# Information Aggregation on Networks: an Experimental Study

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# Introduction

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- In many cases, information aggregation occurs through a dynamic process in which individuals form beliefs based on multiple sources:
  - Personal experience (noisy private information).
  - Observing actions of family, friends, neighbors, coworkers, and others.

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  - Learning organizational culture (e.g., wage renegotiation).
  - Purchasing goods that are not publicly consumed (e.g., a mattress).

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# This Work

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- The network structure is given (no network formation).
- We focus on common real-life features of networks. Specifically, highly-connected cliques and influential individuals.
- We try to study frictions in information aggregation as interactions between:
  - The structural features.
  - The aggregate quality of the information.
  - Behavioral tendencies.

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- Each individual observes a noisy but informative signal about the true state.
- In every round, individuals observe their neighbors' previous guesses and then guess the state.
- All individuals are incentivised to match the state.
- The architecture of the social network and one's position in it determine the information available to the individual (beyond the noisy signal).

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- In addition, in most cases, the agents are assumed to be myopic and to communicate their beliefs.
- Bottom line: Mild conditions on the network structure, the agents inference abilities and the signal structure are sufficient for a complete convergence to the truth in connected societies.
- Bikhchandani, Hirshleifer, Tamuz and Welch (2024): *"An overarching conclusion ... is that egalitarianism in network structure, formalized in various ways, promotes information aggregation and welfare. This lesson holds across a variety of Bayesian, quasi-Bayesian and heuristic settings."*

# Theoretical Approaches to Inference

- Bayesian updating: Gale and Kariv (2003), Acemoglu, Dahleh, Lobel and Ozdaglar (2011), Mueller-Frank (2013), Mossel, Sly and Tamuz (2015).
- Naive Updating: DeGroot (1974), DeMarzo, Vayanos and Zwiebel (2003), Golub and Jackson (2010, 2012), Acemoglu and Ozdaglar (2011).
- Other updating rules: Bala and Goyal (1998), Goyal and Vega-Redondo (2005).
- Most up-to-date surveys: Golub and Sadler (2016), Bikhchandani, Hirshleifer, Tamuz and Welch (2024).

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- Bottom line: Individuals are not Bayesian but they are also not exactly naive.
    - Lab experiments: Choi, Gale and Kariv (2005, 2012), Choi, Goyal, Moisan and To (2023), Corazzini, Pavesi, Petrovich and Stanca (2012), Mueller-Frank and Neri (2013), Grimm and Mengel (2020), Chandrasekhar, Larreguy and Xandri (2020).
    - Field experiments: Breza and Chandrasekhar (2019), Banerjee, Breza, Chandrasekhar and Mobius (2021).

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- Our approach: Large, laboratory, network specific experiments.
- The closest work: Choi, Goyal, Moisan and To (2023).

# Brief Outline

- Introduction - Done !
- **Experimental design**.
- Theory.
- Network level results.
- Position level results.
- Additional insights.

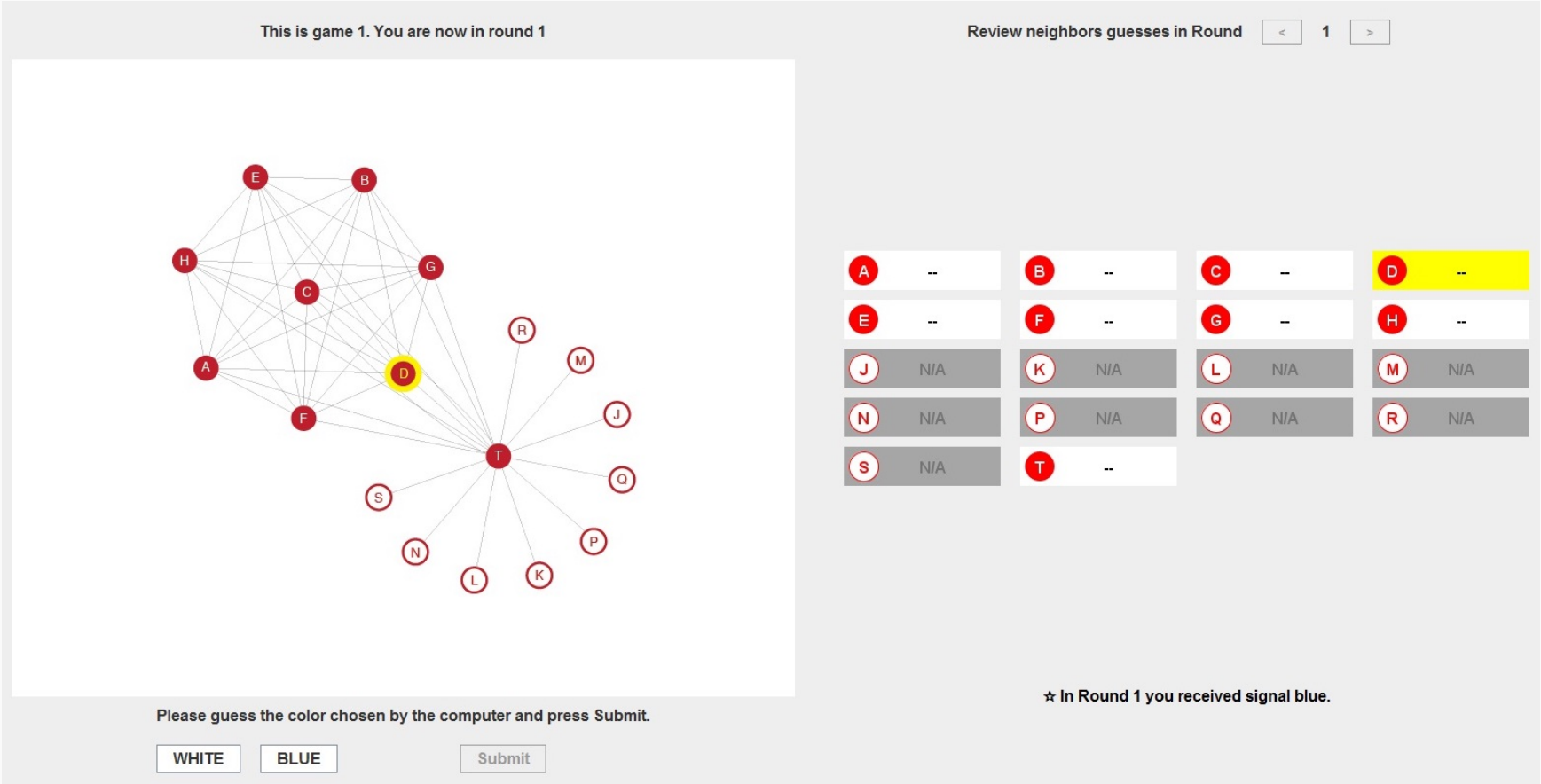
# Experimental Design

- 10 games in a session, same network structure.
  - 18 members in a network.
  - Positions are re-shuffled between games.
- In each game
  - Before Round 1:
    - Nature determines the state (50/50).
    - Each player gets a private signal about the state (iid, 70% correct).
  - Round 1:
    - Each player guesses the state.
  - Rounds 2 onwards:
    - Observe guesses of neighbors and guess the state.
- The game ends if no one changes her guess in three consecutive rounds or with prob 50% after round 50.

