# Information Aggregation in Directed Networks

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# Introduction

Individuals frequently make decisions under uncertainty

- These decisions are rarely made in isolation
- In addition to private information, individuals can obtain information from observing previous actions of others

Can access to previous choices of others improve accuracy of a decision?

We focus on situations when a person makes a single irreversible choice and learning from repetition is not possible

Which choices of others would be best to know?

If a person could obtain information about select previous choices of others, what is the optimal way to go about it?

# Introduction

We use directed networks to impose a formal structure on how one might collect information about previous choices of others, or what can be the sequence of decision-making within an organization.

The structure of the networks would determine which actions individuals observe, and therefore, what information they have when making their own decisions

We examine which properties of networks affect the aggregation of decentralized information and improve the accuracy of choice under uncertainty

# Motivating Example

**Choice of Medical Procedure (Surgery)**

- Individual has an ailment and has to make a choice among available types of surgeries
- Diagnostics provided an estimate of the condition, and the success of the cure depends on the match between the type of surgery and the exact condition, and it is known only after the procedure
- Before making the decision a person may observe choices of procedures by other patients under similar conditions, but without learning their full private medical details

Individual Consumption Problem

# Overview

We consider a sequential social learning environment with agents connected via a directed network which allows for observational learning

- There is an unknown, payoff relevant state of the world
- Agents sequentially make a single, irreversible decision which is their prediction regarding the true state
- Each agent gets a private signal about the state and also observes the actions of (some) individuals acting before them – determined by the structure of the network

Related Literature: Observational Learning  Learning in Networks

# Overview

We use two criteria to evaluate the accuracy of choice and networks performance in this environment

- Social criterion: accuracy of the whole group
- Individual criterion: accuracy of the final decision maker

We conduct an experiment using two main treatment variables:

- the structure (properties) of the network
- exogenous or endogenous assignment to positions within the network

We also design a measure of (over)confidence and study its effect on learning from choices of others – separate paper.

# Overview of Results

- We find, theoretically and experimentally, that network structure affects information aggregation and the accuracy of decision making under uncertainty
- There is efficiency loss compared to all-Bayesian agents
- Properties of networks maximizing performance under each criterion are supported by data
- The propensity to follow own signal is decreasing in the number of observed actions
- Subjects understand the value of information obtained from observing others' actions and are willing to pay more for later positions
- When assignment to positions is endogenous, more sophisticated subjects self-select to be in later positions, which reduces their payoff advantage

# Decision Problem with Observational Learning

**Environment**

- Finite set of agents, $N = \{1, 2, \ldots, n\}$, connected by a (directed) network $G$
- Binary state space, $\Omega = \{A, B\}$, with $P(A) = P(B) = 1/2$

**Information, Decision, Payoff**

- True state, $\omega \in \Omega$, is unknown
- Index agents according to the order in which they make decisions

Individual $i$

- receives a private signal $s_i \in \{a, b\}$; imperfectly informative with precision $q = P(a \mid A) = P(b \mid B) \in (1/2, 1)$
- observes actions of (some) individuals acting before them – determined by the network
- makes a single, irreversible decision; $x_i \in \{A, B\}$.
- receives a payoff $V$ if choice matches the state and nothing otherwise

# Observational Learning in Networks

## Network Structures

- Represented by a collection of links
- $ij \in G$ indicates the link from $i$ to $j$ in $G$
  ($i$ makes decision before $j$, $i < j$, and $j$ observes choice of $i$ prior to making own decision)
- The *observation set* of each agent is the collection of prior choices that they observe
- Each agent $j$ observes the action of every agent $k$ for which there exists a *directed path* from $k$ to $j$ in $G$. So, if $ij \in G$, $j$ also observes the full observation set of agent $i$

Sequential Networks

# Beliefs

## Bayesian Agents

- Individual information set is $I_i = \{s_i, O_i\}$
- Agents form posterior beliefs, $p_i = P(A \mid I_i)$ using Bayes' rule
- Choose $x_i = A$ if $p_i > 1/2$ and $x_i = B$ if $p_i < 1/2$

## Tie Breaking

- **Assumption**: An agent $i$ with posterior belief $p_i = 1/2$ chooses $x_i = A$ if $s_i = a$ and $x_i = B$ if $s_i = b$
- In the event that posterior probabilities are equal, agents side with their private information (Anderson & Holt, 1997; Çelen & Kariv, 2004a; Weizsäcker, 2010)

# Choices

**Optimal Decision Rule**

Posterior beliefs can be expressed as a linear decomposition of *private beliefs*, $P(A \mid s_i)$, and *social beliefs*, $P(A \mid O_i)$

**The action of agent $i$, $x_i$:**

$$x_i = A \text{ if } \begin{cases} s_i = a \text{ and } P(A \mid O_i) \geqslant 1 - q \\ s_i = b \text{ and } P(A \mid O_i) > q \end{cases}$$

$$x_i = B \text{ if } \begin{cases} s_i = b \text{ and } P(A \mid O_i) \leqslant q \\ s_i = a \text{ and } P(A \mid O_i) < 1 - q \end{cases}$$

# Informative Actions

- The action of an agent $i$, $x_i$, is **informative** if that agent's signal, $s_i$, can be inferred by observing $x_i$
- The action of an agent $i$, $x_i$, is **guaranteed informative** in $G$ if it is informative for any sequence of private signals

