

Identification of a rank-dependent peer effect model

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- However,
 - Peer effects might be heterogeneous
 - The effect of a peer might depend on the group you interact with
- We introduce a model where the effect of each peer is endogenously determined by the distribution of the outcomes of an individual's peers

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$$d_i = \sum_{j=1}^n A_{i,j} = \text{number of peers for individual } i$$

$$\begin{aligned} \tilde{Y}_{i,k} &= \text{outcome of the } k\text{-th lowest performing peer of individual } i \\ &= k\text{-th ordered statistic from } \{Y_j : A_{i,j} = 1\}. \end{aligned}$$

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- Our model is:

$$Y_i = \sum_{k=1}^{d_i} \beta_{k,d_i} \tilde{Y}_{i,k} + \mathbf{x}_i^T \boldsymbol{\gamma} + \varepsilon_i \quad (1)$$

for $i = 1, \dots, n$. \mathbf{x}_i are exogenous covariates that may depend on the network.

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 - $\beta_{3,3}$ is the effect of the highest outcome friend for people with 3 friends.
- Application-specific simplifying assumptions can give more interpretable coefficients

$$Y_i = \tilde{Y}_{i,1}\beta_{\min} + \tilde{Y}_{i,d_i}\beta_{\max} + \bar{Y}_{i,-1,-d_i}\beta_{\text{mean}} + x_i\gamma + \epsilon_i$$

- Assumes homogeneity across d_i and all “middle” peers to have a homogeneous effect.
- Creates a separate min/max peer effect, with the rest following “linear-in-means”.

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- This is a weakened version of the “classic” existence assumption of the Linear-in-Mean model

Reduced form

- Assume the network and covariates are exogenous to ϵ_j .

Assumption 2 ((Exogenous Network and Covariates)).

For each $i = 1, \dots, n$

$$\mathbf{E}_n[\epsilon_i] = \mathbf{E}[\epsilon_i | \{x_i, A_{i,j}\}_{1 \leq j \leq n}] = 0.$$

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- Then under Assumption 1 and 2 we have

$$\mathbf{E}_n[Y_i] = \sum_{j=1}^n \theta_{i,j} x_j^\top \gamma + \eta_i$$

Where $\theta_{i,j}, \eta_i$ are complicated functions of $A_{i,j}$ and β Definitions

Identification through Instruments

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- With many instruments and many instrumental variables, this becomes a rank-condition on

$$\mathbf{E}_n[\mathbb{Z}\mathbb{W}],$$

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- Discussion in the paper, but easily checked in the data. Conditions for instrument

Identification

Theorem 1.

Suppose that Assumptions 1-3 hold and $n \geq \frac{\bar{d}(\bar{d}+1)}{2} + 1$. Then, β and γ are identified from the moment condition below:

$$\mathbf{E}_n[\mathbf{Z}^\top \mathbf{W}] \begin{pmatrix} \beta \\ \gamma \end{pmatrix} = \mathbf{E}_n[\mathbf{Z}^\top \mathbf{Y}]. \quad (2)$$

Simulation set-up

- We simulate from the DGP

$$Y_i = \gamma_0 + \gamma_1 X_i + \tilde{Y}_i^\top \beta + \varepsilon_i$$

with X_i and ε_i as independent standard normals and $n = 200$.

- We fix \bar{d} to either 2 or 5 for the simulations and vary γ_1 to see the effect of the instruments strength.
- We set $\beta_{d,d} = 0.4$ and $\beta_{k,d} = \frac{0.4}{d}$ for $k < d$.

Simulation results - Bias for People with two friends

	(1)	(2)	(3)	(4)	(5)
$\beta_{1,2}$	-0.005	-0.000	-0.004	-0.001	0.001
$\beta_{2,2}$	0.002	-0.000	0.000	-0.001	-0.000
γ_1	1	1	2	3	5
\bar{d}	2	5	5	5	5

Simulation results - MSE for People with 2 friends

	(6)	(7)	(8)	(9)	(10)
$\beta_{1,2}$	0.049	0.260	0.023	0.010	0.003
$\beta_{2,2}$	0.025	0.109	0.012	0.006	0.002
γ_1	1	1	2	3	5
\bar{d}	2	5	5	5	5

Simulation results - Bias for People with 5 friends

	(1)	(2)	(3)	(4)	(5)
$\beta_{1,5}$		0.058	-0.008	-0.002	-0.002
$\beta_{2,5}$		0.044	0.021	-0.009	0.007
$\beta_{3,5}$		-0.022	-0.019	0.031	0.000
$\beta_{4,5}$		-0.001	0.022	-0.045	-0.006
$\beta_{5,5}$		-0.029	-0.016	0.018	0.004
γ_1	1	1	2	3	5
\bar{d}	2	5	5	5	5