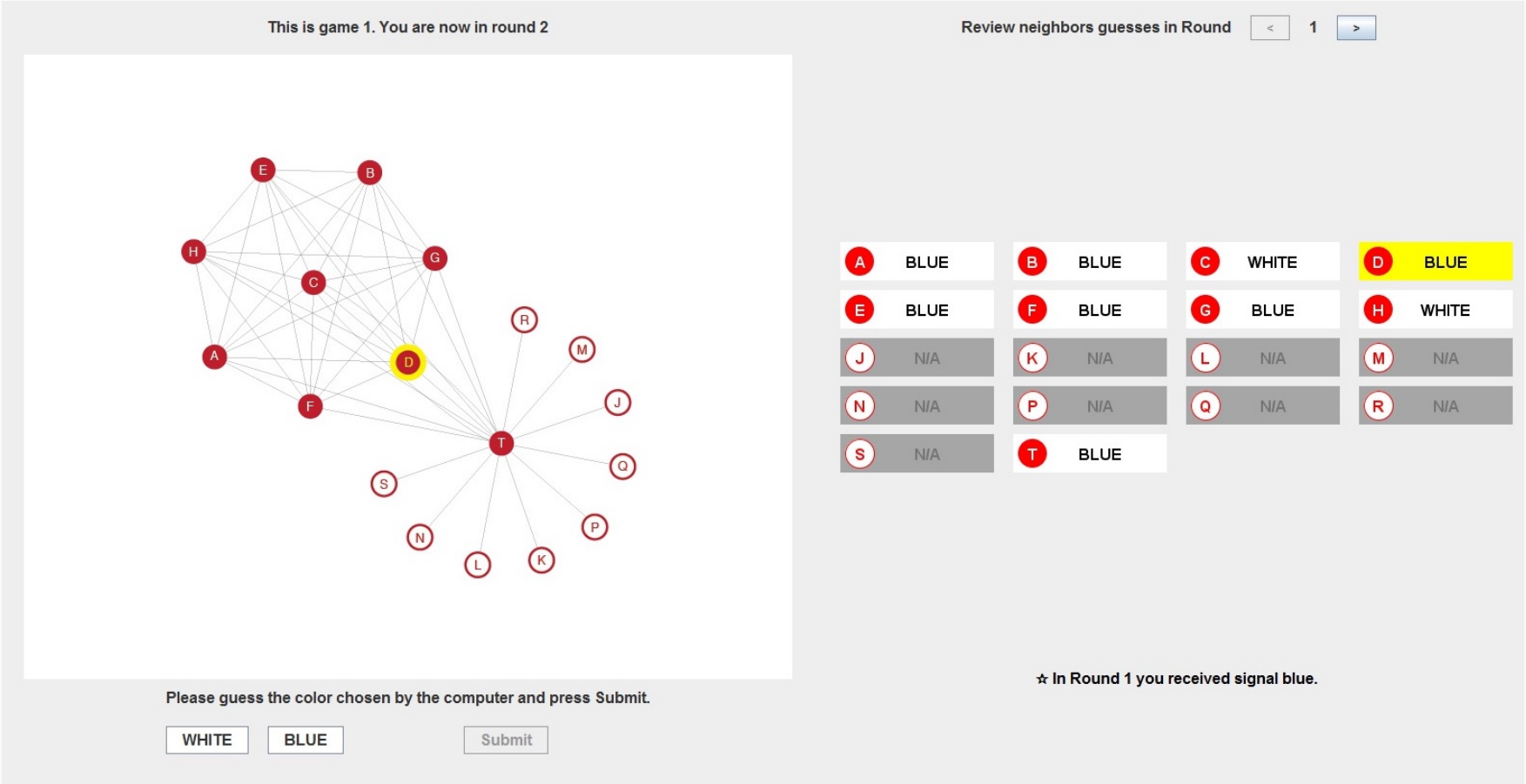
# Payoffs

- Show up fees.
- payment on a performance in one randomly chosen round of a randomly chosen game: correct guess $20, wrong $5.
- Incentivised control tasks: risk attitudes, probability matching (Rubinstein (2002)), demographics.