Information Cascades | k-informative Networks

# Network Structures

**Complete History Network (linear network)**

- The *complete history network*, $G^C$, has $ij \in G^C$ if and only if $j = i + 1$
- The complete history network generates an information structure, $I(G^C)$, with $O_1 = \varnothing$ and $O_i = \{x_1, \ldots, x_{i-1}\}$ for $i \in \{2, \ldots, n\}$

Proposition

**Star Network**

- The *star network*, $G^S$, has $ij \in G^S$ if and only if $j = n$ for any $i \in \{1, \ldots, n-1\}$
- The star network generates an information structure, $I(G^S)$, with $O_i = \varnothing$ for $i \in \{1, \ldots, n-1\}$ and $O_n = \{x_1, \ldots, x_{n-1}\}$

# Evaluating Networks Performance

**Expected Payoffs**

- Given the optimal decision rule, for a fixed network structure and signal precision, the actions of all agents are determined by the sequence of private signals
- Let $\mathbf{s} = (s_1, s_2, \ldots, s_n)$ be a sequence of individual signals, $S(n)$ – the set of all possible sequences of length $n$, and $x_i(\mathbf{s})$ – the choice of agent $i$ for a given sequence
- Then, the expected payoff of agent $i$ is

$$E_{S(n)}[u_i(x_i, \omega; G)] = \sum_{\mathbf{s} \in S(n)} P(\mathbf{s}) u_i(x_i(\mathbf{s}), \omega; G)$$

- We use two criteria to compare outcomes across networks

# Individual Criterion

In some settings it is most important that a key individual, a leader or CEO, makes the correct decision

We use *individual criterion* to compare networks based on the *expected payoff of the* ***final agent***

$$E_{S(n)}[u_n(x_n, \omega; G)] = \sum_{\mathbf{s} \in S(n)} P(\mathbf{s}) u_n(x_n(\mathbf{s}), \omega; G)$$

**Proposition**: For fixed $n$ and $q$, the expected payoff of the final agent is maximized by any network that is fully informative

- Maximizes the number of independent private signals reaching the final agent
- The final agent effectively has $n$ private signals

# Social Criterion

In some settings, we are interested in group accuracy and evaluate networks performance based on aggregate expected payoffs

We use a *social criterion* to compare networks based on *total expected payoff of* ***all agents***

$$E_{S(n)}[U(\mathbf{x}, \omega; G)] = \sum_{\mathbf{s} \in S(n)} P(\mathbf{s}) \sum_{i=1}^{n} u_i(x_i(\mathbf{s}), \omega; G)$$

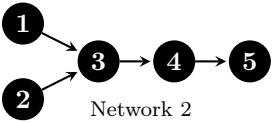
Results Non-monotonicity of Observed Actions

# Experimental Design

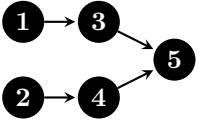
- Groups: $n = 5$
- States: $P(A) = P(B) = 0.5$
- Signals: $P(a \mid A) = P(b \mid B) = 0.7$
- Payoffs: $V = \$9$



Network 1



Network 2



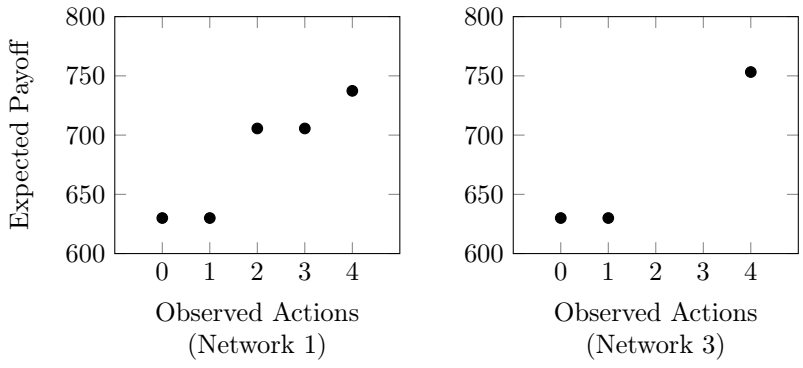
Network 3

Signal Precision

# Expected Payoffs (by Network, Observed Actions)

Individual Expected Payoffs

| | Number of Observed Actions | | | | | Average |
|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | |
| Network 1 | 630 | 630 | 705.6 | 705.6 | 737.35 | 681.71 |
| Network 2 | 630 | - | 705.6 | 705.6 | 737.35 | 681.71 |
| Network 3 | 630 | 630 | - | - | 753.23 | 654.65 |



# Experimental Treatments

| Treatment | Sessions | Subjects |
|---|---|---|
| Network 1: Exogenous (N1) | 2 | 40 |
| Network 2: Exogenous (N2) | 2 | 35 |
| Network 3: Exogenous (N3) | 2 | 40 |
| Network 1: Endogenous (N1A) | 3 | 50 |
| Network 3: Endogenous (N3A) | 3 | 50 |

Procedures Signal Sequences Endogenous Position Procedure

**Endogenous allocation mechanism:**

In equilibrium subjects bid amounts are equal to the expected payoff premiums over position 1.

This allows us to elicit subjects valuations, while (theoretically, for homogeneous case) resulting in the same random assignment.

