, while for the PI treatment we find $Z = 3.4$. In both cases, $p < 0.01$. Therefore, informed subjects are more likely to form a link to the second agent provided that a link between the first and the second exists.[12]

Observation 4 is remarkable because, at least in the PI treatment, the latter network signals that the second subject was *informed*, while the former network signals that he was *uninformed*. Therefore, the Bayesian model would predict a higher frequency of link formation in the latter network than in the former network. However, it is still true that $\mu^{\text{PI}}(L) < \mu^{\text{FI}}(L)$; specifically, a two-sample proportions test of the corresponding one-sided test gives $Z = 2.90$ ($p < 0.01$). Therefore, it appears that subjects in the PI treatment do recognize that there is less informational value to linking when the second has already linked to the first.

Remark 1. *Of course, in a relaxed model, the type of behavior summarized by Observation 4 may actually be optimal depending upon the beliefs that the third agent holds about the second agent. In the* FI *treatment, if the third agent believes that the second agent always follows her*

[12] This observation is further supported in Table 11 by noting the positive and highly significant estimated marginal effect on the network dummy.

*own signal, regardless of agent 1's observed action, then for a larger range of link costs it will be optimal to form a link. However, to the extent that agent 3 believes agent 2 has a tendency to conform to the first agent, the positive "two-signals-for-the-price-of-one" effect will be mitigated because now the second agent's signal cannot be perfectly inferred by the observed action.*

*In the* PI *treatment, the two-for-the-price-of-one influence remains, but is mitigated by the fact that the probability that the first agent (resp. second agent) is informed is only 66.7% (resp. 52.3%).*[13] *Thus, in this scenario, there is substantially less information to be gained from linking.*

### 4.4 Observed Network & Link Decisions

Finally, we want to understand the relationship between the observed network and the link decisions of the third and fourth subjects. Specifically, we look at the binary decision of forming at least one link and how this depends upon the observed network. Tables 11 and 12 report the results of a series of estimations similar in spirit to those reported in Section 4.2.5. As before, the variable `informed` is a dummy variable which takes value 1 if the subject was informed and zero otherwise, and `link cost` is the cost of link formation. Similarly, variables depicted as networks are dummy variables which take value 1 if the subject observes that particular network and zero otherwise. Also as before, we employ a random effects logit estimation procedure and report marginal effects. For continuous variables (such as `link cost` and `period`) they are reported at the mean of the independent variables. Since the networks are mutually exclusive, the marginal effects reported are the discrete change in the probability of a link as the network dummy in question goes from zero to one, evaluating all other network dummies at zero. We also examined session effects by including a dummy variable indicating whether the subject participated in the first or second session. In no case was this coefficient significant at the 5% level. Therefore, we only report results based on the pooled data.

These tables nicely reinforce some points that we have already made in our descriptive analysis. First, the negative coefficient on `link cost` that was found for the second agent is also present for both the third and fourth agents. That is, the greater is the cost of forming links, the lower is the probability that they will be formed. Interestingly, the effect seems quite stable across treatments and across players: almost universally, for each unit increase in the cost of link formation, the probability of link formation declines by about 5 percentage points. Second, informed subjects are less likely to form links than their uninformed counterparts, though this is only significant for the third subject. Notice also that the estimated marginal effects on the network dummies are often smaller

[13] We arrive at 52.3% using Bayes' rule and the facts that the probability of being informed is $\frac{2}{3}$, 30.7% of informed subjects formed links and 56% of uninformed subjects formed links.

Table 11: Random Effects Logit Regressions:
Third Subject

| | FI | FI | PI | PI |
|---|---|---|---|---|
| informed | NA | NA | -0.432 | -0.435 |
| | NA | NA | (0.097) | (0.097) |
| (2.A) 1 ← 2 | 0.404** | 0.384** | 0.483 | 0.468 |
| | (0.176) | (0.175) | (0.101) | (0.104) |
| link cost | -0.049* | -0.049* | -0.049 | -0.050 |
| | (0.029) | (0.030) | (0.015) | (0.015) |
| period | NA | -0.003 | NA | -0.003 |
| | NA | (0.003) | NA | (0.004) |
| LL | -98.03 | -96.97 | -105.12 | -104.89 |
| N | 360 | 360 | 360 | 360 |

Estimated standard errors are in parentheses.
Highlighted cells significant at 1%, ** significant at 5% & * significant at 10%.
Marginal effects at mean of independent variables and assuming R.E. is zero.

in the PI treatment than in the FI treatment. Thus our subjects do have a sense in which information matters, even if they tend to form links more often than the theory predicts.

However, there is more that can be seen from these tables. First, notice that Observation 4 carries through to the fourth subject. When the second decision maker has linked to the first, the third decision maker is approximately 48 percentage points more likely to form a link, while for the fourth decision maker, in the FI treatment, when faced with network 3.A, she is 82 percentage points more likely to form a link. In the PI treatment, the fourth decision maker is only 56 percentage points more likely to form a link. Therefore, in the FI treatment, and to a lesser extent in the PI treatment, there is a strong tendency towards what we call **herding in link formation**.

Finally, one can see further evidence that subjects understand the informativeness of networks. For the FI treatment compare the estimated marginal effects on the (non-equilibrium) network 3.B and the (equilibrium) networks 3.C/3.F. For both estimations the effect is substantially larger in the latter case, indicating a greater propensity to form a link when faced with the equilibrium network as opposed to the out-of-equilibrium network 3.B. Unfortunately, this result is not robust. The same comparison in the PI treatment leads to the opposite conclusion (although both networks are potentially equilibrium path networks). Moreover, it appears generally to be the case that, the fourth subject almost always forms a link to the *larger* sub-network, rather than to the most informative node. For example, when faced with the network 3.B, in all but one instance,