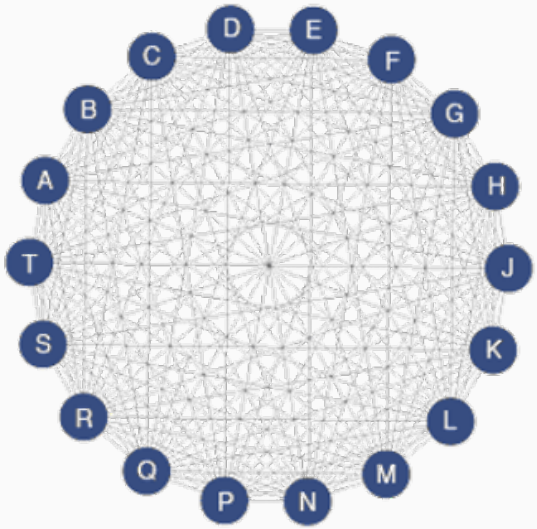
# Screenshot 1



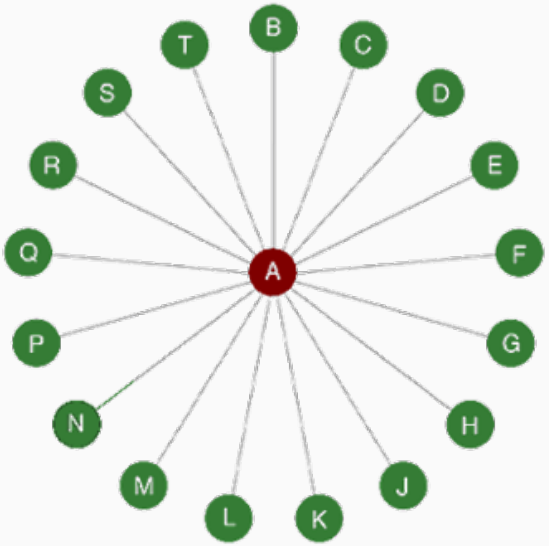
# Screenshot 2



# Networks




COMPLETE




STAR

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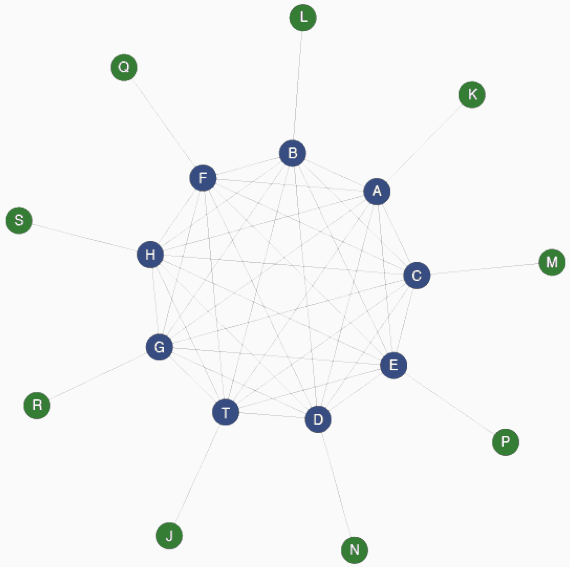
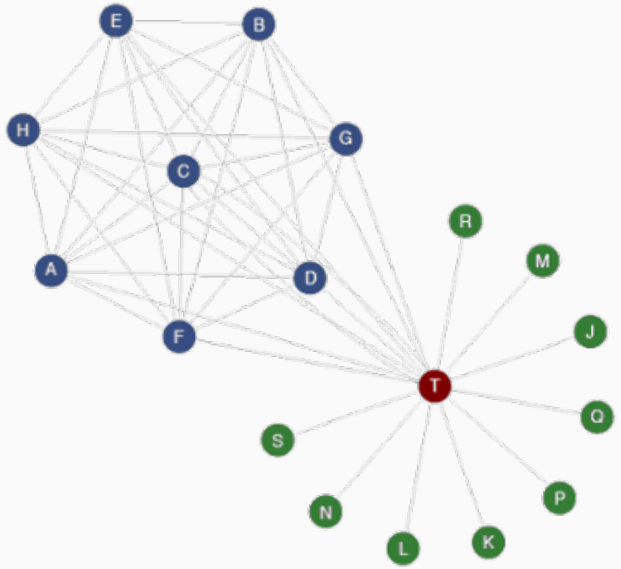
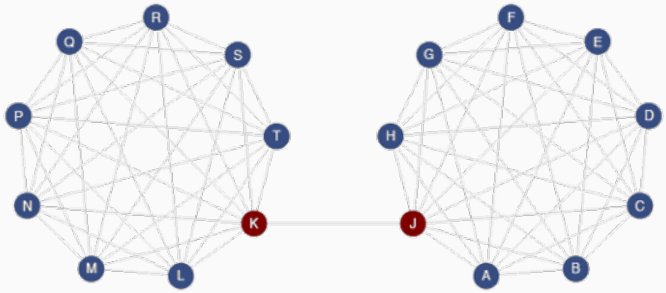


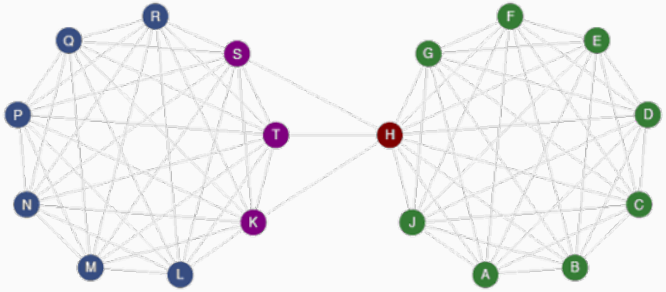

CORE PERIPHERY



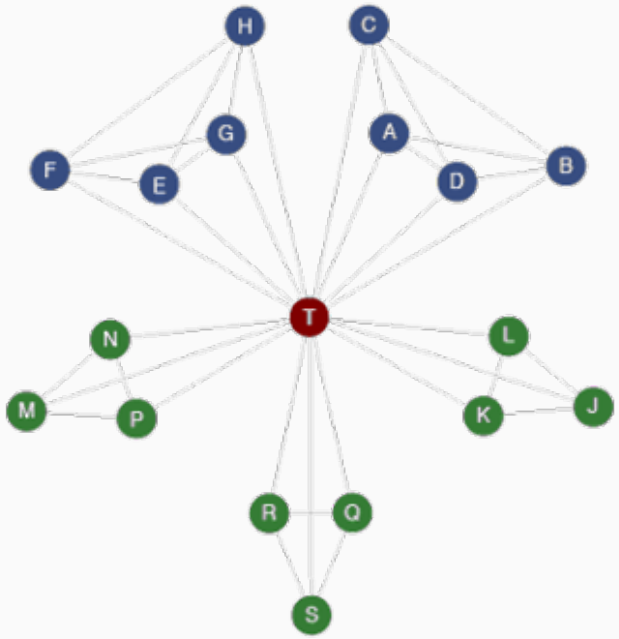

ONE GATE




TWO CORES ONE LINK




TWO CORES THREE LINKS




SINGLE MEDIATOR

# Dataset

| | # sessions |
|---|---|
| COMPLETE | 5 sessions |
| CORE PERIPHERY | 6 sessions |
| STAR | 5 sessions |
| ONE GATE | 6 sessions |
| SINGLE MEDIATOR | 6 sessions |
| TWO CORES ONE LINK | 6 sessions |
| TWO CORES THREE LINKS | 6 sessions |
| | 40 sessions |
| | over 800 subjects |

Notes: Sessions conducted at UCI, UCSD, OSU, TAU and BGU. Other structures on which we do not report today are small complete, small star, complex. We also do not report today on "observers" behavior.

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- Introduction - Done !
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- **Theory**.
- Network level results.
- Position level results.
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Assume common knowledge that all agents are Myopic Bayesian.

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The agents' objective function is to guess the majority of signals in the network. [If tie, everything goes.]

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   - Agranov, Gillen and Persitz (2024): $C(i)$ is either empty and no imitation takes place or it is a singleton, $C(i) = \{j\}$ and $\forall t > 2 : a_i^t = a_j^{t-1}$.