# Consistency with Bayesian Updating

**Result**: About 15% of choices are not consistent with Bayesian

Experimental Choices Consistent with Bayesian Updating

| | N1 | N2 | N3 | N1A | N3A | Total |
|---|---|---|---|---|---|---|
| All | 233 | 204 | 250 | 291 | 309 | 1287 |
| Bayesian | (0.83) | (0.83) | (0.89) | (0.83) | (0.88) | (0.86) |
| Conditional | 242 | 215 | 250 | 304 | 318 | 1329 |
| on History | (0.86) | (0.88) | (0.89) | (0.87) | (0.91) | (0.88) |

# Consistency with Tie-Breaking Assumption

**Result**: The tie-breaking assumption is not supported by the data

Experimental Choices Consistent with Tie-breaking Assumption

| | N1 | N2 | N3 | N1A | N3A | Total |
|---|---|---|---|---|---|---|
| Posterior 0.5 | 39 | 16 | 52 | 50 | 62 | 219 |
| Consistent | 24 | 11 | 41 | 33 | 44 | 153 |
| Frequency | (0.62) | (0.69) | (0.79) | (0.66) | (0.71) | (0.70) |

One sample t-tests

- For all treatments, observed frequency is significantly different from one ($p < 0.05$)
- Observed frequency is also significantly different from 0.5 ($p < 0.05$) in all except two treatments (N1: $p = 0.152$; N2: $p = 0.138$)

# Consistency with Tie-Breaking Assumption

**Result**: Propensity to break a tie in favor of own signal decreases with the number of observed actions

Choices Consistent with Tie Breaking Assumption by Number of Observed Actions

| Treatment | | Number of Observed Actions | | |
|---|---|---|---|---|
| | | 1 | 3 | 4 |
| N1 | Posterior 0.5 | 21 | 15 | 3 |
| | Consistent | 18 | 6 | 0 |
| | Frequency | (0.86) | (0.40) | (0.00) |
| N2 | Posterior 0.5 | - | 14 | 2 |
| | Consistent | - | 10 | 1 |
| | Frequency | - | (0.71) | (0.50) |
| N1A | Posterior 0.5 | 27 | 21 | 2 |
| | Consistent | 23 | 10 | 0 |
| | Frequency | (0.85) | (0.48) | (0.00) |

One sample t-tests

- One observed action: significantly different from 0.5 in both treatments ($p < 0.001$)
- Three observed actions: not significantly different from 0.5 in any treatment ($p > 0.1$)

# Individual Earnings

**Result**: There is, on average, payoff loss compared to Bayesian benchmark. This loss is more pronounced when social beliefs can dominate private signals.

Difference in Individual Earnings (Experimental minus All Bayesian)

| Treatment | Number of Observed Actions | | | | |
|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 |
| N1 | 16.07 | 16.07 | -80.36 † | -48.21 | -80.36 † |
| | (27.44) | (36.65) | (51.59) | (58.14) | (47.59) |
| N2 | -9.18 | - | -91.84 | -73.47 | -128.57** |
| | (30.90) | - | (63.24) | (51.54) | (55.19) |
| N3 | -40.18† | 8.04 | - | - | -64.29 |
| | (25.80) | (31.42) | - | - | (44.49) |
| N1A | -12.86 | -38.57 | -102.86* | -12.86 | -51.43 |
| | (34.07) | (39.54) | (52.91) | (50.29) | (48.84) |
| N3A | -12.86 | -6.43 | - | - | -154.29*** |
| | (18.27) | (26.83) | - | - | (40.63) |

Average, standard errors (clustered at subject level) reported in parentheses

† $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Conditional Bayesian

# Correct Unanimity in a Group

Difference in Proportion of Groups with Five Correct (All Bayesian)

| | N2 | N3 | N1A | N3A |
|---|---|---|---|---|
| N1 | 0.0459 | 0.3036*** | 0.0214 | 0.3071*** |
| | (0.0977) | (0.0873) | (0.0895) | (0.0834) |
| N2 | - | 0.2577*** | -0.0245 | 0.2612*** |
| | - | (0.0910) | (0.0931) | (0.0873) |
| N3 | - | - | -0.2821*** | 0.0036 |
| | - | - | (0.0822) | (0.0755) |
| N1A | - | - | - | 0.2857*** |
| | - | - | - | (0.0780) |

Cells denote difference in proportions of row treatment minus column treatment

Standard errors reported in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# Correct Unanimity in a Group

Difference in Proportion of Groups with Five Correct (Experimental)

| | N2 | N3 | N1A | N3A |
|---|---|---|---|---|
| N1 | -0.0153 | 0.2143** | 0.0214 | 0.0929 |
| | (0.0959) | (0.0829) | (0.0871) | (0.0852) |
| N2 | - | 0.2296*** | 0.0367 | 0.1082 |
| | - | (0.0869) | (0.0909) | (0.0891) |
| N3 | - | - | -0.1929** | -0.1214 |
| | - | - | (0.0772) | (0.0750) |
| N1A | - | - | - | 0.0714 |
| | - | - | - | (0.0796) |

Cells denote difference in proportions of row treatment minus column treatment

Standard errors reported in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Result**: Theoretical predictions for group performance are supported by data, except for treatment N3A. Specifically, N1, N1A, and N2 are more accurate, as a group, than N3.