Table 12: Random Effects Logit Regressions:
Fourth Subject

| | FI | FI | PI | PI |
|---|---|---|---|---|
| `informed` | NA | NA | -0.124 | -0.124 |
| | NA | NA | (0.086) | (0.087) |
| (3.B)  | 0.133 | 0.099 | 0.319** | 0.300** |
| | (0.107) | (0.103) | (0.130) | (0.129) |
| (3.A)  | 0.819 | 0.812 | 0.572 | 0.551 |
| | (0.072) | (0.074) | (0.116) | (0.122) |
| (3.D)  | 0.790 | 0.783 | 0.732 | 0.746 |
| | (0.081) | (0.084) | (0.089) | (0.084) |
| (3.C)  | 0.665 | 0.666 | 0.184 | 0.172 |
| | (0.107) | (0.106) | (0.137) | (0.137) |
| `link cost` | -0.039 | -0.042 | -0.052 | -0.053 |
| | (0.010) | (0.010) | (0.014) | (0.014) |
| `period` | NA | -0.007* | NA | -0.006* |
| | NA | (0.004) | NA | (0.003) |
| `LL` | -111.97 | -110.03 | -134.82 | -133.18 |
| `N` | 360 | 360 | 360 | 360 |

Estimated standard errors are in parentheses.
Highlighted cells significant at 1%, ** significant at 5% & * significant at 10%.
Marginal effects at mean of independent variables and assuming R.E. is zero.

the fourth agent first chose to link to the second, even though by her link choice, she was revealed to be uninformed. Thus, subjects would seem to prefer to observe more action decisions, even if, *from a strictly informative* point of view, doing so is suboptimal.

## 4.5 Learning

Since subjects played the network formation game for 40 periods one might expect some learning to occur, especially with respect to link formation. To examine this our logit regressions reported in Tables 6, 11 and 12 included the variable `period`. Our findings show that most learning is concentrated in subjects in the second position. As previously reported, in both treatments, the probability that a link was formed declines by between 1.1 and 1.6 percentage points. Put differently, for the FI treatment, in the first 10 rounds the frequency of link formation was $\frac{40}{90}$, while in the last 10 rounds it was down to $\frac{17}{90}$. Interestingly, in the PI treatment learning was concentrated amongst informed subjects, with uninformed subjects showing less pronounced changes over time in link formation. Specifically, if we interact `informed` and `period`, the marginal effect on `period` is no longer significant, while the marginal effect on the interaction term is significantly negative.[14] In the PI treatment, learning by informed decision makers is even more pronounced than in the FI treatment: in the first 10 rounds the frequency of link formation was $\frac{26}{53}$, while in the last 10 rounds it was $\frac{10}{65}$.

As for the subjects in the third position, the marginal effect on `period` is never significantly different from zero. Moreover, if we interact `period` with the network dummy, we also do not find any significant learning effects in either treatment, nor do we find any differences in learning between informed an uninformed players. Finally, for subjects in the fourth position, in both treatments, we estimate a negative marginal effect for `period`, which is significant at the 10% level. In this case, it seems that learning is largely confined to the empty network; *i.e.,* subjects appear to learn *not* to form links when faced with the empty network. In the PI treatment, there is also weak evidence that subjects learn to link to the two complete networks (i.e., Networks 3.A and 3.D), neither of which appear optimal from a purely Bayesian perspective. Finally, for there does not appear to be any differences in learning between informed and uninformed subjects in the fourth position.

## 4.6 Does It Pay To Link?

In theory, by forming links, subjects should gain an informational advantage and more accurately predict the state of nature. Of course, in practice, due to systematic deviations from the Bayes rational benchmark in both linking and action decisions, this need not actually be true. We briefly investigate whether or not, even ignoring the cost of forming links, linking increases subjects' prediction power. Our results are summarized in Table 13, where $\mu_c$ is the empirical frequency of correctly predicting the state and $\pi$ is the empirical average payoff for each sub-group. Notice that in 6 of 9 instances, on average, those subjects who formed at least one link more accurately predicted the correct state of nature, while in the remaining three instances these same subjects were actually worse at predicting the correct state of nature. However, in no case are we able to reject, using a two-sample proportions test, the hypothesis that the probability of correctly predicting the state is independent of whether or not a link was formed. Indeed, when we factor in the cost of link formation, in only three cases is the average payoff higher for those who formed links than those who did not, and in no case is the difference

[14] Of course, when the cost is low, uninformed subjects should learn to link more often, and when the cost is high, uninformed subjects should learn to link less often. If we try to account for this then there weak evidence of learning but, importantly, it goes in the opposite direction as theory predicts.

Table 13: Analysis of Payoffs and Prediction Accuracy by Link Decision

The Second Subject

| | FI Treatment | | PI Treatment | | | |
|---|---|---|---|---|---|---|
| | | | Informed | | Uninformed | |
| | Link | No Link | Link | No Link | Link | No Link |
| $\mu_c$ | 0.653 | 0.644 | 0.667 | 0.728 | 0.585 | 0.510 |
| $\pi$ | 59.6 | 64.4 | 61.1 | 72.8 | 51.3 | 51.0 |
| N | 121 | 239 | 75 | 169 | 65 | 51 |

The Third Subject

| | FI Treatment | | PI Treatment | | | |
|---|---|---|---|---|---|---|
| | | | Informed | | Uninformed | |
| | Link | No Link | Link | No Link | Link | No Link |
| $\mu_c$ | 0.690 | 0.630 | 0.627 | 0.641 | 0.531 | 0.617 |
| $\pi$ | 63.8 | 63.0 | 51.3 | 64.1 | 43.6 | 61.7 |
| N | 130 | 230 | 83 | 153 | 64 | 60 |

The Fourth Subject

| | FI Treatment | | PI Treatment | | | |
|---|---|---|---|---|---|---|
| | | | Informed | | Uninformed | |
| | Link | No Link | Link | No Link | Link | No Link |
| $\mu_c$ | 0.686 | 0.644 | 0.646 | 0.583 | 0.604 | 0.516 |
| $\pi$ | 61.8 | 64.4 | 58.0 | 58.3 | 53.6 | 51.6 |
| N | 169 | 191 | 99 | 151 | 48 | 62 |

$\mu_c$ is the empirical frequency of correctly predicting the state, while $\pi$ is the empirical average payoff for each sub-group. Highlighted cells indicate significantly higher payoffs (at the 10% level or better) for those who formed **no** links.

significant.[15] Moreover, for the highlighted cells in Table 13, those who *did not* form any links obtained a significantly higher average payoff than those who did (p-value of two-sided test 0.076 or lower). Therefore, it would appear that subjects, though sometimes more often predicting the correct state, paid too much for the information and would have often been better off not forming any links at all.