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  - If 5-4, the specific tie breaking rule kicks in.

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  - The case where the connectors disagree in R2 is very hard computationally - Therefore we say that these structures also potentially suffer from a structural friction.

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- Theory - Done !
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- Signals' strength
  - weak signals (11 or less) / average strength / strong signals (14 or more).

# Information Aggregation Measure

Aggregate level Learning Index (ALI)

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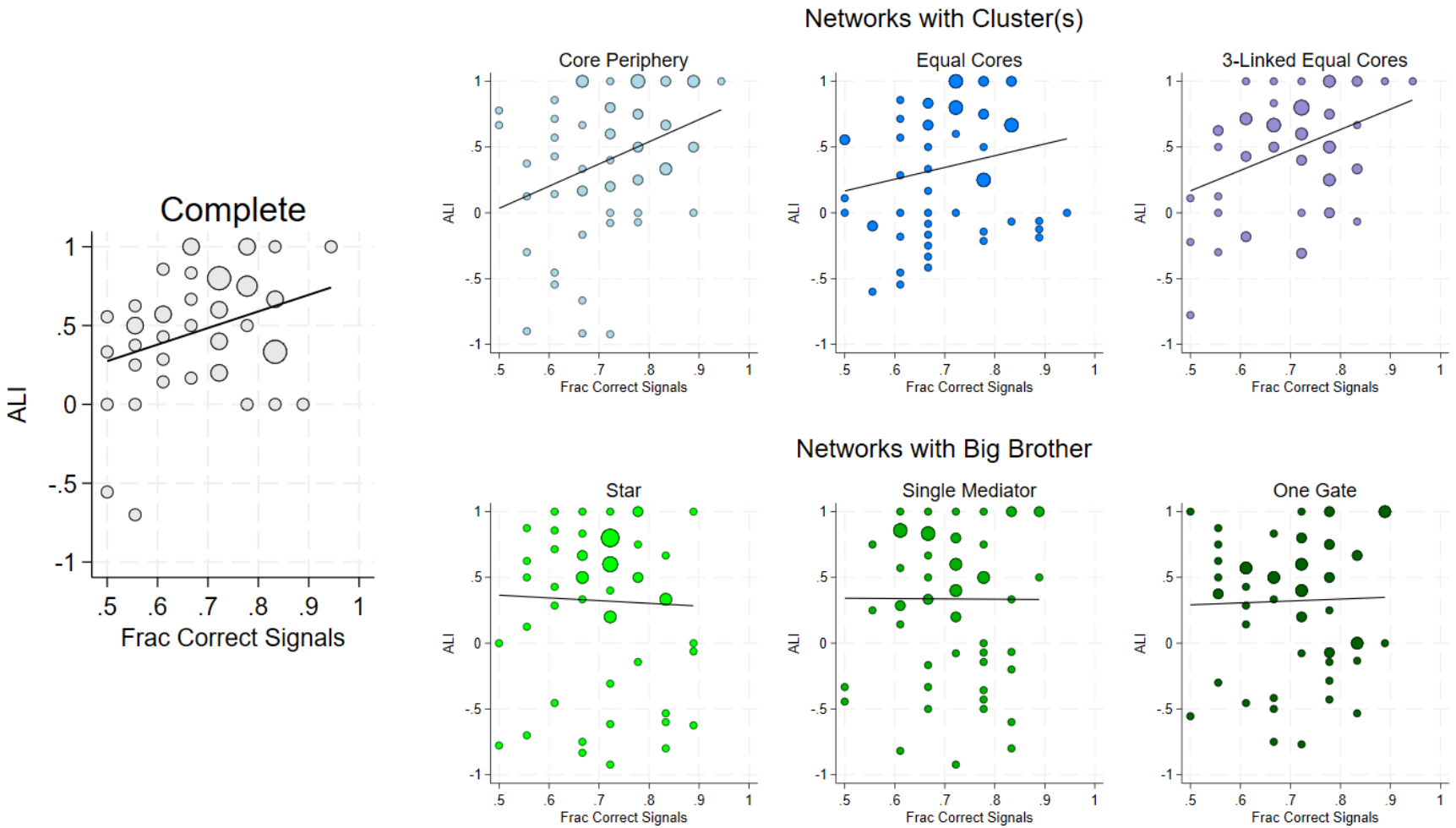
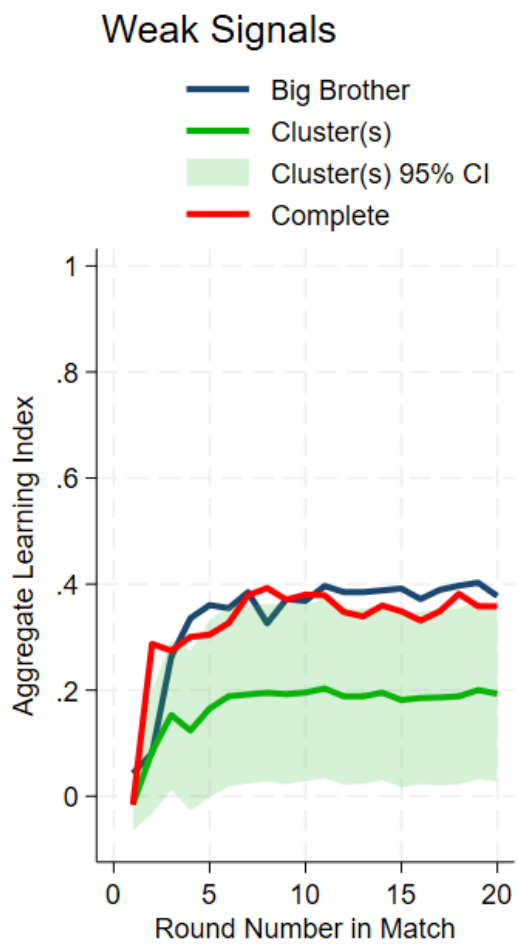
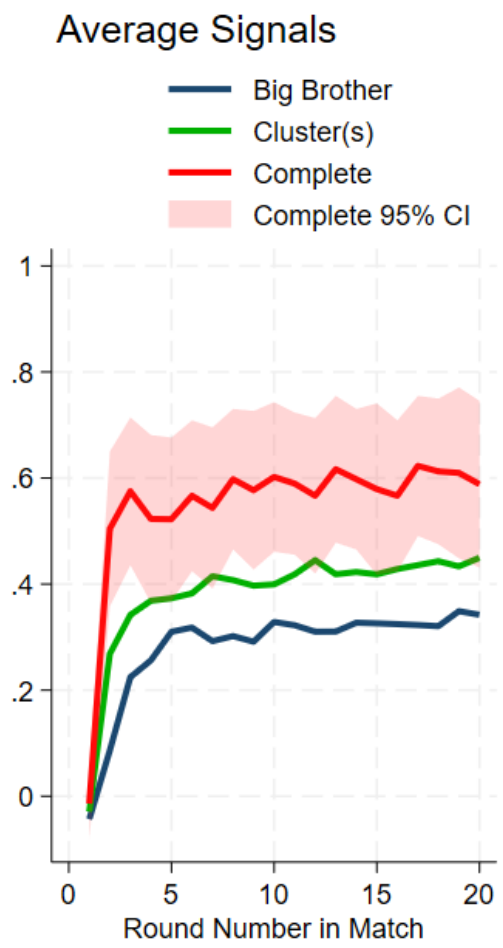
- Results are qualitatively similar if we use a measure that takes into account the composition of learners.