Group Correct Graphs

# Individual Criterion

**Observation**: The accuracy of choices of the final agent in networks N3 and N3A are not greater than in other networks

Difference in Proportion of Final Agents making Correct Choice (Experimental)

| | N2 | N3 | N1A | N3A |
|---|---|---|---|---|
| N1 | 0.0740 | -0.0357 | -0.0179 | 0.0679 |
| | (0.0867) | (0.0775) | (0.0748) | (0.0786) |
| N2 | - | -0.1097 | -0.0918 | -0.0061 |
| | - | (0.0846) | (0.0821) | (0.0856) |
| N3 | - | - | 0.0179 | 0.1036 |
| | - | - | (0.0723) | (0.0763) |
| N1A | - | - | - | 0.0857 |
| | - | - | - | (0.0735) |

Cells denote difference in proportions of row treatment minus column treatment

Standard errors reported in parentheses

$^{\dagger}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All Bayesian Effect of Observed Informative Actions

# Demand for Information

**Result**: There is heterogeneous demand for information in endogenous positions assignment

Number of Different Positions (by subject within session)

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Exogenous | 0 | 3 | 28 | 61 | 23 |
| | (0.00) | (0.03) | (0.24) | (0.53) | (0.20) |
| Endogenous | 10 | 17 | 39 | 28 | 6 |
| | (0.10) | (0.17) | (0.39) | (0.28) | (0.06) |

**Result**: Subjects increase their bids for positions with the number of observed actions greater than one. Bid premiums are consistent with expected payoff gains

Bids Regression

# Concluding Remarks

We study choice under uncertainty where in addition to own private signal, a person observes select choices of others, specified by a directed network

- Identify properties of networks that affect the informativeness of observed actions, thus whether an action should be considered by the observer
- Identify properties of networks that maximize performance under individual and social criteria, and show that there is a tradeoff between properties that improve each criterion

We design and conduct an experiment to test our theoretical predictions

Two main treatment variables:

- Network structure
- Assignment to positions within the network: exogenous or endogenous

# Concluding Remarks

- Subjects, on average, understand the value of observational learning, however there is efficiency loss compared to Bayes-rational benchmark
- When facing a *50-50* posterior, people do not break a tie in favor of own private information, thus the tie-breaking assumption is not supported overall. Subjects tend to go against own private signal when the number of observed actions of others becomes larger
- Group performance/accuracy (social criterion) predictions are supported by data
- Accuracy of individual choice increases in the number of informative actions, which is the property underlying individual criterion predictions
- When assignment is endogenous, subjects with greater understanding of observational learning self-select to be in later positions. This in turn increases the noise in decisions of early positions and reduces the payoff-advantage of being the final agent

Thank you

# Supplemental Slides

# Motivating Examples

**Individual Consumption Problem**

- Suppose you're in the market for a new phone but aren't sure which of two major brands would be the better purchase
- You may look to previous purchasing decisions made by friends, family, etc. to acquire additional information about which is the better product

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# Related Literature

**Observational Learning: Theory**

- Theories based on information cascades and herd behavior have been used to explain conformity in social behavior
- Often limited to cases where full history of actions is observed (Bikchandani et al., 1992; Banerjee, 1992; Smith & Søorensen, 2000)
- Later extended to cases where individuals observe: (i) a random subset of past actions (Banerjee & Fudenberg, 2004), and (ii) Only the action of immediate predecessor (Çelen & Kariv, 2004)

**Observational Learning: Experiments**

- Cascades occur regularly (Anderson & Holt, 1997); however, subjects have a tendency to overvalue their private information (Nöth & Weber, 2003; Weizsäcker, 2010)
- As a result, cascade formation may be delayed, and cascades, once formed, may be short-lived or even reversible (Goeree et al., 2007)

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# Related Literature

**Learning in Networks**

- *Sequential*: Information aggregation and asymptotic learning (convergence in proportion of agents choosing the correct action) depend on network topology (Acemoglu et al., 2011; Lobel and Sadler, 2015; Arieli & Mueller-Frank, 2018)
- *Repeated*: Convergence in actions/beliefs over time depends on the topology of the social network and the influence of agents. (Gale & Kariv, 2003; Golub & Jackson, 2010; Mossel et al., 2015)
- *Experimental*: Studies of learning in networks have, so far, been limited to environments with repeated learning over multiple periods (Choi, Gale, & Kariv, 2012; Grimm & Mengel, 2018)

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## Sequential Networks

- A directed network, $G$, is a *sequential network* if
  - (i) for all $i \in N$, there is no $l < i$ such that $il \in G$
  - (ii) for all $i \in \{1, 2, \ldots, n-1\}$, there is a unique $k > i$ such that $ik \in G$
- Eliminates possibility of networks with an isolated set of agents
- Decision making process eventually concludes with a unique final agent

Observation Set Information Back

# Observation of Prior Actions

**Observed Actions**

- In sequential networks, the set of actions observed by each agent $i$ is denoted by $O_i \subseteq \{x_1, x_2, \ldots, x_{i-1}\}$

**Information Structure**

- The *information structure* of a network $G$ is $I(G) \equiv \{O_1, O_2, \ldots, O_n\}$

