Information Resonance

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Overview

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This paper Information resonance:

- The same information is processed differently depending on the messenger
- People respond more to the experiences of people more "similar" to them

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This paper Information resonance:

- The same information is processed differently depending on the messenger
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What does this paper do?

- Framework to think about information resonance
- Information resonance vs. information access (differences in information diffusion)
- Measurement of information resonance
- Evidence on information resonance from occupational choice

Model

- Two dates $t = 0, 1$
- Heterogeneous agents $i = 1, ..., N$ with characteristics θ^i (*myopic* in dynamic setting)
- Action $a_{it} \in \{0, 1\}$ with payoff

$$U(a_{it}) = \mathbb{E}\left[a_{it} z_i + \epsilon_{it} \middle| \mathcal{I}_i\right],$$

where $z \sim N(\mu_z, \Sigma_z)$ and $\epsilon_{it} \overset{iid}{\sim} N\left(0, \sigma_\epsilon^2\right)$

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  where $z \sim N(\mu_z, \Sigma_z)$ and $\epsilon_{it} \overset{iid}{\sim} N\left(0, \sigma_\epsilon^2\right)$
- Information set $\mathcal{I}_i$:
  - if agent j took an action at $t = 0$, agent i may observe agent j's **payoff** at date 1

$$a_{j0} z_j + \epsilon_{j1}$$

  - Information access matrix $\mathcal{Z}^i$ with

$$\mathcal{Z}^i_{jh} = \begin{cases} 1 & \text{if investor } i \text{ observes agent's } j = h \text{ payoff and action 1} \\ 0 & \text{otherwise} \end{cases}$$

  - For now full access $\mathcal{Z}^i = \mathcal{Z}^j$ and signals

$$s = \mathcal{Z} z + \epsilon_1$$

Belief updating

- Belief updating: agents only learn from actions that they see taken

$$\mathbb{E}\left[z_i \middle| \mathcal{I}_i\right] = \mu_z + K_i \left(s^i - \mu_z 1\right) = \mu_z + K_{ii}\left(\mathcal{Z} z + \epsilon_1\right)$$

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- Bayesian updating: Kalman gain

$$K_{ii}^{\star} = \left(\mathcal{Z} \Sigma_z \mathcal{Z}' + \sigma_\epsilon^2 I\right)^{-1} \mathcal{Z} \Sigma_z \mathbf{1}_i$$

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- Information resonance: "tilted Kalman gain"

$$K_{ii}^R = \left(\overline{\omega}_i \omega_i\right) \circ \left(\left(\mathcal{Z}\Sigma_z\mathcal{Z}' + \sigma_\epsilon^2 I\right)^{-1} \mathcal{Z}\Sigma_z \mathbf{1}_i\right),$$

where $\overline{\omega}_i$ is chosen such that $K_{ii}^R \cdot \mathbf{1} = K_{ii}^\star \cdot 1$

- Belief weight depends on distance between characteristics. between agents

$$\omega_{ij}\left(\theta\right) = \underbrace{\left(2 - 2\Phi\left(\chi \left\|\theta_i, \theta_j\right\|\right)\right)}_{\rho_{ij}} \sigma_\epsilon^2$$

Information diffusion

- Choice characteristic space is crucial to understand patterns in information diffusion
  - Geographic space $\rightarrow$ random adoption
  - Characteristic space $\rightarrow$ diffusion

- Experts vs. role models: reach vs. closeness

- Network selection: whose action is seen may be correlated with similarity: captured by $\mathcal{Z}$
  - selection reinforces the effect of resonance!

Measurement

$$\mathbb{E}\left[z_j \middle| \mathcal{I}_{it} \right] = \mu_z + K_i \left(\mathcal{Z} z + \epsilon_1 \right)$$

Measurement

$$\mathbb{E}\left[z_j \middle| \mathcal{I}_{it}\right] = \mu_z + K_i \mathcal{Z}' \left(z + \epsilon_{it}\right) + \left(I - \mathcal{Z}'\right) \epsilon_{it}$$

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- Regression

$$\mathbb{E}\left[z_j \middle| \mathcal{I}_{it}\right] = \alpha + \beta_i \left(z + \epsilon_{it}\right) + \eta_{it}$$

  - $\mathbb{E}\left[z_j \middle| \mathcal{I}_{it}\right]$: agent j's expected payoffs reported by agent i
  - $z + \epsilon$: self reported payoffs

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  - $z + \epsilon$: self reported payoffs
- Matching coefficients

$$\beta_i = K_i \mathcal{Z}' = \left(\overline{\omega}_i \omega_i\right) \circ \left(\left(\mathcal{Z}\Sigma_z\mathcal{Z}' + \sigma_\epsilon^2 I\right)^{-1} \mathcal{Z}\Sigma_z\mathcal{Z}'\right)$$

- Resonance estimate:

$$\overline{\omega}_i \omega_i = \left(I + \sigma_\epsilon^2 \left(\mathcal{Z}\Sigma_z\mathcal{Z}'\right)^{-1}\right) \beta_i$$

- Need estimates for
  - $\mathcal{Z}$: information access matrix - ok if actions are observed + full observability
  - Σ_z: payoff covariance

Comments/Suggestions

1. Very nice framework to think about drivers of information diffusion
    - smart way of modeling resonance to use existing tools
    - well suited for measurement!
        - Whose experience will resonate with us? Best way to disseminate information?
    - ...There is a lot going on!

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3. Measuring information resonance vs information access
   - With full access, all resonance
   - Can we separate them with partial access?
     - Network selection: social connectedness data can make $\mathcal{Z}$ matrix observable (?)
     - Other moments that may help you measure resonance