Recall Observation 1 which states that the *ex ante* expected utility of the third and fourth agents is higher when the cost of link formation is small but positive. To examine this result, Table 14 reports the empirical frequencies with which subjects correctly guessed the state when the cost of link formation is 0 and 2, respectively. Consistent with Observation 1, in all cases subjects are more likely to correctly guess the state when the cost of each link is 2 rather than when it is 0. Moreover, in two of these instances (the third subject in the PI treatment and the fourth subject in the FI treatment), the frequency

[15] Among all subjects who formed at least one link, the average cost of link formation was approximately 6 experimental points and the average number of links was approximately 1.13.

Table 14: Analysis of Prediction Accuracy by Link Cost

| | DM3-FI | DM3-PI | DM4-FI | DM4-PI |
|---|---|---|---|---|
| $\mu_c(c=0)$ | 0.718 | 0.464 | 0.625 | 0.536 |
| $\mu_c(c=2)$ | 0.765 | 0.744 | 0.824 | 0.581 |
| Prop. Test | 0.427 | 2.393 | 1.810 | 0.379 |
| p-value | 0.335 | 0.008 | 0.035 | 0.352 |

$\mu_c(c = x)$ is the empirical frequency of correctly predicting the state when the cost of link formation is $c = x \in \{0, 2\}$. The row labeled "Prop. Test" reports the $Z$ statistic for a two sample proportions test of the null hypothesis $\mu_c(c = 0) = \mu_c(c = 2)$ versus the one-sided alternative.

of correct responses is significantly higher under the higher link cost.[16] Thus efficiency is enhanced for a small but positive link cost.

# 5 Econometric Analysis

In the previous sections, we have described behavior of the second, third and fourth subjects in various situations. That analysis showed that subjects often made systematic deviations from the rational theory as espoused by the BSLP. Our goal in this section is to uncover the origins of these deviations. In particular, we will build an econometric model which allows us to estimate the subjects' beliefs about the state of the world as a function of their information (*i.e.*, signals and link decisions). We show that many of the deviations can be explained by *over-optimism* about the information obtained by forming links.

## 5.1 The Second Agent

In the standard model of stochastic best response, agents experience a random shock to each of their possible decisions. For simplicity, consider the second agent receiving signal $\sigma_2 = 1$. Let $\ell_{i,j} = 1(0)$ denote the existence (lack) of a link between the $i^{\text{th}}$ and the $j^{\text{th}}$ agents when $j > i$. The expected utility of forming a link is given by:

$$\varphi(\sigma_2 = 1, \ell_{1,2} = 1) := r \max\{sm, (1-s)m\} + (1-r)\max\{tm, (1-t)m\} - c + \epsilon_1 \quad (6)$$

[16] For the fourth decision maker, in the partial information treatment, if we compare the frequency of a correct decision when the cost is 0 versus when the cost is 4, we see that it is significantly higher in the latter case. That the effect only shows up when the cost is four is likely due to the increased tendency to herd when the cost is low.

where $r = \Pr(a_1 = 1|\sigma_2 = 1)$, $s = \Pr(\theta = 1|\sigma_2 = a_1 = 1)$ and $t = \Pr(\theta = 1|\sigma_2 = 1, a_1 = -1)$. Whereas the expected utility of not forming a link is given by:

$$\varphi(\sigma_2 = 1, \ell_{1,2} = 0) = \max\{pm, (1-p)m\} + \epsilon_0 \tag{7}$$

where $p = \Pr(\theta = 1|\sigma_2 = 1)$. Under standard assumptions on $\epsilon_1$ and $\epsilon_0$, the probability that a link is formed is given by:

$$\Pr(\ell_{1,2} = 1|\sigma_2, c) = \Big[1 + \exp\big\{\lambda^l\big(\varphi(\sigma_2, \ell_{1,2} = 0) - \varphi(\sigma_2, \ell_{1,2} = 1)\big)\big\}\Big]^{-1} \tag{8}$$

where $\lambda^l$ is a parameter to estimate and captures the subject's ability to best-respond in his link decision. In the experiment, subjects were told the value of $p$, but not the values of $r$, $s$ or $t$. Therefore, through their link and action decisions, we can obtain estimates of what they must have been, and compare these estimates to the rational theory. Note that if we only consider the link decision, we cannot separately identify $r$, $s$ and $t$. However, once we include the action decision, because we will have instances in which $\sigma_2 = a_1$ and $\sigma_2 \neq a_1$, we can identify more of the parameters. For example, if the second subject forms a link to the first and $\sigma_2 = a_1$, then

$$\Pr(a_2 = 1|\sigma_2 = 1, a_1 = 1) = \Big[1 + \exp\big\{\lambda^a_t(1-2s)m\big\}\Big]^{-1} \tag{9}$$

where $\lambda^a$ is a parameter to be estimated and captures the subject's ability to best respond in his action decision. By taking both the link and action decisions into account we can write the *full* likelihood function for the subject's decision problem and obtain maximum likelihood estimates of $(\lambda^l, \lambda^a, s, t)$.[17] The left-hand panel of Table 15 reports a limited set of results considering only the link decision. In that estimation procedure, $r$ and $t$ are fixed at their theoretical values, leaving $\lambda^l$ and $s$ to be estimated. The right-hand panel of the table reports the results of the full estimation, which allows us to estimate $t$ and $\lambda^a$. For the PI treatment, we also have another parameter: $s^{ui} = \Pr(\theta = a_1|\sigma_2 = 0, a_1)$. Likelihood Ratio test statistics of estimated parameters are in parentheses below the estimates,[18] and parameters which were fixed in a given estimation are in italics.

First notice that both $\lambda^l$ and $\lambda^a$ are both highly significantly different from zero, with $\lambda^l > \lambda^a$. Regarding the other parameters, when we look only at the link decision, we see that $s > s^{\text{BSLP}}$. That is, subjects over-weight the informational gain from forming links, which causes them to form more links than is optimal. Of course, since we cannot sepa-

[17]Identification of $r$ appeared to be rather poor even when considering the full decision problem, so we omitted it from our estimates and fixed it at the true value.