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# Information Cascades

## Information Cascades

- If a cascade is formed, all subsequent individuals disregard own private information and choose the majority action in observation set
- An individual is in a cascade if $P(\omega = z \mid O_i) > \frac{1}{2}$ and $P(\omega = z \mid I_i) > \frac{1}{2}$ for any $s_i \in \{a, b\}$, $z \in \{A, B\}$
- Prior to the formation of a cascade, individuals' actions are informative. Actions taken by individuals in a cascade are uninformative

**Property**: The action of an agent $i$, $x_i$, is uninformative if $P(A \mid O_i) \in (0, 1-q) \cup (q, 1)$; otherwise, it is informative

- In the standard linear network, cascades are irreversible. In more general networks, cascades may be reversible

Back Lemma

# Information Cascades: Lemma

**Lemma**: For any network, $G$, in the binary states case, an individual $i$ can be in a cascade only if $|O_i| \geqslant 2$

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# Network Structures

## k-informative Networks

- A sequential network, $G$, is *k-informative* if the actions of $k \leqslant n-1$ non-final agents are guaranteed informative

## Fully Informative Networks

- A sequential network, $G$, is *fully informative* if the actions of all $n-1$ non-final agents are guaranteed informative
- A *fully informative* network, $G$, generates an information structure, $I(G)$, such that $|O_i| \leqslant 1$ for all $i \in \{1, 2, \ldots, n-1\}$ and $O_n = \{x_1, x_2, \ldots, x_{n-1}\}$

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# Complete History Network: Proposition

**Proposition**: In the complete history network, $G^C$, an information cascade can start with an agent $i \geqslant 3$ only if $i$ is odd

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# Social Criterion

**Proposition**: For any network, $G$, and any agents $i$ and $j$ such that $|O_j| \leqslant 1$ and $|O_i| = 2$,

$$E_{S(n)}[u_i(x_i, \omega; G)] > E_{S(n)}[u_j(x_j, \omega; G)]$$

**Proposition**: For any network, $G$, and any two agents $i$ and $j$ such that $x_j \in O_i$,

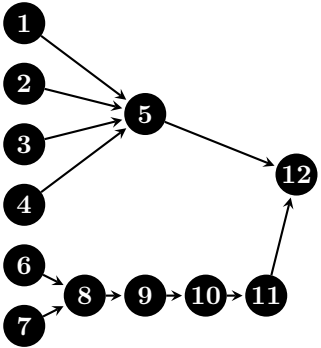
$$E_{S(n)}[u_i(x_i, \omega; G)] \geqslant E_{S(n)}[u_j(x_j, \omega; G)]$$

**Proposition**: Aggregate expected payoffs are at least as large in the complete history network as in any fully informative network and strictly greater if $n \geqslant 4$

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# Non-monotonicity of Observed Actions

- In expectation, individuals are better off with more information. However, observing more actions does not necessarily imply more information is inferred since some actions may be uninformative.

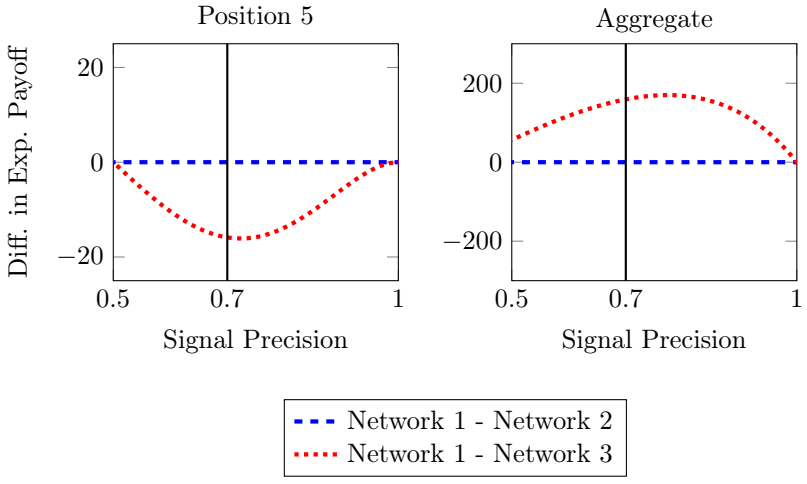



Consider agents 5 and 11

- $|O_5| = 4$
- $|O_{11}| = 5$
- $E[u_5] = q^4 + 4q^3(1-q) + 6q^3(1-q)^2$
- $E[u_{11}] = q^2 + 2q^3(1-q) + 4q^3(1-q)^2$
- $E[u_5] > E[u_{11}]$

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# Experimental Signal Precision




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# Procedures

## Session Details

- Seven identical decision making rounds; one randomly selected for payment.
- Subjects were randomly re-matched into new groups of five at the start of each round. For exogenous treatments, positions within the network were also randomly assigned. For endogenous treatments, subjects we assigned to positions via bidding allocation mechanism.
- Each session lasted between 60 and 90 minutes with subjects earning $14.48 on average, including a $7.00 show-up fee.

## Experiment

- All session were conducted at the XS/FS laboratory at Florida State University using z-Tree (Fischbacher, 2007).
- Subjects randomly recruited from a pool of FSU students who had previously registered to participate in experiments, ORSEE (Greiner, 2015).

