Populism and Polarization in Social Media
Without Fake News: the Vicious Circle of Bias, Beliefs and Network Homophily

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Civil Security France: “[...] All means are being used, except for water-bombing aircrafts which, if used, could lead to the collapse of the entire structure of the cathedral.”
Research Question

Why do people feel more and more ok about ignoring expert opinion lately?
Why we care

Why we care


Why we care

- Hamilton, Hartter and Saito (2015): “\textbf{Trust in scientists on climate change and vaccines}” \textdownarrow

- Rodrik (2018), Guiso (2018): \textbf{Populism} \textuparrow

- Bloom (2016, 2019): Populism $\Rightarrow$ policy uncertainty $\Rightarrow$ economic performance $\downarrow$
What we do

Develop a **model/method** using **evolutionary games on networks** in order to provide a **partial explanation**

- Use an info-seeking “beauty-contest” game of higher-order beliefs (Morris-Shin, 2002).
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- **Vicious Circle**: network dynamics $\leftrightarrow$ trust-in-science dynamics
What we do NOT do

Fake News

Lots of nice measurement work (computer science): Shao et al. (2016, 2018)

future extension
Outline of Mechanism

Everyone is structurally inclined to push facts slightly away from reality: “biased assimilation”

Everyone is structurally inclined to partially align actions with friends: “belongingness”

Social media offer a cheap way of making internet friends

Speed of finding friends with similar biases \( \uparrow \Rightarrow \text{Homophily} \uparrow \)

Homophily \( \uparrow \Rightarrow \text{Peer-reduced bias amplification} \uparrow \Rightarrow \text{Homophily} \uparrow \)
Model: representing the network through a matrix

Network of \( N < \infty \) persons.

In \( t \in \{0, 1, \ldots\} \), network represented by an \( N \times N \) adjacency matrix \( \mathbf{M}_t \) of \( \{0, 1\} \) entries.

\( \mathbf{M}_t \) is symmetric: \( M_{ij}^t = M_{ji}^t = 1 \) (not a directed graph)

No self-loops (all diagonal elements of \( \mathbf{M}_t \) are equal to 0)

Key matrix normalization: let \( d_i(\mathbf{M}_t) \equiv \sum_{j=1}^{N} M_{ij}^t \) be the sum of other individuals \( i \) is connected to; then transform \( \mathbf{M}_t \) into a row stochastic matrix,

\[
\gamma_t = \Gamma(\mathbf{M}_t) \quad \text{with} \quad \gamma_{ij}^t \equiv \frac{M_{ij}^t}{d_i(\mathbf{M}_t)} \quad \text{← state variable}
\]
Model: structural (direct) utility functions

Two agent types, $A$ and $B$, with different fundamental biases.

Each period’s objective of player i: to take an action, $a_i$, as close as possible to a random variable, $\theta_t +/-$ some bias, while conforming to network-peer actions.

\[
u^A_i (a_t, \theta_t) = - (1 - r) [a_{i,t} - (\theta_t + b)]^2 - r \sum_{j=1}^{N} \gamma_{ij} t (a_{j,t} - a_{i,t})^2
\]

\[
u^B_i (a_t, \theta_t) = - (1 - r) [a_{i,t} - (\theta_t - b)]^2 - r \sum_{j=1}^{N} \gamma_{ij} t (a_{j,t} - a_{i,t})^2
\]

where $r \in (0, 1)$, $b > 0$, and $a_t = [a_{1,t}, ..., a_{N,t}]$.

$b$: “biased assimilation” or “confirmation bias” (see Lord et al., 1979, and Nickerson, 1998)
Model: signals

**Key assumption**: in each period \( t \in \{0, 1, \ldots\} \), there is a **new task** carrying a new fundamental value, \( \theta_t \), that is unknown

**Player** \( i \)’s **information set** in \( t, I_{i,t} \), regarding \( \theta_t \):

\[
I_{i,t} = \begin{pmatrix}
\{y_t, \ x_{i,t}\} \\
\text{(public signal, private signal)}
\end{pmatrix}
\]

\[
y_t = \theta_t + \eta_t , \quad \eta_t \sim N \left(0, \sigma^2_{\eta}\right) , \quad t = 0, 1, \ldots \quad \rightarrow \text{expert opinion!}
\]

\[
x_{i,t} = \theta_t + \epsilon_{i,t} , \quad \epsilon_{i,t} \sim N \left(0, \sigma^2_{\epsilon}\right) , \quad t = 0, 1, \ldots
\]

**Important**: \( \eta_t \) is independent from \( \epsilon_{i,t} \) for all \( i \in \{1, \ldots, N\} \), and \( \epsilon_{i,t} \) is independent from \( \epsilon_{j,t} \) for all \( i \neq j \).
Individual response functions in the info game

\[
a_{i,t}^{k*} = \arg \max_{a_{i,t}} E(u_i^k (a_t, \theta_t) \mid \mathcal{I}_{i,t}) , \quad k \in \{A, B\}
\]

\[
a_{i,t}^{A*} = (1 - r) E(\theta \mid \mathcal{I}_{i,t}) + (1 - r) b + r \sum_{j=1}^N \gamma_{ij}^t E(a_{j,t} \mid \mathcal{I}_{i,t})
\]

\[
a_{i,t}^{B*} = (1 - r) E(\theta \mid \mathcal{I}_{i,t}) - (1 - r) b + r \sum_{j=1}^N \gamma_{ij}^t E(a_{j,t} \mid \mathcal{I}_{i,t})
\]

where (apply Bayes' rule),

\[
E(\theta \mid \mathcal{I}_{i,t}) = \frac{\alpha y_t + \beta x_{i,t}}{\alpha + \beta} , \quad \alpha = 1/\sigma^2_\eta \text{ and } \beta = 1/\sigma^2_\epsilon \text{ (signal precisions)}
\]

\[
E(a_{j,t} \mid \mathcal{I}_{i,t}) \text{ unknown!}
\]
Individual strategies in the info game

