

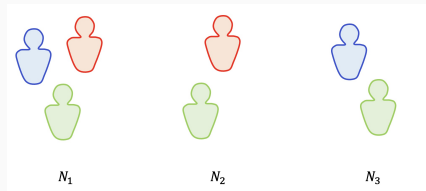
# Revealed Social Network

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- Our goal is to develop a revealed preference style test and identification results for a specific model of peer effects in networks.
  - The linear in means model (LiM)

- A person,  $i$ , makes choices in the context of a group of agents,  $N$
- Choice is made from a fixed set of alternatives  $X$
- Choice is probabilistic
  - $p_i^N(x)$  is how often agent  $i$  chooses  $x$  in the context of group  $N$
  - $p_i^N$  denotes the entire vector of agent  $i$ 's choice frequencies in group  $N$
  - $p_{-i}^N$  denotes the choices of every agent besides  $i$  in group  $N$

- $|X| > 1$  finite set of alternatives (**fixed**)
- No menu variation
- **group variation**



- $\mathcal{A}$ : the grand set of agents, and  $N$ : a typical group of agents
- Data:  $p_i^N(x)$  for  $i \in N$

$$p_i^N(x) > 0 \text{ for all } x \in X \quad \text{and} \quad \sum_{x \in X} p_i^N(x) = 1$$

$$p_i^N(x) = \pi_i^N(i)v_i(x) + \sum_{j \in N \setminus i} \pi_i^N(j)p_j^N(x) \quad \text{for all } x$$

- An agent's choice is a convex combination of their bliss point and the other agents' choices
  - $v_i$  is agent  $i$ 's bliss point
  - $\pi_i^N(j)$  is the weighting agent  $i$  puts on agent  $j$  in group  $N$
- As many have noted, this choice function arises from quadratic loss utility

$$u(p_i^N, p_{-i}^N) = -\pi_i^N(i) \sum_{x \in X} (p_i^N(x) - v_i(x))^2 - \sum_{j \in N \setminus i} \pi_i^N(j) \sum_{x \in X} (p_i^N(x) - p_j^N(x))^2$$

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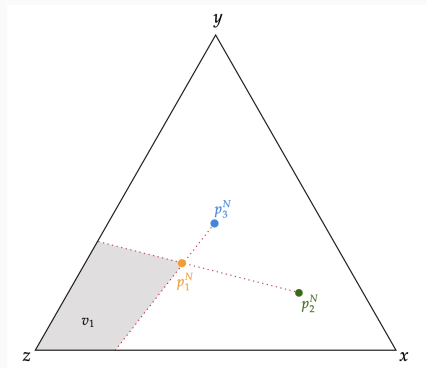
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- In the paper we consider three models of group variation
- General (GLM):
  - $\pi_i^N(i) > 0$  for all  $N$
  - No other restrictions on  $\pi_i^N(j)$  across groups
- Luce (LLM)
  - $w_i(j) > 0$  is a weighting function
  - $\pi_i^N(j) = \frac{w_i(j)}{\sum_{k \in N} w_i(k)}$
- Uniform (ULM)
  - $\pi_i^N(j) = \frac{1}{|N|}$

## Feasible Bliss Points

- Given observed choices in a group, we can directly recover the set of feasible bliss points for each agent
- It is the set of points for which  $p_i^N$  is a convex combination of that point at  $p_{-i}^N$
- This turns out to be a cone (intersected with the simplex)
- For each agent, there must be some bliss point which is feasible in each of their groups



$$co^{-1}(\Delta(p^N), p_i^N) = \{v \in \Delta(X) | v = \sum_{j \in N} \gamma_j p_j^N, \gamma_j \leq 0 \ \forall j \in N \setminus i, \sum_{j \in N} \gamma_j = 1\}$$



### Theorem

The following are equivalent.

- A data set  $\{p^N\}_{N \in \mathcal{N}}$  is consistent with GLM.
  - For every  $i$ , the collection of sets  $\{co^{-1}(\Delta(p^N), p_i^N)\}_{N \in \mathcal{N}_i}$  has a point of mutual intersection.
- 
- The only testable content of GLM is the existence of a feasible bliss point for each agent
  - We can test this agent by agent

- Our first test is fully geometric
- Can we develop a linear programming approach?
- Yes!
- We will interpret this test as the existence of a profitable bet on agent  $i$ 's behavior

### Definition

A set of vectors  $\{b^N\}_{N \in \mathcal{N}_i}$  with  $b^N \in \mathbb{R}^X$  for each  $N \in \mathcal{N}_i$  is called a **bet on agent  $i$** .

## Definition

A bet on agent  $i$  is **strictly feasible** if  $\sum_{N \in \mathcal{N}_i} b^N \ll 0$ .

- Feasibility is a statement about ex-ante profitability of the bet
- A bank is willing to front the bet if, for each  $x \in X$ , the bank makes a profit

### Definition

A bet on agent  $i$  is **individually rational** if  $b^N \cdot p_i^N > 0$  for each  $N \in \mathcal{N}_i$ .

- Individual rationality is a statement about profitability of the bet to the bet maker
- An outside observer is willing to make the bet if, in each group, they make a profit (in expectation)

### Definition

A bet on agent  $i$  is **incentive compatible** if  $b^N \cdot (p_i^N - p_j^N) \geq 0$  for each  $N \in \mathcal{N}_i$  and each  $j \in N \setminus i$ .