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# Experimental Signal Sequences

Experimental Signal Sequences (by group)

| Sequence | Frequency | Percent | Sequence | Frequency | Percent |
|---|---|---|---|---|---|
| AAAAA | 21 | 8.57 | ABAAA | 2 | 0.82 |
| AAAAB | 8 | 3.27 | ABAAB | 5 | 2.04 |
| AAABA | 12 | 4.90 | ABABA | 15 | 6.12 |
| AAABB | 10 | 4.08 | ABABB | 5 | 2.04 |
| AABAA | 10 | 4.08 | ABBAA | 10 | 4.08 |
| AABAB | 5 | 2.04 | ABBAB | 3 | 1.22 |
| AABBA | 9 | 3.67 | ABBBA | 15 | 6.12 |
| BBAAB | 7 | 2.86 | ABBBB | 20 | 8.16 |
| BBABA | 13 | 5.31 | BAABA | 15 | 6.12 |
| BBABB | 10 | 4.08 | BABAB | 10 | 4.08 |
| BBBAA | 3 | 1.22 | BABBA | 5 | 2.04 |
| BBBBA | 10 | 4.08 | BBAAA | 5 | 2.04 |
| BBBBB | 17 | 6.94 | - | - | - |

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# Endogenous Position Assignment

Individuals submit bids for each position in the network.

| | Position 1 | Position 2 | Position 3 | Position 4 | Position 5 |
|---|---|---|---|---|---|
| Agent 1 | $b_{11}$ | $b_{12}$ | $b_{13}$ | $b_{14}$ | $b_{15}$ |
| Agent 2 | $b_{21}$ | $b_{22}$ | $b_{23}$ | $b_{24}$ | $b_{25}$ |
| Agent 3 | $b_{31}$ | $b_{32}$ | $b_{33}$ | $b_{34}$ | $b_{35}$ |
| Agent 4 | $b_{41}$ | $b_{42}$ | $b_{43}$ | $b_{44}$ | $b_{45}$ |
| Agent 5 | $b_{51}$ | $b_{52}$ | $b_{53}$ | $b_{54}$ | $b_{55}$ |

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# Endogenous Position Assignment

The highest among all 25 bids is identified and that position is assigned to that agent.

| | Position 1 | Position 2 | Position 3 | Position 4 | Position 5 |
|---|---|---|---|---|---|
| Agent 1 | $b_{11}$ | $b_{12}$ | $b_{13}$ | $b_{14}$ | $b_{15}$ |
| Agent 2 | $b_{21}$ | $b_{22}$ | $b_{23}$ | $b_{24}$ | $b_{25}$ |
| Agent 3 | $b_{31}$ | $b_{32}$ | $b_{33}$ | $b_{34}$ | $b_{35}$ |
| Agent 4 | $b_{41}$ | $b_{42}$ | $b_{43}$ | $b_{44}$ | $b_{45}$ |
| Agent 5 | $b_{51}$ | $b_{52}$ | $b_{53}$ | $b_{54}$ | $b_{55}$ |

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# Endogenous Position Assignment

All bids by that agent and for that position are removed from further consideration.

| | Position 1 | Position 2 | Position 3 | Position 4 | Position 5 |
|---|---|---|---|---|---|
| Agent 1 | $b_{11}$ | $b_{12}$ | $b_{13}$ | $b_{14}$ | $b_{15}$ |
| Agent 2 | ~~$b_{21}$~~ | ~~$b_{22}$~~ | ~~$b_{23}$~~ | ~~$b_{24}$~~ | ~~$b_{25}$~~ |
| Agent 3 | $b_{31}$ | $b_{32}$ | $b_{33}$ | $b_{34}$ | $b_{35}$ |
| Agent 4 | $b_{41}$ | $b_{42}$ | $b_{43}$ | $b_{44}$ | $b_{45}$ |
| Agent 5 | $b_{51}$ | $b_{52}$ | $b_{53}$ | $b_{54}$ | $b_{55}$ |

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# Endogenous Position Assignment

The highest among the remaining 16 bids is identified and that position is assigned to that agent.

| | Position 1 | Position 2 | Position 3 | Position 4 | Position 5 |
|---|---|---|---|---|---|
| Agent 1 | $b_{11}$ | $b_{12}$ | $b_{13}$ | $b_{14}$ | $b_{15}$ |
| Agent 2 | ~~$b_{21}$~~ | ~~$b_{22}$~~ | ~~$b_{23}$~~ | ~~$b_{24}$~~ | ~~$b_{25}$~~ |
| Agent 3 | $b_{31}$ | $b_{32}$ | $b_{33}$ | $b_{34}$ | $b_{35}$ |
| Agent 4 | $b_{41}$ | $b_{42}$ | $b_{43}$ | $b_{44}$ | $b_{45}$ |
| Agent 5 | $b_{51}$ | $b_{52}$ | $b_{53}$ | $b_{54}$ | $b_{55}$ |

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# Endogenous Position Assignment

All bids by that agent and for that position are removed from further consideration.