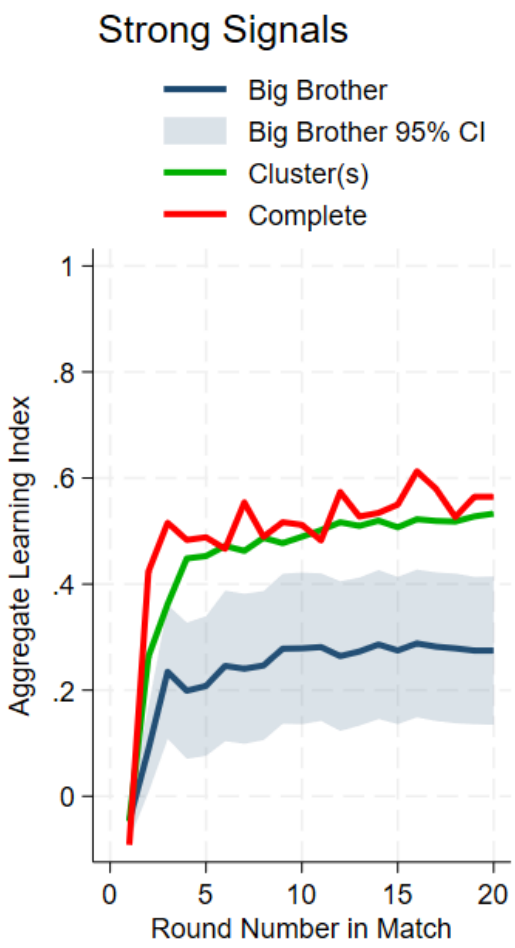
# Networks Classification



# Evolution of Learning Index throughout the Game



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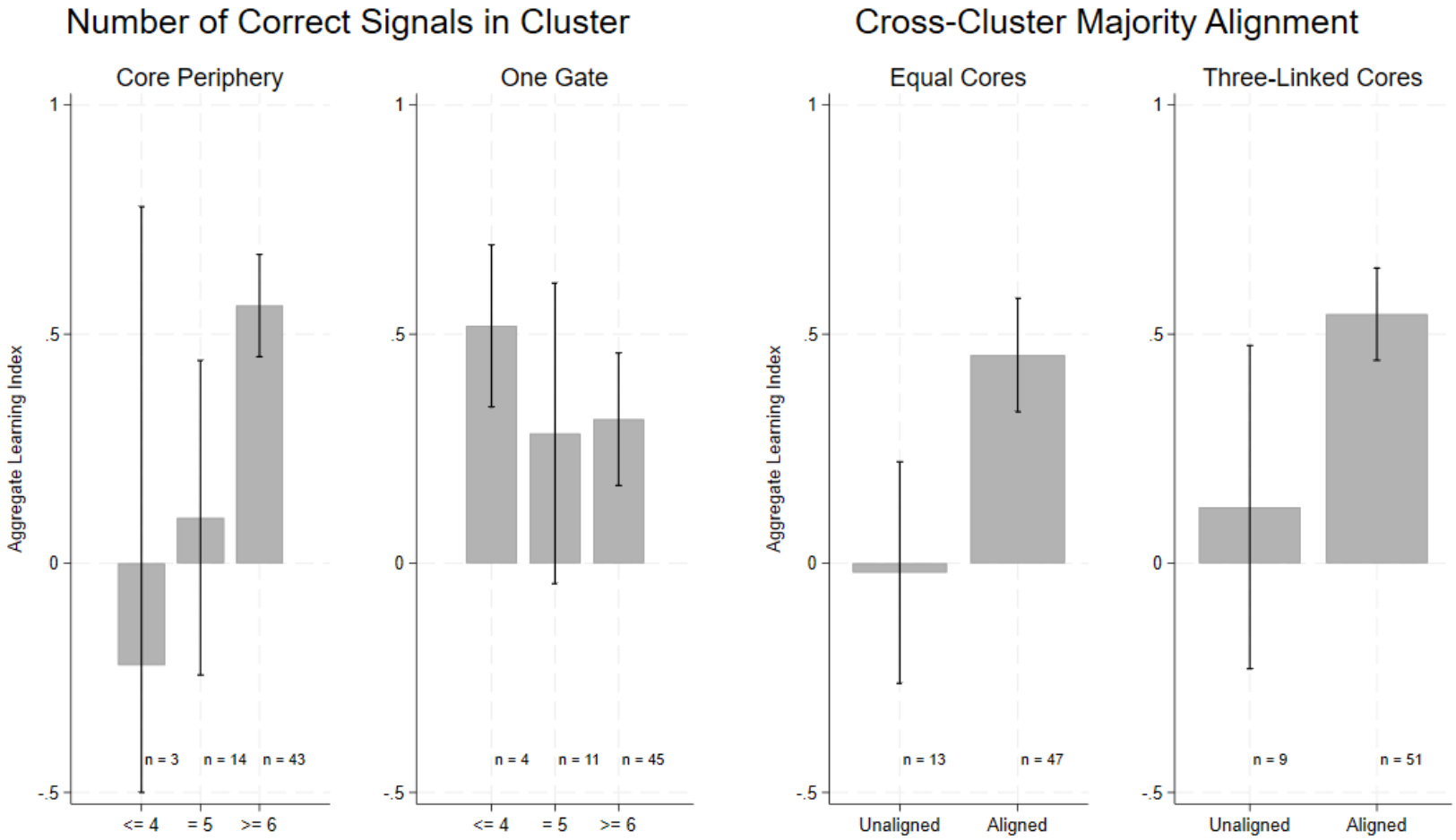
- Cluster(s) networks respond monotonically to the quality of initial information and reach the same level of learning as the Complete network when initial signals are highly informative.
  - When the initial signals are poor, these networks often fail, inline with the structural frictions mentioned earlier.