Solving a **linear problem through matrix inversion**, the **fixed-point strategies** are:

\[
A^*_i, t = A_i \left( y_t, x_{i,t} \mid \gamma_t \right) = \omega^y_i \left( \gamma_t \right) y_t + \omega^b_i \left( \gamma_t \right) b + \omega^x_i \left( \gamma_t \right) x_{i,t}
\]

\[
B^*_i, t = B_i \left( y_t, x_{i,t} \mid \gamma_t \right) = w^y_i \left( \gamma_t \right) y_t + w^b_i \left( \gamma_t \right) (-b) + w^x_i \left( \gamma_t \right) x_{i,t}
\]

where,

\[
\omega^i_y + \omega^i_b + \omega^i_x = 1 \quad \text{and} \quad w^i_y + w^i_b + w^i_x = 1
\]
Key output of the game: value functions

Substituting these strategies in the objective function of each player gives the **value functions (indirect utility functions)**,

\[
V^A_i (\gamma_t) = E \left( u^A_i \left( \left\{ \left\{ a^A_{j,t} \right\}_{j=1}^{N_A} , \left\{ a^B_{j,t} \right\}_{j=1}^{N_B} \right\} , \theta_t \right) \mid \mathcal{I}_{i,t} \right)
\]

and

\[
V^B_i (\gamma_t) = E \left( u^B_i \left( \left\{ \left\{ a^A_{j,t} \right\}_{j=1}^{N_A} , \left\{ a^B_{j,t} \right\}_{j=1}^{N_B} \right\} , \theta_t \right) \mid \mathcal{I}_{i,t} \right)
\]

**These value functions drive decisions on who to make your friend and who not!**
Myopic search-and-matching mechanism

Each period, player $i$:

(a) **Sends one random invitation to non-friends**: it is drawn from a uniform distribution, by counting the total number of 0’s in the $i$-th row of $\gamma_t$.

(b) **Causes one random annoyance to friends** it is drawn from a uniform distribution, by counting the total number of 1’s in the $i$-th row of $\gamma_t$.

**Decision-Making**
1. Player $i$ examines received invitations and experienced annoyances
2. Player $i$ calculates value functions of all possible matrices $\gamma_t$ resulting from simultaneous invitations and annoyances
Peer-induced bias vs. expert opinion

For all $\gamma_t$, the optimal weight on the private signal is given by

$$\omega_x^i (\gamma_t) = 1 - \omega_y^i (\gamma_t) - \omega_b^i (\gamma_t) = \frac{(1 - r) \beta}{(1 - r) \beta + \alpha}, \quad i = 1, \ldots, N_A,$$

(1)

$$w_x^i (\gamma_t) = 1 - w_y^i (\gamma_t) - w_b^i (\gamma_t) = \frac{(1 - r) \beta}{(1 - r) \beta + \alpha}, \quad i = 1, \ldots, N_B.$$

(2)

Therefore,

$$\underbrace{\omega_y^i (\gamma_t)}_{\text{expert-opinion weight}} + \underbrace{\omega_b^i (\gamma_t)}_{\text{bias weight}} = \underbrace{w_y^i (\gamma_t)}_{\text{weight on the private signal}} + \underbrace{w_b^i (\gamma_t)}_{\text{bias weight}} = \frac{\alpha}{(1-r)\beta+\alpha}$$

(3)

Whenever the weight on the bias, $\omega_b^i (\gamma_t)$ increases, the weight and the attention to the public signal, the expert opinion, $\omega_y^i (\gamma_t)$, has to decrease.
Monte-Carlo simulations

- “beauty-contest” term: $r = 0.65$
- noisiness of private signals, $\sigma_\varepsilon > \sigma_\eta$, noisiness of expert signals, $\sigma_\eta$
- $\sigma_\varepsilon = 0.32 \rightarrow \beta = 10$, and $\sigma_\eta = 0.18 \rightarrow \alpha = 30$.
- Small fundamental bias value, $b = 0.02$, about 9 times smaller than one standard deviation of the noisiness of the expert signal.
- $N = 100$ and $N_A = N_B = 50$.
- $\theta_t^* = 0$ for all $t$ (Nature’s data-generating process)
- The probability of randomly appearing 0’s in the original network matrix $\gamma_0$ is set to $p = 0.7$ (uniform distribution)
- 200 Monte-Carlo simulation trials
Monte-Carlo simulations (equi-sized groups)
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Homophily, $IH_A$

Subnetwork density, $D_A$

Subnetwork closeness centrality, $CC_A$

Homophily, $IH_B$

Subnetwork density, $D_B$

Subnetwork closeness centrality, $CC_B$
Monte-Carlo simulations (equi-sized groups)
Monte-Carlo simulations (group A: 65, group B: 35)
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Conclusions

First dynamic model of networks,
– suggesting a search-and-matching framework
– using the calculation of high-order beliefs in order to map the network structure to social-media-user actions
– studying the interplay between peer-induced amplification of biases and network dynamics (vicious circle: homophily and biases)

Smaller groups seem to be more resistant to vicious circle: interesting for future work

Important to add fake news in such a model: interesting for future work