| | Position 1 | Position 2 | Position 3 | Position 4 | Position 5 |
|---|---|---|---|---|---|
| Agent 1 | $b_{11}$ | $b_{12}$ | $b_{13}$ | $b_{14}$ | $b_{15}$ |
| Agent 2 | ~~$b_{21}$~~ | ~~$b_{22}$~~ | ~~$b_{23}$~~ | ~~$b_{24}$~~ | $b_{25}$ |
| Agent 3 | $b_{31}$ | $b_{32}$ | $b_{33}$ | $b_{34}$ | $b_{35}$ |
| Agent 4 | ~~$b_{41}$~~ | ~~$b_{42}$~~ | $b_{43}$ | ~~$b_{44}$~~ | ~~$b_{45}$~~ |
| Agent 5 | $b_{51}$ | $b_{52}$ | ~~$b_{53}$~~ | $b_{54}$ | ~~$b_{55}$~~ |

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# Endogenous Position Assignment

The highest among the remaining 9 bids is identified and that position is assigned to that agent.

| | Position 1 | Position 2 | Position 3 | Position 4 | Position 5 |
|---|---|---|---|---|---|
| Agent 1 | $b_{11}$ | $b_{12}$ | $b_{13}$ | $b_{14}$ | $b_{15}$ |
| Agent 2 | ~~$b_{21}$~~ | ~~$b_{22}$~~ | ~~$b_{23}$~~ | ~~$b_{24}$~~ | ~~$b_{25}$~~ |
| Agent 3 | $b_{31}$ | $b_{32}$ | $b_{33}$ | $b_{34}$ | $b_{35}$ |
| Agent 4 | ~~$b_{41}$~~ | ~~$b_{42}$~~ | ~~$b_{43}$~~ | ~~$b_{44}$~~ | ~~$b_{45}$~~ |
| Agent 5 | $b_{51}$ | $b_{52}$ | $b_{53}$ | $b_{54}$ | $b_{55}$ |

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# Endogenous Position Assignment

All bids by that agent and for that position are removed from further consideration.

| | Position 1 | Position 2 | Position 3 | Position 4 | Position 5 |
|---|---|---|---|---|---|
| Agent 1 | ~~$b_{11}$~~ | ~~$b_{12}$~~ | ~~$b_{13}$~~ | $b_{14}$ | ~~$b_{15}$~~ |
| Agent 2 | ~~$b_{21}$~~ | ~~$b_{22}$~~ | ~~$b_{23}$~~ | ~~$b_{24}$~~ | $b_{25}$ |
| Agent 3 | $b_{31}$ | $b_{32}$ | $b_{33}$ | $b_{34}$ | $b_{35}$ |
| Agent 4 | ~~$b_{41}$~~ | ~~$b_{42}$~~ | $b_{43}$ | ~~$b_{44}$~~ | ~~$b_{45}$~~ |
| Agent 5 | $b_{51}$ | $b_{52}$ | $b_{53}$ | $b_{54}$ | $b_{55}$ |

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# Endogenous Position Assignment

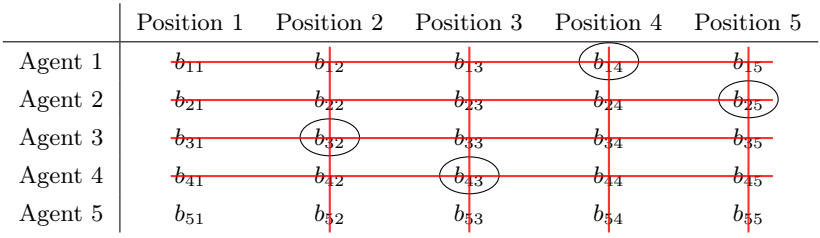
The highest among the remaining four bids is identified and that position is assigned to that agent.

| | Position 1 | Position 2 | Position 3 | Position 4 | Position 5 |
|---|---|---|---|---|---|
| Agent 1 | ~~$b_{11}$~~ | ~~$b_{12}$~~ | ~~$b_{13}$~~ | $b_{14}$ | ~~$b_{15}$~~ |
| Agent 2 | ~~$b_{21}$~~ | ~~$b_{22}$~~ | ~~$b_{23}$~~ | ~~$b_{24}$~~ | $b_{25}$ |
| Agent 3 | $b_{31}$ | $b_{32}$ | $b_{33}$ | $b_{34}$ | $b_{35}$ |
| Agent 4 | ~~$b_{41}$~~ | ~~$b_{42}$~~ | $b_{43}$ | ~~$b_{44}$~~ | ~~$b_{45}$~~ |
| Agent 5 | $b_{51}$ | $b_{52}$ | $b_{53}$ | $b_{54}$ | $b_{55}$ |

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# Endogenous Position Assignment

All bids by that agent and for that position are removed from further consideration




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# Endogenous Position Assignment

The remaining position is assigned to the last agent.

| | Position 1 | Position 2 | Position 3 | Position 4 | Position 5 |
|---|---|---|---|---|---|
| Agent 1 | $b_{11}$ | $b_{12}$ | $b_{13}$ | $b_{14}$ | $b_{15}$ |
| Agent 2 | $b_{21}$ | $b_{22}$ | $b_{23}$ | $b_{24}$ | $b_{25}$ |
| Agent 3 | $b_{31}$ | $b_{32}$ | $b_{33}$ | $b_{34}$ | $b_{35}$ |
| Agent 4 | $b_{41}$ | $b_{42}$ | $b_{43}$ | $b_{44}$ | $b_{45}$ |
| Agent 5 | $b_{51}$ | $b_{52}$ | $b_{53}$ | $b_{54}$ | $b_{55}$ |