# Structural Frictions



# Brief Outline

- Introduction - Done !
- Experimental design - Done !
- Theory - Done !
- Network level results - Done !
- **Position level results.**
- Additional insights.

# Focusing on R1, R2 and R3

- We saw that the interesting things happen right away.
- Additional methodological argument: Switching after round 4 is confusing (except in the Two Cores).
- Switching in R4 onwards is correlated with low-quality choices in the initial rounds of the game and with tendency towards probability matching.

# R1 behavior

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| | *Complete* | *Star* | *Single Mediator* | *One Gate* | *Core Periphery* | *Equal Cores* | *3-Linked Eq Cores* |
| All nodes | 91% | 93% | 91% | 90% | 94% | 92% | 91% |
| Big brothers | | 90% | 92% | 92% | | | |
| Cluster members | 91% | | 91% | 88% | 94% | 92% | 91% |
| leaves | | 93% | | 92% | 95% | | |
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- In 95% of the games in which the initial distribution of signals was not 50- 50, misreporting did not change the derived state.
- *Subjects tend to report their private signals in the first round of the game. Mistakes are relatively rare and are not systematic across network structures and network positions.*

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- Our data: If own signal is consistent with local majority, the agent should repeat her previous guess (R1 maj), otherwise the agent should change her guess (R1 min). [No leaves]

| | Benchmark | | *Big Brother* networks | | | | | | *Cluster(s)* networks | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Complete | | Star | | Single Mediator | | One Gate | | Core Periphery | | Equal Cores | | 3-Linked Eq Cores | |
| | maj | min | maj | min | maj | min | maj | min | maj | min | maj | min | maj | min |
| All nodes | 96% | 59% | 97% | 45% | 93% | 55% | 93% | 37% | 95% | 58% | 94% | 59% | 93% | 54% |
| Big brothers | | | 97% | 45% | 89% | 63% | 98% | 55% | | | | | | |
| Cluster members | | | | | 94% | 54% | 93% | 34% | 95% | 58% | 94% | 57% | 94% | 51% |
| Connectors | | | | | | | | | | | 97% | 73% | 94% | 51% |

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- Also discussed is relevant contexts in Conlon, Mani, Rao, Ridley and Schilbach (2022), Esponda, Oprea and Yuksel (2023), Bikhchandani, Hirshleifer, Tamuz and Welch (2024)

# Determinants of R2 guesses

| | *Dependent Variable:* Correct Round 2 Guess | |
|---|---|---|
| | All Non-Leaf Nodes | |
| | Reg (1) | Reg (2) |
| *Minority Characteristics* | | |
| R1 Minority Status | -0.380*** (0.019) | -0.333*** (0.047) |
| R1 Minority Size | | -0.132** (0.048) |
| R1 Minority Size × Status | | -0.599*** (0.123) |
| *Node Characteristics* | | |
| Node Degree | | 0.050 (0.050) |
| Node Degree × R1 Minority Status | | 0.193** (0.072) |
| Individual controls | no | yes |
| R-squared | 0.307 | 0.341 |
| # of Observations | 4,904 | 4,904 |
| # of Clusters | 756 | 756 |
| # of Session-Match Fixed Effects | 404 | 404 |

* p<0.05, ** p<0.01, *** p<0.001. Standard errors in parentheses

# Summary of R2 behavior

- Subjects are roughly 40% less likely to report the correct guess in R2 if they are part of R1 minority group in their local neighborhood.
  - Pure behavioral friction, all nodes, all networks.
  - Increases with minority group size (which affects majority subjects as well).
  - Partially mitigated by the size of the local neighborhood (i.e. decreases with degree centrality).
- Recall that both myopic Bayesian subjects and Naive subjects are predicted to aggregate locally independent if they belong to the minority or majority after the first round.

# R3 behavior

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| | *Big Brother* networks | | | | | | *Cluster(s)* networks | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Star | | Single Mediator | | One Gate | | Core Periphery | | Equal Cores | | 3-Linked Eq Cores | |
| Guesses in R2 | same | diff | same | diff | same | diff | same | diff | same | diff | same | diff |
| leaves | 94% (659) | 46% (361) | | | 95% (364) | 46% (176) | 97% (367) | 60% (173) | | | | |
| Cluster member small | | | 95% (650) | 35% (370) | | | | | | | | |
| medium | | | | | 94% (331) | 31% (149) | | | 97% (714) | 22% (246) | 95% (621) | 27% (219) |

# Under-Imitation

- Subjects are strongly reluctant to imitate the influential player if they disagree in R2.
  - Pure behavioral friction, all (relevant) nodes, all (relevant) networks.
  - Increases with the size of the local neighborhood (unlike under-reaction to new information).
- Naive subjects that decide by simple majority are not expected to imitate.

# Determinants of R3 guesses (of potential imitators)

| | *Dependent Variable:* Round 3 guess matches Round 2 guess of the influencer | | |
|---|---|---|---|
| | leaves | cluster members | leaves cluster members |
| | Reg (1) | Reg (2) | Reg (3) |
| Constant | 0.94*** (0.01) | 0.93*** (0.02) | 0.93*** (0.03) |
| *Local information in Round 2* | | | |
| Disagree with influencer | -0.48*** (0.03) | -0.54*** (0.04) | -0.45*** (0.05) |
| Influencer switch | 0.06 (0.04) | -0.06 (0.05) | 0.09 (0.06) |
| Disagree with influencer × Influencer switch | 0.14*** (0.05) | 0.178*** (0.05) | 0.302*** (0.07) |
| R2 maj | | 0.03 (0.02) | 0.01 (0.03) |
| Disagree with influencer × R2 maj | | -0.16*** (0.04) | -0.04 (0.04) |
| R2 maj × Influencer switch | | 0.04 (0.04) | -0.04 (0.04) |
| Disagree with influencer × R2 maj × Influencer switch | | -0.22*** (0.07) | -0.17*** (0.06) |
| *Individual type* | | | |
| Guess wrong in Round 1 | -0.15*** (0.03) | -0.10*** (0.02) | -0.12*** (0.02) |
| Guess wrong in Round 2 | 0.05 (0.07) | -0.05* (0.03) | -0.01 (0.03) |
| *Network structural feature* × Local Information | | | |
| Ratio | | | -0.01 (0.04) |
| Ratio × Influencer switch | | | -0.05 (0.05) |
| Ratio × Disagree with influencer | | | -0.23*** (0.05) |
| Ratio × Disagree with influencer × Influencer switch | | | -0.33*** (0.10) |
| R-squared | 0.286 | 0.449 | 0.386 |
| # of Game Fixed Effects | 180 | 240 | 360 |
| # of Observations | 2,100 | 3,300 | 5,400 |
| # of Clusters | 362 | 484 | 724 |

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  - These effects interact.