Simulation results - MSE for People with 5 friends

	(6)	(7)	(8)	(9)	(10)
$\beta_{1,5}$	1.872	0.305	0.082	0.017	
$\beta_{2,5}$	4.371	1.500	0.523	0.094	
$\beta_{3,5}$	5.635	2.233	0.788	0.143	
$\beta_{4,5}$	4.531	1.339	0.428	0.086	
$\beta_{5,5}$	1.300	0.240	0.072	0.013	
γ_1	1	1	2	3	5
\bar{d}	2	5	5	5	5

Simulation Results - Bias in Restricted model

	(1)	(2)	(3)	(4)	(5)
$\beta_{-\max}$		-0.005	-0.002	0.000	0.001
β_{\max}		-0.010	-0.000	-0.001	-0.001
γ_1	1	1	2	3	5
\bar{d}	2	5	5	5	5

Simulation results - MSE for People with 5 friends

	(6)	(7)	(8)	(9)	(10)
$\beta_{-\max}$		0.104	0.011	0.004	0.001
β_{\max}		0.082	0.008	0.003	0.001
γ_1	1	1	2	3	5
\bar{d}	2	5	5	5	5

Set-up

- We investigate peer effects in GPA in two Norwegian middle schools using data from Alne et al. (2025)
- Sample consists of two schools with a total of around 550 students.
- Data is merged to registry data allowing for a large set of controls
 - See paper and Alne et al. (2025) for details.
- Compare Linear-in-Means with alternative models that separate out the highest/lowest performing peers of each individual.

	(1)	(2)	(3)	(4)	(5)
\bar{Y}	0.483*** (0.131)				
\bar{Y}_{-d_i}			-0.003 (0.278)		
\bar{Y}_{-1}		0.678** (0.295)			
$\bar{Y}_{-1,-d_i}$				0.156 (0.475)	
\tilde{Y}_{d_i}			0.43 (0.313)	0.303 (0.391)	0.407*** (0.151)
\tilde{Y}_1		-0.067 (0.221)		0.138 (0.202)	0.18* (0.106)
Observations	529	529	529	529	529
Adjusted R ²	0.476	0.474	0.450	0.480	0.476

Conclusion

- We show how to identify and estimate rank-dependent peer effects.
- The identifying conditions are natural extensions to standard assumptions, but with stronger requirements for the instruments.
- Simulations show the estimator performs well even in small samples
- In the paper we also show how to relate the estimand of the Linear-in-Mean model to our parameters and derive the asymptotic distribution of the estimators.

References I

Alne, R., E. I. Herstad, and A. Myhre (2025). How socioeconomic and parental background shape peer networks and educational spillovers. Available on SSRN: <https://www.ssrn.com/abstract=5160331>.

Definitions of θ and η

Define π as an ordering on $\{1, \dots, n\}$ in terms of $\{y_i\}_{i=1}^n$ and $\mathbb{B}(\pi)$ denotes a $n \times n$ peer effect coefficient matrix such that its i -th row j -th column component corresponds to the peer effect coefficient for individual j 's outcome on individual i 's outcome, given the ordering π .

Then the reduced form coefficients can be written as

$$\theta_{i,j} = \sum_{\pi \in \Pi} \theta_{i,j}(\pi) \Pr_n \{ \pi \}$$

$$\eta_i = \sum_{\pi \in \Pi} \sum_{j=1}^n \theta_{i,j}(\pi) \mathbb{E} [\varepsilon_j | \pi] \cdot \Pr_n \{ \pi \}$$

and $(\theta_{i,1}(\pi), \dots, \theta_{i,n}(\pi))$ is the i -th row of the $n \times n$ matrix $(I_n - \mathbb{B}(\pi))^{-1}$

Instrument conditions

- 1 (EXOGENEITY) $\{z_{i,1}, \dots, z_{i,\bar{d}}\}_{i=1}^n$ are known, predetermined functions of $\{x_i, A_{i,j}\}_{1 \leq i,j \leq n}$.
- 2 (RELEVANCE) The construction of the instrument z_i and the reduced-form representation of

$$\mathbb{E} [\tilde{Y}_{i,k}] = \sum_{j=1}^n \tilde{\theta}_{i,k,j} x_j^\top \gamma + \tilde{\eta}_{i,k}$$

from Corollary 1 satisfy that

$$\sum_{i=1}^n \begin{pmatrix} z_{i,d} \\ x_i \end{pmatrix} \begin{pmatrix} \sum_{j=1}^n \tilde{\theta}_{i,1,j} x_j^\top \gamma + \tilde{\eta}_{i,1} \\ \vdots \\ \sum_{j=1}^n \tilde{\theta}_{i,d_i,j} x_j^\top \gamma + \tilde{\eta}_{i,d_i} \\ x_i \end{pmatrix}^\top \mathbf{1}\{d_i = d\}$$

has full rank, for each $d = 1, \dots, \bar{d}$.