[18]Specifically, for $\lambda^l$ and $\lambda^a$, we test the hypothesis that $\lambda^i = 0$, while for $\theta \in \{s, t, s^{ui}\}$, we test $\theta = \theta^{\text{BSLP}}$.

Table 15: Second Subject: Uncovering Beliefs

| | Link Only | | Link & Actions | |
|---|---|---|---|---|
| | FI | PI | FI | PI |
| $\lambda^l$ | 3.6426 | 3.6426 | 3.7808 | 3.7808 |
| | (118.63) | (120.17) | (129.97) | (138.81) |
| $\lambda^a$ | NA | NA | 1.1441 | 1.7125 |
| | | | (229.57) | (270.61) |
| $s$ | 0.8862 | 0.8330 | 0.8392 | 0.8125 |
| | (29.86) | (12.26) | (1.87) | (3.35) |
| $t$ | *0.5000* | *0.4400* | 0.5588 | 0.4091 |
| | | | (6.266) | (1.76) |
| $s^{ui}$ | NA | 0.6125 | NA | 0.6125 |
| | | (0.0156) | | (0.7588) |
| $r$ | *0.5556* | *0.5556* | *0.5370* | *0.5370* |
| LL | -190.2244 | -189.4492 | -324.9717 | -303.6794 |
| N | 360 | 360 | 360 | 360 |

The number in parentheses is LR statistic from test that coefficient is 0 in the case of $\lambda$ or that coefficient is equal to the theoretical value in the case of $s$, $t$ and $s^{ui}$. The 1%, 5% & 10% critical values are 6.64, 3.84 & 2.71.

rately identify $s$ and $t$ when we only analyze link decisions, we cannot say whether subjects *over-weight* information consistent with their signals or *under-weight* contradictory information. Looking now at the right-hand panel of Table 15, for the FI treatment, we cannot reject the hypothesis that $s = s^{\text{BSLP}}$, but we can reject the hypothesis that $t = t^{\text{BSLP}}$. In particular, our estimate of $t$ indicates that subjects significantly under-weight contradictory information. This is consistent with our descriptive analysis (recall Table 4) in which we showed that subjects in the second position had a tendency to conform to their predecessor's action choice. In the PI treatment, the situation is reversed: informed subjects are extremely pessimistic about contradictory information (though the result is not significant), and marginally over-confident about consistent information.

## 5.2 The Third Agent

The empirical analysis of the third agent is in the same spirit as for the second agent. However, matters are substantially more complicated. In particular, the third agent may face one of two different networks and has the option of forming 0, 1 or 2 links to his predecessors. Instead of giving a full derivation of the empirical choice model, we simply note the key steps required.

In addition to the required calculations from the previous section, we need more tedious calculations to be able to solve for the value of information. The task is even more complicated since we assume that the third agent anticipates the errors made by the first and the second agents. For example, consider the case in which the third agent observes that the second linked to the first. For ease of exposition, let us introduce the following notation:

| $\Pr(a_1, a_2 \mid \sigma_3, \ell_{1,2} = 1)$ | | | | $\Pr(\theta = 1 \mid a_1, a_2, \sigma_3, \ell_{1,2} = 1)$ | | | |
|---|---|---|---|---|---|---|---|
| $(a_1, a_2)$ | $\sigma_3$ | | | $(a_1, a_2)$ | $\sigma_3$ | | |
| | $-1$ | $0$ | $1$ | | $-1$ | $0$ | $1$ |
| $(1, 1)$ | $a_{11}$ | $a_{12}$ | $a_{13}$ | $(1, 1)$ | $c_{11}$ | $c_{12}$ | $c_{13}$ |
| $(1, -1)$ | $a_{21}$ | $a_{22}$ | $a_{23}$ | $(1, -1)$ | $c_{21}$ | $c_{22}$ | $c_{23}$ |
| $(-1, 1)$ | $a_{31}$ | $a_{32}$ | $a_{33}$ | $(-1, 1)$ | $c_{31}$ | $c_{32}$ | $c_{33}$ |
| $(-1, -1)$ | $a_{41}$ | $a_{42}$ | $a_{43}$ | $(-1, -1)$ | $c_{41}$ | $c_{42}$ | $c_{43}$ |

Then, the ex ante expected utility of the third who observes a link between the first and the second is

$$\begin{aligned} \varphi_j &= a_{1j} \max\left\{c_{1j} m, (1 - c_{1j}) m\right\} + a_{2j} \max\left\{c_{2j} m, (1 - c_{2j}) m\right\} \\ &\quad + a_{3j} \max\left\{c_{3j} m, (1 - c_{3j}) m\right\} + a_{4j} \max\left\{c_{4j} m, (1 - c_{4j}) m\right\}, \end{aligned}$$

where $j = 1$ for $\sigma_3 = -1$, $j = 2$ for $\sigma_3 = 0$, and $j = 3$ for $\sigma_3 = 1$, and an informed third agent will form a link if and only if:

$$\max\left\{pm, (1 - p)m\right\} + \epsilon_1 < \varphi_j - c + \epsilon_0.$$

If no link is observed, the decision is even more complicated since now the agent must decide whether to link to the first agent, second agent or not to link at all; then, if he decides to link, he must decide whether to form another link and only then to make his action decision.

First consider the aforementioned case in which the third agents observes a link between the second and the first agents. In order to reduce the number of parameters to estimate, we make the following restrictions:

$$\begin{aligned} c_{32} &= 1 - c_{22}, \quad & c_{42} &= 1 - c_{12} \\ c_{13} &= 1 - c_{41}, \quad & c_{23} &= 1 - c_{31} \\ c_{33} &= 1 - c_{21}, \quad & c_{43} &= 1 - c_{11} \end{aligned} \tag{10}$$

In the FI treatment, when we consider the full decision problem, this means that there are four $c_{ij}$ parameters to estimate as well as $\lambda^l$ and $\lambda^a$, for a total of six parameters. In the PI treatment, there are two more parameters to estimate ($c_{12}$ and $c_{22}$), for a total of eight parameters. Because the identification problem, if we were to consider only the link decision, is even more severe for the third agent, we immediately consider the full decision problem.