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  - Previous actions of the influential person.
  - The signals of the (non-influential) neighbors.
- BIG BROTHER networks suffer the most.
- In the other networks behavioral frictions and structural frictions are intertwined.

# Brief Outline

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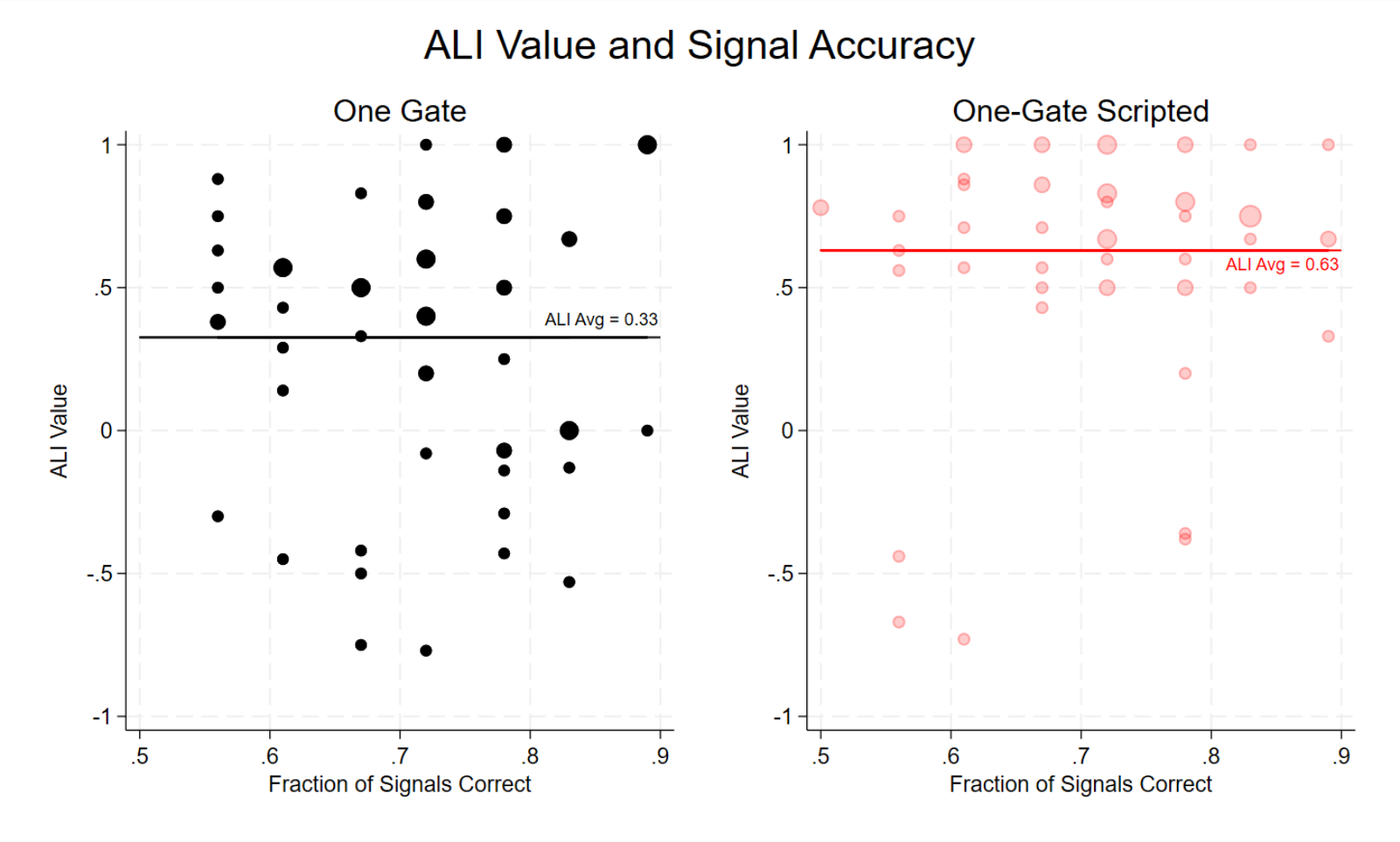
- Focus on the "hardest" case where a cluster member observes the influencer in addition to having large neighborhood: One Gate.
- Removing Big Brother's signal
  - Six additional sessions One Gate Scripted
  - No signal to the Big Brother, same signals to all other members