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# Individual Earnings

Difference in Individual Earnings
(Experimental minus Conditional Bayesian)

| Treatment | Number of Observed Actions | | | | |
|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 |
| N1 | 16.07 | 16.07 | -96.43* | 16.07 | -80.36* |
| | (28.00) | (36.20) | (49.61) | (58.43) | (47.43) |
| N2 | -9.18 | - | -55.10 | -55.10 | -18.37 |
| | (30.60) | - | (40.73) | (55.10) | (41.41) |
| N3 | -40.18† | 8.04 | - | - | -32.14 |
| | (26.50) | (29.09) | - | - | (39.49) |
| N1A | -12.86 | -38.57 | -38.57 | 0.00 | -12.86 |
| | (34.23) | (33.95) | (46.46) | (48.45) | (34.23) |
| N3A | -12.86 | -6.43 | - | - | -38.57* |
| | (18.22) | (29.56) | - | - | (21.94) |

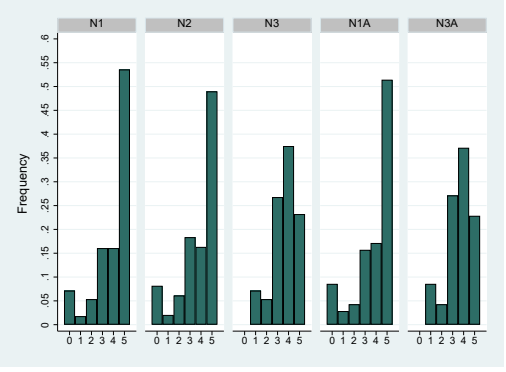
Average, standard errors reported in parentheses

† $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

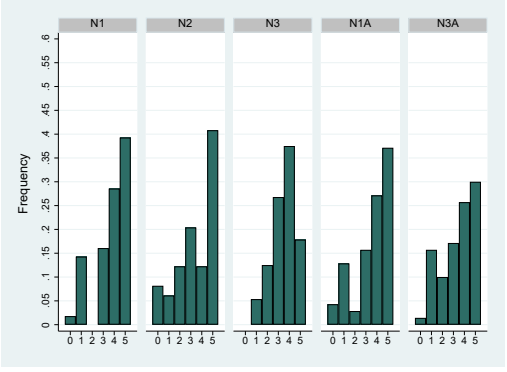
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# Correct Choices in a Group

**All Bayesian**




**Experimental**




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# Individual Criterion

Difference in Proportion of Final Agents making Correct Choice (All Bayesian)

| | N2 | N3 | N1A | N3A |
|---|---|---|---|---|
| N1 | 0.0204 | -0.0179 | 0.0143 | -0.0143 |
| | (0.0705) | (0.0643) | (0.0639) | (0.0615) |
| N2 | - | -0.0383 | -0.0061 | -0.0347 |
| | - | (0.0689) | (0.0684) | (0.0662) |
| N3 | - | - | 0.0321 | 0.0036 |
| | - | - | (0.0620) | (0.0596) |
| N1A | - | - | - | -0.0286 |
| | - | - | - | (0.0591) |

Cells denote difference in proportions of row treatment minus column treatment

Standard errors reported in parentheses

† $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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# Effect of Observed Informative Actions on Earnings

All Bayesian

| | N1 | N2 | N3 | N1A | N3A |
|---|---|---|---|---|---|
| Informative Actions | 19.87 | 19.30 | 36.01** | 26.55† | 38.57*** |
| | (18.47) | (18.40) | (16.19) | (16.68) | (14.55) |
| Constant | 673.10*** | 654.70*** | 612.50*** | 645.70*** | 604.30*** |
| | (38.61) | (36.74) | (30.72) | (35.29) | (27.60) |

Experimental

| | N1 | N2 | N3 | N1A | N3A |
|---|---|---|---|---|---|
| Informative Actions | -23.08 | -17.21 | 27.98** | 8.15 | 1.67 |
| | (21.00) | (23.07) | (13.11) | (18.00) | (15.19) |
| Constant | 711.30*** | 646.30*** | 596.40*** | 633.90*** | 610.00*** |
| | (42.71) | (41.92) | (30.15) | (38.28) | (24.96) |

Standard errors (clustered at subject level) reported in parentheses

† $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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# Demand for Information

Subject Bids by Number of Observed Actions

| | OLS | Tobit |
|---|---|---|
| N3A | 2.96 | 7.44 |
| | (2.61) | (7.49) |
| 1 Observed Action | 0.73† | 5.03* |
| | (0.45) | (2.68) |
| 2 Observed Actions | 4.51*** | 17.72*** |
| | (1.43) | (4.92) |
| 3 Observed Actions | 18.78*** | 36.75*** |
| | (4.52) | (8.62) |
| 4 Observed Actions | 20.35*** | 37.21*** |
| | (4.74) | (9.11) |
| N3A × 1 Observed Action | 3.68** | 5.14 |
| | (1.47) | (4.08) |
| N3A × 4 Observed Actions | 13.28* | 15.31 |
| | (7.10) | (12.12) |
| Constant | 4.97*** | -19.20*** |
| | (1.08) | (6.34) |

Standard errors (clustered at subject level) reported in parentheses

† $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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