For the FI treatment, the results are presented in Table 16. As can be seen, when the actions of the first and second agents agree, the third agent becomes somewhat *over-confident* that the state is consistent with the observed actions, and that this is true whether or not the observed actions are consistent with his signal. When the observed actions disagree, as we saw in the descriptive analysis, the third agent's signal becomes decisive, with his beliefs biased in favor of his own signal. Rather interestingly, the results seem to show that the third agent is more strongly influenced by the action choice of the second agent. In particular, when the action of the second agent agrees with the third's observed signal, the third agent appears substantially more confident about the state than when the action (of the second agent) and the signal (of the third agent) disagree. With regard to the estimated $\lambda$'s, we simply note that they are fairly similar to (but slightly smaller than) those obtained in our estimation of the second agent's problem. Therefore, it appears that the third agents did not find the decision problem (much) more difficult than the second agent's problem.

TABLE 16: THIRD SUBJECT (FI): UNCOVERING BELIEFS

| $\Pr(\theta = 1 \mid a_1, a_2, \sigma_3, \ell_{1,2} = 1)$ | | | |
|---|---|---|---|
| $(a_1, a_2)$ | $\sigma_3$ | | |
| | $-1$ | 0 | 1 |
| $(1, 1)$ | 0.611 | NA | 0.921 |
| | [0.523] | | [0.814] |
| $(1, -1)$ | 0.061 | NA | 0.594 |
| | [0.345] | | [0.678] |
| $(-1, 1)$ | 0.406 | NA | 0.939 |
| | [0.322] | | [0.655] |
| $(-1, -1)$ | 0.079 | NA | 0.389 |
| | [0.186] | | [0.477] |
| $\lambda^l$ | 3.283 | LL | -106.613 |
| $\lambda^a$ | 0.996 | N | 121 |

For each $c_{ij}$, *theoretical* value is below in brackets.

We repeat the analysis in Table 17 for the PI treatment. As the reader can see, the results are not too different. As was the case with the FI treatment, the third agent is generally over-confident (relative to the theory) whenever $a_1 = a_2$. This over-confidence is even greater when also $\sigma_3 = a_1 = a_2$. The one difference between the results for

Table 17: Third Subject (pi): Uncovering Beliefs

| $\Pr(\theta = 1 \mid a_1, a_2, \sigma_3, \ell_{1,2} = 1)$ | | | |
|---|---|---|---|
| $(a_1, a_2)$ | $\sigma_3$ | | |
| | $-1$ | $0$ | $1$ |
| $(\ 1,\ \ 1)$ | 0.548 | 0.647 | 0.8734 |
| | [0.446] | [0.617] | [0.763] |
| $(\ 1, -1)$ | 0.000 | 0.500 | 1.000 |
| | [0.257] | [0.409] | [0.580] |
| $(-1,\ \ 1)$ | 0.000 | 0.500 | 1.000 |
| | [0.420] | [0.592] | [0.743] |
| $(-1, -1)$ | 0.266 | 0.353 | 0.452 |
| | [0.237] | [0.383] | [0.554] |
| $\lambda^l$ | 2.961 | LL | -130.115 |
| $\lambda^a$ | 1.534 | N | 140 |

For each $c_{ij}$, *theoretical* value is below in brackets.

the FI and PI treatments is that in the PI treatment, the third agent does not appear to consistently place more weight on the action of the second agent than on the first; instead when the actions of the first and second disagree, the third agent's signal becomes the decisive factor. Given the predictions of the theory, this is a welcome finding.

The results above provide insight only for the case in which the third agent observes a link between the first and second. Ideally, we would like to repeat the analysis for the more general setting in which the third agent can observe either of the two possible networks and makes his decisions accordingly. However, as is often the case in structural models of this sort, doing so would introduce many more parameters, making it difficult to obtain precise estimates. As an alternative, we now discuss a more reduced form, regression approach which gets at the same points but in a less computationally demanding way.

It is fairly obvious that for the third decision maker, contemplating choosing $a_3 = 0$ or $a_3 = 1$, the more times he observes $a_i = 1$ (or $\sigma_3 = 1$), the more confident he should be that the true state of the world is actually $\theta = 1$.[19] Therefore, consider the following

[19] Of course, by how much each observation influences the third agent's beliefs depends on the parameters of the underlying structural model, but the direction of influence is clear in the reduced form framework on which we now focus.

latent variable model:

$$\begin{aligned} y_i &= \beta_0 + \beta_1[\sigma_3 = 0] + \beta_2([\sigma_3 \neq 0] \times \sigma_3) + \beta_3[a_1(l_{1,2} = 0)] \\ &+ \beta_4[a_2(l_{1,2} = 0)] + \beta_5[a_1(l_{1,2} = 1)] + \beta_6[a_2(l_{1,2} = 1)] + u_i \\ y_i^* &= 1 \text{ iff } y_i \geq 0 \end{aligned}$$

where $y_i^* \in \{0, 1\}$ is what we observe, $[\cdot]$ denotes a dummy variable which takes value 1 if $\cdot$ is true, and $a_i(l_{1,2} = j)$ is the action of the $i^{\text{th}}$ agent assuming that there is (resp. is not) a link between the first and second agents if $l_{1,2} = 1$ (resp. $l_{1,2} = 0$).

The results of this exercise are reported in Table 18. Generally speaking, all of the estimated marginal effects are of the expected sign and are significantly positive at the 5% level or better. The one exception to this is that the estimated marginal effect $[a_1(l_{1,2} = 1)]$ is not significantly positive. That is, when the third agent observes a link between the first and the second agents, and himself forms a link, in neither the FI nor the PI treatments is he influenced by the action taken by the first agent. This is especially striking when combined with the significantly positive coefficient on $[a_2(l_{1,2} = 1)]$ since, at least for the PI treatment, a link by the second to the first signals that the second is *not* informed. Therefore, the third agent should be more heavily influenced by the decision of the first and not the second agent.[20] Another surprising result from the table is that the marginal effect of $a_2$ on the probability that $a_3 = 1$ appears to be the same whether or not the third agent observes a link between the first and second. In contrast, $a_1$ only has a positive effect when $l_{1,2} = 0$.