# One Gate vs. One Gate Scripted

One Gate Scripted performs better than One Gate



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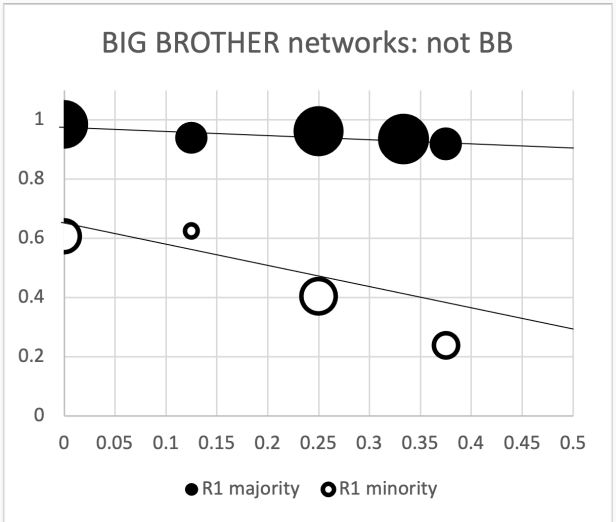
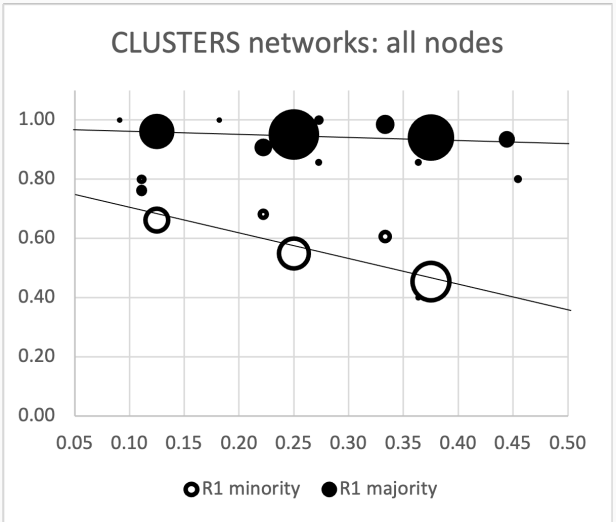
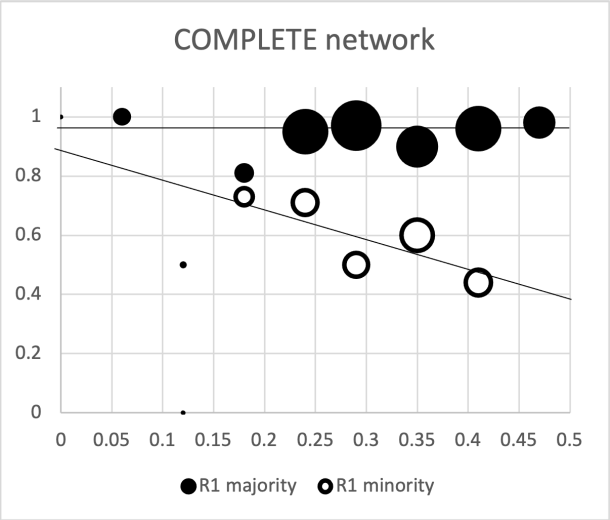
  2. The other members imitate the influencer more (trust?)
     - Leaves imitate the influencer 13% more when disagree in R2.
     - Cluster members imitate the influencer 22% more when they disagree in R2 and are part of R2 minority.
     - No improvement in imitation rates for cluster members who disagree with the influencer and part of R2 majority.

# What is wrong with the Big Brother?



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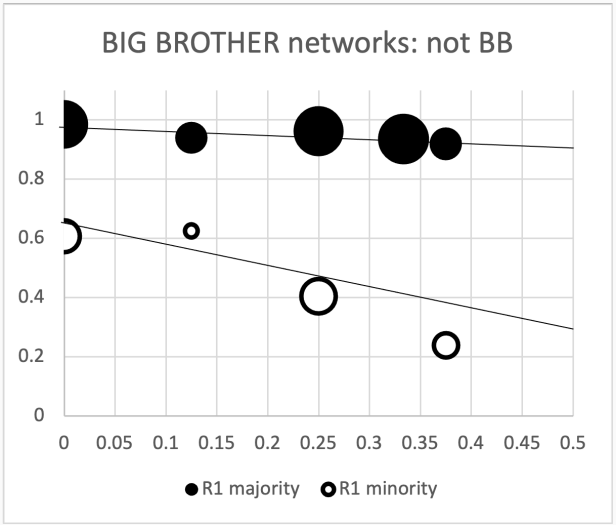


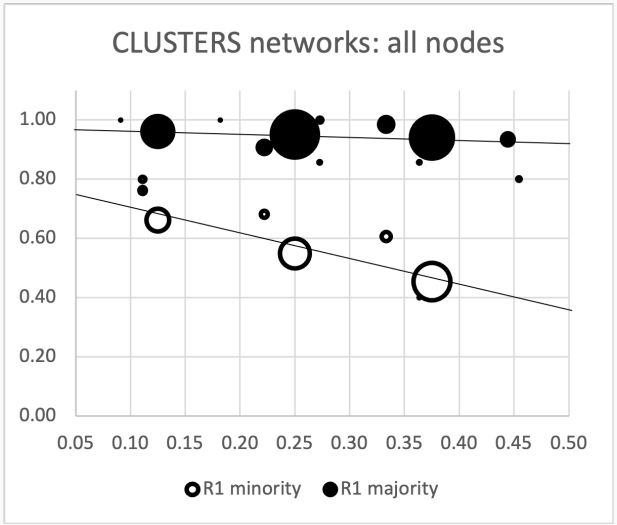


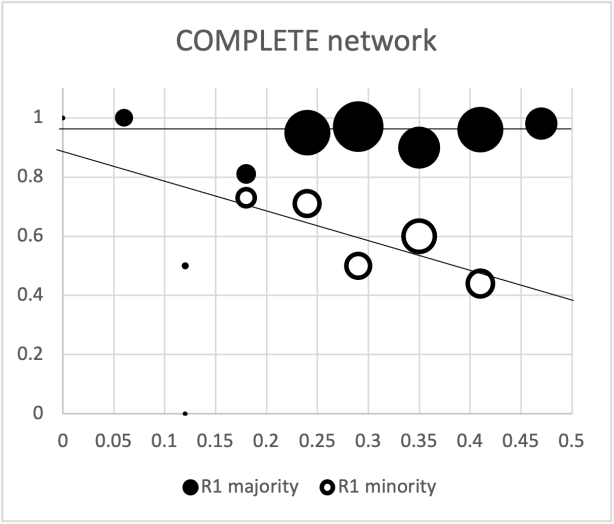


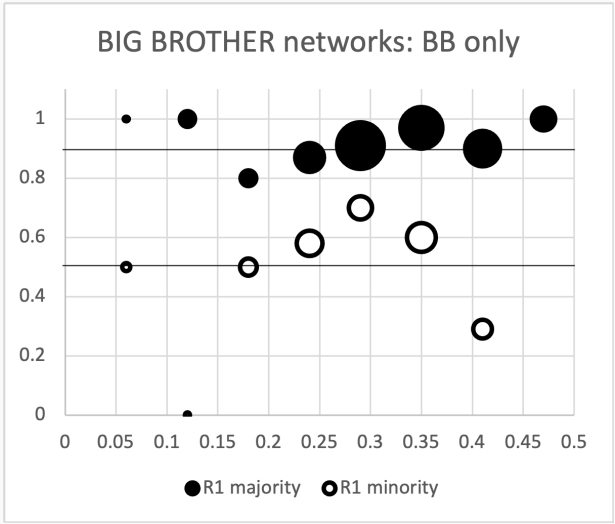

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- Why? Lack of monitoring? (when compared to the complete network)

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- These frictions interact with structural properties.
- Players are aware to these frictions and react to them.

# Brief Outline

- Introduction - Done !
- Experimental design - Done !
- Theory - Done !
- Network level results - Done !
- Position level results - Done !
- Additional insights - Done !

# Thanks


THANK
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