Forecasting the Forecasts of Others on Social Networks

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Introduction

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 - social networks exhibit strong connectivity and diverse opinions
 - existing models predict consensus on strongly connected networks

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 - ▶ introduce a simple method to solve Bayesian games for any network structure

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 - social networks exhibit strong connectivity and diverse opinions
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- Our contributions are twofold
 - develop a dynamic game of imperfect communication to explain "failure of social consensus"
 - introduce a simple method to solve Bayesian games for any network structure
- We study opinion formation in media networks
 - does mainstream media have incentive to report truthfully?
 - can citizen journalism improve information transmission?

The Road Ahead...

1 Model: Bayesian Network Game, Frequency-Domain Solution

2 Analysis: Mainstream Media, Citizen Journalist

Finite network of rational agents with asset demand

$$d_{i,t} = \mathbb{E}_{i,t} p_{t+1} - (1+r) p_t, \quad i \in N$$

Exogenous asset supply

$$s_t = rac{1}{1-
ho\,\mathrm{L}} heta_t + \eta_t, \quad heta_t \sim \mathcal{N}(0,\sigma_{ heta}^2), \quad \eta_t \sim \mathcal{N}(0,\sigma_{\eta}^2)$$

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Agent i's information set (i.e. type)

$$\mathcal{I}_{i,t} = \{p_s\}_{s \leq t}$$

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► Agent *i*'s information set (i.e. type)

$$\mathcal{I}_{i,t} = \{p_s\}_{s \leq t} \vee \{q_{i,s}\}_{s \leq t}$$

- ightharpoonup public signal: p_t
- lacktriangledown private signal: $q_{i,t}= heta_t+v_{i,t},\ v_{i,t}\sim\mathcal{N}(0,\sigma_{v_i}^2)$

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Agent i's information set (i.e. type)

$$\mathcal{I}_{i,t} = \{p_s\}_{s \le t} \vee \{q_{i,s}\}_{s \le t} \vee \{\mathbb{E}_{i,s}^* p_{s+1}\}_{j \in N_i, s \le t}$$

- ightharpoonup public signal: p_t
- private signal: $q_{i,t} = \theta_t + v_{i,t}$, $v_{i,t} \sim \mathcal{N}(0, \sigma_{v_i}^2)$
- neighbors' noisy opinions: $\mathbb{E}_{j,t}^* p_{t+1} = \mathbb{E}_{j,t} p_{t+1} + u_{j,t}, j \in N_i,$ $u_{j,t} \sim \mathcal{N}(0, \sigma_{u_j}^2)$

Nash Equilibrium

► Market clearing introduces higher-order expectations (HOE)

$$p_t = \frac{1}{1+r} \left(\sum_{i \in N} \lambda_i \mathbb{E}_{i,t} p_{t+1} - s_t \right), \quad \sum_{i \in N} \lambda_i = 1$$

- lacktriangle failure of law of iterated expectations \Rightarrow intertemporal HOE
- ▶ informational network linkages ⇒ intratemporal HOE

Nash Equilibrium

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- ightharpoonup failure of law of iterated expectations \Rightarrow intertemporal HOE
- ▶ informational network linkages ⇒ intratemporal HOE
- Pure-strategy Nash equilibrium: profile of asset positions and information flows $\{(d_{i,t}, \mathcal{I}_{i,t})\}_{i \in N, t \in \mathbb{Z}}$ satisfying $\forall t \in \mathbb{Z}$
 - given $\{\mathcal{I}_{i,t}\}_{i\in N}$, $\{d_{i,t}\}_{i\in N}$ are chosen optimally
 - ▶ given $\{d_{i,t}\}_{i\in N}$, p_t clears market and is consistent with $\{\mathcal{I}_{i,t}\}_{i\in N}$