# 6 Concluding Remarks

In this paper we have presented the results of an experiment on endogenous information acquisition. Not surprisingly, we observed deviations from the Bayesian theory. In particular, subjects in the second position tended to form many links, in some instances there was a tendency to conform to the decision of one's predecessor, the observed network is *extremely* important in driving linking behavior: rather than linking to the most informative node, subjects tended to prefer linking to larger networks. There was also a noticeable pattern of herding in link formation. However, behavior did conform to many of our expectations: the frequency of link formation is negatively related to the cost, and there are important differences in behavior between the FI and PI treatments which suggests that subjects do grasp certain aspects of information transmission through the

[20] For the FI treatment, we can reject the hypothesis that the marginal effects for $[a_1(l_{1,2} = 1)]$ and $[a_2(l_{1,2} = 1)]$ are equal ($\chi^2(1) = 4.28$, $p = 0.0385$), while for the PI treatment we cannot ($\chi^2(1) = 1.48$, $p = 0.223$).

TABLE 18: THIRD SUBJECT: DECOMPOSING ACTION DECISIONS

| Variable | FI | PI |
|---|---|---|
| $[\sigma_3 = 0]$ | NA | 0.455 |
| | | (0.078) |
| $[\sigma_3 \neq 0] \times \sigma_3$ | 0.692 | 0.768 |
| | (0.042) | (0.052) |
| $[a_1(l_{1,2} = 0)]$ | 0.503 | 0.478 |
| | (0.098) | (0.097) |
| $[a_2(l_{1,2} = 0)]$ | 0.301** | 0.488 |
| | (0.140) | (0.083) |
| $[a_1(l_{1,2} = 1)]$ | 0.014 | 0.184 |
| | (0.171) | (0.172) |
| $[a_2(l_{1,2} = 1)]$ | 0.534 | 0.478 |
| | (0.080) | (0.103) |
| LL | -147.23 | -148.74 |
| N | 360 | 360 |

Random Effects Logit with dependent variable $a_3$.
Marginal effects at mean of independent variables and assuming R.E. is zero, *except* that m.e. for $a_i(l_{1,2} = j)$ assumes that $a_i(l_{1,2} = k)$ for $i = 1, 2$ and $j \neq k \in \{0, 1\}$.
Highlighted cells significant at 1% and ** significant at 5%.

networks.

The richness of our data allowed us to identify and estimate the underlying beliefs of our subjects and to compare them with the Bayesian benchmark. Here the results were quite striking. For agents in both the second and third position, our results differed depending on the information treatment. For the agents in the second position, in the FI treatment, subjects tended to under-weight contradictory information, while in the PI treatment, contradictory information was heavily discounted. For subjects in the third position, if they observed agreement between the first and second agent, regardless of the information treatment, they tended to be over-confident about the state of nature. In contrast, when the first and second agents disagreed, in the FI treatment, the third decision maker tended to over-weight the action of the second agent and under-weight the action of the first, while in the PI treatment, when the third observes disagreement between the first and second, he appears to throw out both bits of information and focus solely on his observed signal. One possible reason for the differences in behavior between information treatments may be the following: when an agent observes information (*i.e.,* the actions choices of those to whom the agent has linked) that is inconsistent with his/her current “belief", in the PI treatment, it is very easy to dismiss the inconsistent information as coming from an uninformed agent, while in the FI treatment, such inconsistent information is less easily dismissed, and for some reason, the agents have a tendency to conform.

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# Appendices

## Appendix A: Omitted Proofs

Corollary 1. *The optimal decision rule of the second agent is characterized as follows:*

1. *Let $\sigma_2 \in \{-1, 1\}$ and $q \in (0, 1]$. For any $c > 0$, the second agent does not form a link and takes action $a_2 = \sigma_2$.*
2. *Let $\sigma_2 = 0$ and $q \in (0, 1]$. There exists a threshold $c^* = \frac{qm}{6}$ such that for any $c < c^*$, the second agent links to the first and takes action $a_2 = a_1$; if $c \geq c^*$, the second agent does not form a link and randomizes between the two actions.*

*Proof.*

1. Let $q \in (0, 1]$, and without loss of generality, suppose that $\sigma_2 = 1$. Then, the value of information from linking to the first agent when the unit cost of a link is $c > 0$ is

$$\begin{aligned} v(\sigma_2) &= \sum_{a_1} \Pr(a_1|\sigma_2) \max_{a_2} \left\{ \sum_{\theta} \Pr(\theta|\sigma_2, a_1) u(a_2, \theta) \right\} - \max_{a_2} \left\{ \sum_{\theta} \Pr(\theta|\sigma_2) u(a_2, \theta) \right\} - c \\ &= \sum_{a_1} \Pr(a_1|\sigma_2) \sum_{\theta} \Pr(\theta|\sigma_2, a_1) u(1, \theta) - \sum_{\theta} \Pr(\theta|\sigma_2) u(1, \theta) - c < 0 \end{aligned}$$

   The second equality comes from the fact that choosing $a_2 = 1$ is always optimal, regardless of $a_1$ and hence the first two terms are canceled out. Therefore, it is never optimal to form a link to the first agent for any positive unit cost $c > 0$. The case of $\sigma_2 = -1$ is similar.

2. Let $q \in (0, 1]$, and suppose that $\sigma_2 = 0$. Then a simple computation leads the value of information from linking to the first agent to be

$$v(\sigma_2) = \frac{qm}{6} - c.$$

   Therefore, when $c < \frac{qm}{6}$ the second agent forms a link to the first. However, when $c \geq \frac{qm}{6}$ the second agent does not form a link.