- Incentive compatibility is a statement about the better's incentives to deviate from their bet
- A bet is a bet on agent  $i$
- An outside observer is willing to stick with their bet if, in each group, there is no other agent  $j$  in that group that gives higher (expected) profit

### Definition

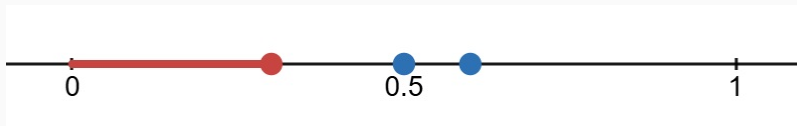
We say that a dataset  $\{p^N\}_{N \in \mathcal{N}}$  satisfies **no incentive compatible money pump** if for each  $i$  there are no strictly feasible, individually rational, and incentive compatible bets on agent  $i$ .

### Theorem

The following are equivalent.

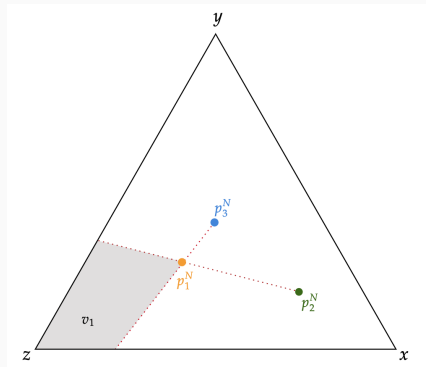
- A data set  $\{p^N\}_{N \in \mathcal{N}}$  is consistent with GLM.
- For every  $i$ , the collection of sets  $\{co^{-1}(\Delta(p^N), p_i^N)\}_{N \in \mathcal{N}_i}$  has a point of mutual intersection.
- $\{p^N\}_{N \in \mathcal{N}}$  satisfies no incentive compatible money pump.

## The Special Case of One Dimension



- Suppose  $|X| = 2$  (i.e. labor vs leisure or test scores)
- $co^{-1}(\Delta(p^N), p_i^N)$  is  $[0, 1]$  unless  $p_i^N(x)$  is either the min or max among  $\{p_j^N(x)\}$
- Let  $p_i^-$  be the min value of  $p_i^N(x)$  over  $N$  where  $p_i^N(x)$  is the min among  $\{p_j^N(x)\}$ 
  - Define  $p_i^+$  similarly
- Ignoring a lower dimensional case for today, we have consistency with GLM iff for each  $i$  we have  $p_i^- \geq p_i^+$

- So far we have focused on testing
- Our goal now is to show how we can get identification
  - Of  $v_i$
  - Of  $\pi_i^N$
- We start with partial identification bounds



## Proposition

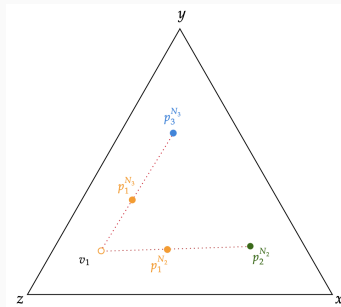
In GLM, the tight identified set for  $v_i$  is given by  $\bigcap_{N \in \mathcal{N}_i} co^{-1}(\Delta(p^N), p_i^N)$ .



### Corollary

Let  $N_j = \{i, j\}$  and  $N_k = \{i, k\}$ . Suppose that  $\{p^N\}_{N \in \mathcal{N}}$  is consistent with GLM,  $N_j, N_k \in \mathcal{N}_i^{ext}$ , and that the vectors  $(p_i^{N_j} - p_j^{N_j})$  and  $(p_i^{N_k} - p_k^{N_k})$  are linearly independent. Then  $v_i$  is point identified.

- With two binary groups, we are able to identify  $v_i$
- The logic extends to larger group sizes
- We effectively need  $|N|$  groups of size  $|N|$  (plus linear independence) to identify  $v_i$ 
  - These have to be groups where  $co^{-1}(\Delta(p^N), p_i^N)$  is not the entire simplex



### Proposition

Suppose that  $v_i$  is point identified. Then  $\pi_i^N$  is point identified if the set of vectors including  $v_i$  and  $\{p_j^N\}_{j \in N \setminus i}$  is linearly independent.

- When we have more alternatives than people ( $|X| \geq |N|$ ), we can generically recover each  $\pi_i^N$
- Recovering  $\pi_i^N$  for each  $i$  in a group recovers the entire network structure of that group

- Varying network structure instead of group variation
  - Suppose we observe some instrument  $Z$  which is independent of  $v_i$  but is correlated with network structure
  - All of our tests and identification results go through
  - Each realization of  $R$  corresponds to a different group
- Exogenous vs Endogenous components of choice
  - Suppose  $v_i$  varies with some set of observed characteristics
  - Our procedure lets us recover endogenous effects ( $\pi_i^N$ ) and exogenous effects ( $v_i$ ) from choices
  - Once we do so, we can treat  $v_i$  as our outcome variable
- Product Attribute Variation
  - Suppose we keep  $X$  fixed but now vary the attributes of some of the choice alternatives
  - Since we can identify  $v_i$  in our setup, we can treat  $v_i$  as an outcome variable and estimate how it responds to attribute variation

- We develop revealed preference style tests and identification results for the linear in means model of peer effects
- A key takeaway from our analysis is that identification can be recovered when data is more granular
  - Instead of data on labor vs leisure time, we want data on how labor and leisure time is used
- All of our analysis carries through with either group variation or network variation

*Thanks!*