1. **Initialization.** Initialize agents' z-transform opinions

$$\mathbb{E}_{i,t} p_{t+1} = \sum_{k=0}^{\infty} P_{i,k} \, \mathcal{L}^k \, \boldsymbol{\epsilon}_t \quad \Leftrightarrow \quad P_i(z) = \sum_{k=0}^{\infty} P_{i,k} z^k$$

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2. **Aggregation.** Aggregate to obtain implied price

$$P(z) = \frac{1}{1+r} \left(\sum_{i \in N} \lambda_i P_i(z) - S(z) \right)$$

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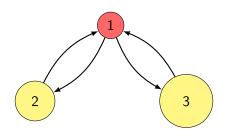
- 3. **Updating.** Update information set $\{P(z), Q_i(z), \{P_j^*(z)\}_{j \in N_i}\}$ and compute $P_i'(z)$ using Wiener-Hopf optimal prediction
- 4. **Recursion.** If $||P_i(z) P_i'(z)|| < \epsilon$, stop; otherwise, set $P_i(z) = P_i'(z)$ and go to step 2

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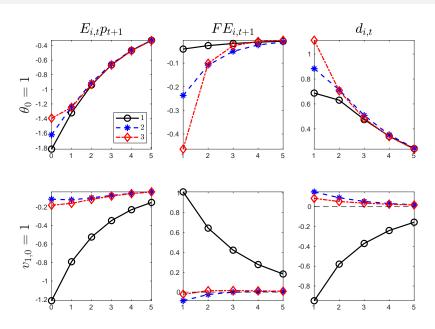
Mainstream Media



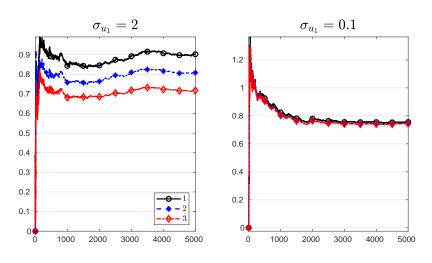
Agent i	1	2	3
λ_i : mass	0.1	0.3	0.6
σ_{u_i} : local opinion uncertainty	2	0.1	0.1
σ_{v_i} : private signal uncertainty	0.1	0.3	5

Notes: Global parameters are r=0.05, $\rho=0.7$, $\sigma_{\theta}=0.5$, and $\sigma_{\eta}=0.5$.

Disparate Opinions

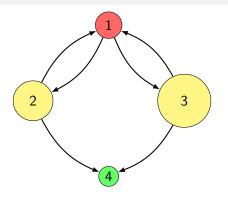


Wealth Distribution



$$w_{i,t+1} = (1+r)w_{i,t} + [p_{t+1} - (1+r)p_t]d_{i,t}, i \in N$$

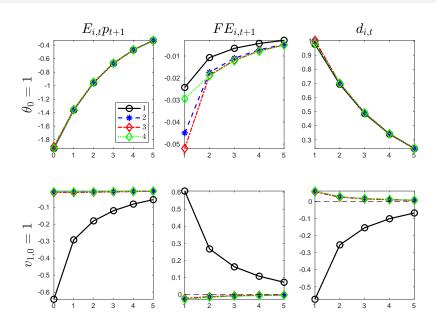
Citizen Journalist



Agent i	1	2	3	4
λ_i : mass	0.09	0.3	0.6	0.01
σ_{u_i} : local opinion uncertainty	2	0.1	0.1	0.1
σ_{v_i} : private signal uncertainty	0.1	0.3	5	0.1

Notes: Global parameters are r=0.05, $\rho=0.7$, $\sigma_{\theta}=0.5$, and $\sigma_{\eta}=0.5$.

Consensus Opinion



Conclusion

- We provide a new framework to study social learning in network games
 - continuous action space and general information-network structure
 - frequency-domain method to characterize equilibrium

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 - continuous action space and general information-network structure
 - frequency-domain method to characterize equilibrium
- ► Two promising extensions
 - DeGroot-type learning with weighted networks
 - network formation games