□

Corollary 2. *The optimal decision rule of the third agent is characterized as follows:*

1. *Suppose there is a link between the first and the second agents.*
   (a) *Let $\sigma_3 \in \{-1, 1\}$ and $q \in (0, 1]$. Then, for any $c > 0$ the third agent does not form a link and takes action $a_3 = \sigma_3$.*
   (b) *Let $\sigma_3 = 0$ and $q \in (0, 1]$. Then, for any $c < c^*$ the third agent links to the second and takes action $a_3 = a_2$; if $c \geq c^*$, the third agent does not form a link and randomizes between the two actions.*
2. *Suppose there is no link between the first and the second agents.*
   (a) *Let $\sigma_3 \in \{-1, 1\}$ and $q \in (0, 1]$.*

i. *There exists a threshold $c^{**} = \frac{2qm}{39}$ such that for any $c < c^{**}$, the third agent links to the second agent. If $a_2 = \sigma_3$, then he does not form a link to the first and takes action $a_3 = a_2$; if $a_2 \neq \sigma_3$, then he links to the first and takes action $a_3 = a_1$.*

ii. *For any $c \geq c^{**}(q, m)$ the third agent does not form a link and takes action $a_3 = \sigma_3$.*

(b) *Let $\sigma_3 = 0$ and $q \in (0, 1]$.*

i. *For any $c < c^*$ the third agent links to the second and takes action $a_3 = a_2$.*

ii. *For any $c \geq c^*$, the third agent does not form a link and randomizes between the two actions.*

*Proof.*

1. Suppose there is a link between the first and the second agents. When there is a link between the first and the second agents, the decision problem of the third agent is equivalent to that of the second agent (see the proof of Corollary 1.)

2. Suppose that there is no link the first and the second agents.

(a) Let $\sigma_3 \in \{-1, 1\}$ and $q \in (0, 1]$.

i. The value of information is

$$
\begin{aligned}
v(\sigma_3) &= -c + \sum_{a_2} \Pr(a_2|\sigma_3) \max\{v(\sigma_3, a_2), 0\} \\
&= -c + \frac{4}{9}\left(\frac{qm}{6} - c\right) = \frac{2qm}{27} - \frac{13}{9}c.
\end{aligned}
$$

Therefore, when $c < \frac{2qm}{39}$ we have $v(\sigma_3) > 0$, hence the third agent links to the second agent. If $a_2 = \sigma_3$, the value of information is $v(\sigma_2, \sigma_3) = v(\sigma_2)$; hence the third does not form a link. If $a_2 \neq \sigma_3$, then the value of information is equivalent to $v(\sigma_3 = 0)$. We already know that in this case the third forms a link.

ii. If $c \geq \frac{2qm}{39}$ we have $v(\sigma_3) < 0$, hence the third agent does not form a link to the second agent.

(b) Let $\sigma_3 = 0$ and $q \in (0, 1]$.

i. The value of information is

$$
\begin{aligned}
v(\sigma_2) = &\sum_{a_2} \Pr(a_2|\sigma_3) \max_{a_3}\left\{\sum_{\theta} \Pr(\theta|\sigma_3, a_2) u(a_3, \theta)\right\} - \max_{a_3}\left\{\sum_{\theta} \Pr(\theta|\sigma_3) u(a_3, \theta)\right\} \\
&- c + \sum_{a_2} \Pr(a_2|\sigma_3) \max\{v(\sigma_3, a_2), 0\} = \frac{m}{6} - c,
\end{aligned}
$$

where $v(\sigma_3, a_2) < 0$ for any $(\sigma_3, a_2)$. Thus, for $0 < c < \frac{qm}{6}$, it is optimal to form a link to the second agent. After forming a link, for any action he observes, the value of information for the third agent is identical to that of an informed second agent. Therefore, the third does not form a link to the first, and takes action $a_3 = a_2$ (see the proof of Corollary 1.) and follow his action decision.

ii. When $c \geq \frac{qm}{6}$, the value is $v(\sigma_3) < 0$. Therefore, the third does not form a link to the second agent.

□

# Appendix B: Instructions

## General Instructions

This is an experiment in the economics of decision-making. Your earnings will depend partly on your decisions and partly on chance. By following the instructions and making careful decisions you will earn varying amounts of money, which will be paid at the end of the experiment. Details of how you will make decisions and earn money will be provided below.

In this experiment, you will participate in 40 independent rounds, each of which contains four decision positions in a decision queue. In each round you will be asked which of two urns has been randomly chosen (called *action decision*); however, before making your action decision, some subjects will be able to observe the actions of those who have gone before them (called *link decision(s)*) by paying a cost that will be determined by the computer at the beginning of each round.

Before the first round, you will be randomly assigned to a position in the decision queue labeled **1**, **2**, **3** or **4**. One-fourth of the participants will be randomly assigned to each of the four positions. Your position depends solely on chance and will remain constant in all rounds throughout the experiment. When you are called to make decisions, in the center of the computer screen you will be informed of your position and any link decisions made by those in preceding decision positions; however, you will not observe their action decisions.

## A Decision Round

Each round starts by having the computer randomly form groups of four participants by selecting one participant from each of the four positions. The groups formed in each round depend only on chance and are independent of the groups formed in any of the other rounds.

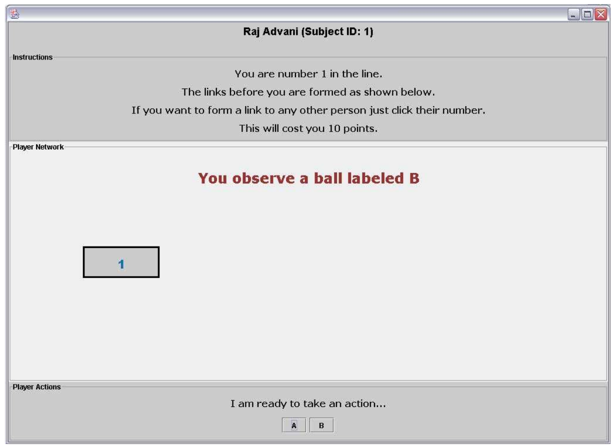
In each round you will be asked to predict which of two urns, labeled **A** and **B**, has been chosen. For each group of four, it is equally likely that urn **A** or urn **B** will be chosen. **Urn *A* contains 2 *balls* labeled *A* and *1 ball* labeled *B*. Urn *B* contains *2 balls* labeled *B* and *1 ball* labeled *A*.**

To help you determine which urn has been selected, you will be allowed to observe one ball, drawn at random, from the urn *at no cost*. In addition, if you are in position **2, 3 or 4**, you will be given a chance to see action decisions in preceding positions at a cost determined by the experimental software.

Your private draw in each round is independent of the draw received by any other participant. The result of your draw will be your private information and should not be shared with any of the other participants. You will see your private draw in the middle portion of the computer screen.

**After each draw, the ball will be returned to the urn before making a private draw for the next participant. This is done by the experimental software.**

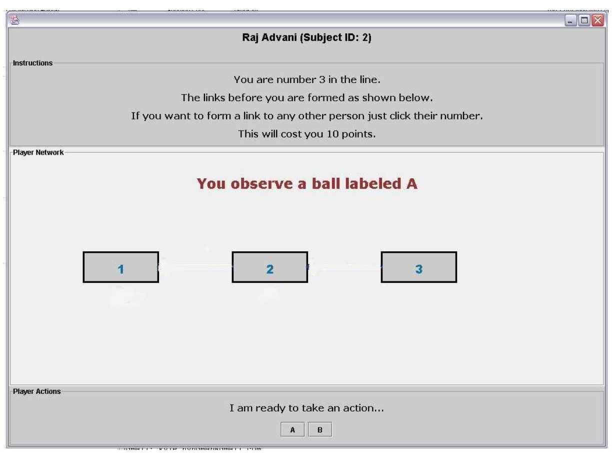
Participants assigned to position **1** may see the following screen on your computer screen:




In this case, since you are in the first position in a decision queue, all you need to do is make your action decision based on your private information. This is done at the bottom of the screen by simply clicking on either **A** or **B**.

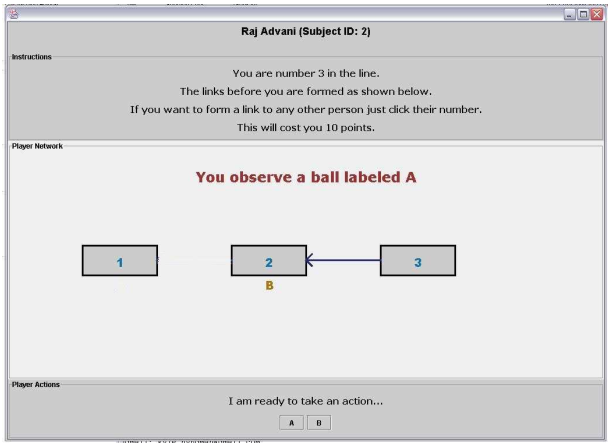
For participants assigned to positions **2**, **3** and **4**, there will be other participants in the same group who have already made their action and link decisions. In addition to your private draw, you will have the opportunity to observe the action decisions of those in preceding positions at a cost determined by the experimental software at the beginning of each round. When it is your turn to move, you will see a graphical representation of all the link decisions made by those who precede you in the decision queue.

For example, suppose that you are assigned to position **3** in the queue. You may see the following screen:




In this example, your private draw was a ball labeled **A**. In addition, you observe that the participant in the second position chose **not** to form a link to the first position. That is, the participant in the second position predicted which urn was more likely to be chosen, while having chosen not to observe the action decision by the participant in the first position.

Continue with the example above and suppose that you wish to form a link to the second position. To do this, simply click on the box labeled **2**. Then you will observe the action decision made by the participant in position **2** while incurring the cost of forming a link. This is depicted below:




**Note that once you form a link to one preceding participant, you see not only his/her action choice *but also* the action choices of all those with whom that person linked.**

For example, suppose that the second person *had* actually formed a link to the first person in the queue. In this situation, by forming a link to the second position in the queue you would see the action decisions of **both** participants in the first and the second positions in the queue.

In this example, if you wish to observe more information, you may form a link to the first position, **at an additional cost**, and observe his or her action decision. If not, and you are ready to make your decision, simply click on the box labeled **A** or **B** at the bottom of your screen, corresponding to which urn you think was more likely to have been chosen.

Once you have made your decision for that round, you will be informed which urn was actually used and what your potential payoffs are for that round. By clicking on the **OK** button you will be taken to a waiting screen and then the next person in the line will be able to make his or her decisions.

This concludes one decision round. All of the participants will then be randomly placed into a new group of four people. In total, you will repeat 40 independent rounds with various levels of costs.

**Remember:** In each round, the same urn applies to all members of a group. That is, the experimental software picks **one** urn for each group in each round.

## Cost of Forming Links

Now, we will describe in detail how the cost of forming a link will be determined in each of the 40, independent, rounds. In all rounds throughout the experiment, the cost of forming a link can be any **even** number between 0 and 20, inclusive; that is, the cost will be one of the following numbers, 0, 2, 4, . . ., 16, 18, 20.

In each round, the computer will randomly assign a cost to each group of four. The chance that the computer selects any even number between 0 and 20 points is exactly the same. That is, the chance that a cost of 2 is selected is the same as the chance that a cost of 14 is selected and so on. Moreover, the cost assigned in one decision round is independent of the cost in any other decision round.

**Remember:** The cost of forming a link in each round is the same for all members of a group. Moreover, the cost for each link is the same (*e.g.,* If you form one link at a cost of 10 points, you are free to form another link by paying an additional cost of 10 points.).

## Payoffs

Your potential earnings for each round are determined as follows. If you made the correct action decision regarding which urn was used, you will be awarded 100 points for that round; otherwise, you will be awarded nothing. From this amount, either 100 or 0, we will subtract the appropriate cost for **each** link decision that you made. For example, if, in round 10, the cost of link formation was 18 points, then in determining your potential earnings for round 10, 18 points will be subtracted, from either 100 or 0, for every link decision that was made. For example, if, after having made one link decision, you correctly guessed which urn was chosen, your potential earnings would be 100 - 18 = 82 points.

At the end of the 40 rounds, the experimental software we will randomly select three rounds from which you will be paid. The total number of points earned will be summed up for each of these three rounds — 100 points for each correct decision, from which we will subtract the appropriate number of points for each link decision. This will be converted to a dollar amount according to the rule:

$1 = 15 points

This amount will then be added to the $8.00 participation fee to give your payment for this experiment. Payments will be made in private via petty cash vouchers at the conclusion of the session.

## Rules

Please do not talk with anyone during the experiment. We ask everyone to remain silent until the end of the last decision problem.

Your participation in the experiment and any information about your earnings will be kept strictly confidential. Your receipt of payment and consent form are the only places on which your name will appear. This information will be kept confidential in the manner described in the consent form.

If you have any questions please ask them now. If not, we will proceed to the experiment.