

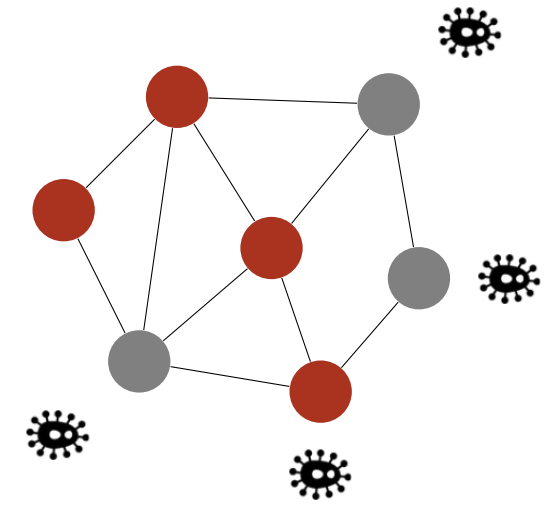
# Estimating peer influence: limitations of linear-in-means models

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## Understanding social influence is a fundamental problem in a highly connected society



**Direct effect:** if I get **vaccinated**, I am less likely to get sick 🦠

**Contagion:** if my friends get sick 🦠, I am more likely to get sick 🦠

**Interference:** if my friends get **vaccinated**, I am less likely to get sick 🦠

## The linear-in-means model is a canonical tool to estimate peer influence in network data

$$\underbrace{Y_i}_{\text{sick?}} = \alpha + \beta \underbrace{\frac{1}{d_i} \sum_{j \in \mathcal{N}(i)} Y_j}_{\text{fraction sick friends}} + \gamma T_i + \delta \underbrace{\frac{1}{d_i} \sum_{j \in \mathcal{N}(i)} T_j}_{\text{fraction vaccinated friends}} + \varepsilon_i$$

Data:

Outcome (sick?)	$Y_i \in \{0, 1\}$
Treatment (vaccinated?)	$T_i \in \{0, 1\}$
Edge $i \sim j$ (friends?)	$A_{ij} \in \{0, 1\}$
Degree (num friends)	$d_i \in \{0, 1, 2, \dots\}$

Parameters:

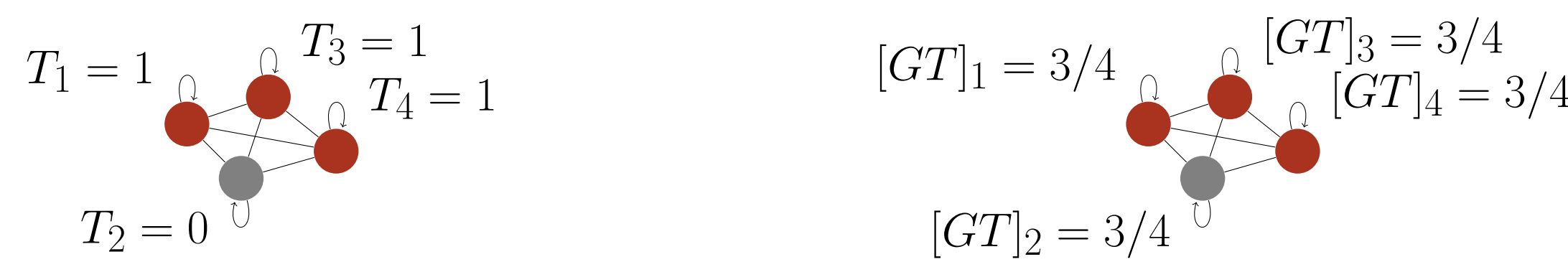
Base rate	$\alpha \in \mathbb{R}$
Contagion	$\beta \in (-1, 1)$
Direct effect	$\gamma \in \mathbb{R}$
Interference	$\delta \in \mathbb{R}$

Letting  $G = D^{-1}A$  be the row-normalized adjacency matrix, can express in matrix-vector form:

$$Y = \alpha 1_n + \beta GY + \gamma T + \delta GT + \varepsilon$$

## Linear-in-means models are famously susceptible to the “reflection problem,” an identification failure due to colinearity

In highly structured networks, the peer effect terms can be perfectly colinear, such that peer effects cannot be estimated from the data. For example, in a fully connected network:



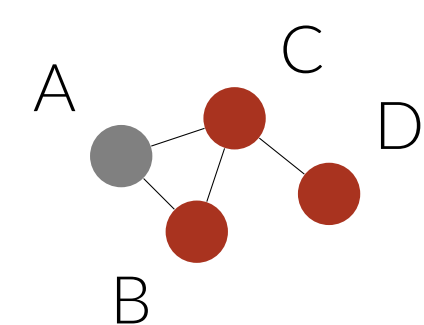
$$\begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \\ Y_4 \end{bmatrix} = \begin{bmatrix} 1 & GY_1 & 1 & 3/4 \\ 1 & GY_2 & 0 & 3/4 \\ 1 & GY_3 & 1 & 3/4 \\ 1 & GY_4 & 1 & 3/4 \end{bmatrix} \begin{bmatrix} \alpha \\ \beta \\ \gamma \\ \delta \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \end{bmatrix}$$

Can't distinguish base rate  $\alpha$  from interference  $\delta$  due to colinearity

## It's widely believed that colinearity problems can be avoided when certain identifying conditions, such as intransitivity, hold

**Proposition:** Suppose  $\mathbb{E}[\varepsilon | T] = 0$  and that  $|\beta| < 1$  and  $\gamma\beta + \delta \neq 0$ . For any fixed  $n$ , if  $I, G$  and  $G^2$  are linearly independent (i.e.,  $aI + bG + cG^2 = 0$  only if  $a = b = c = 0$ ), then  $\alpha, \beta, \gamma$  and  $\delta$  are identified. If  $I, G$  and  $G^2$  are linearly dependent and no node is isolated, then  $(\alpha, \beta, \gamma, \delta)$  are not identified.

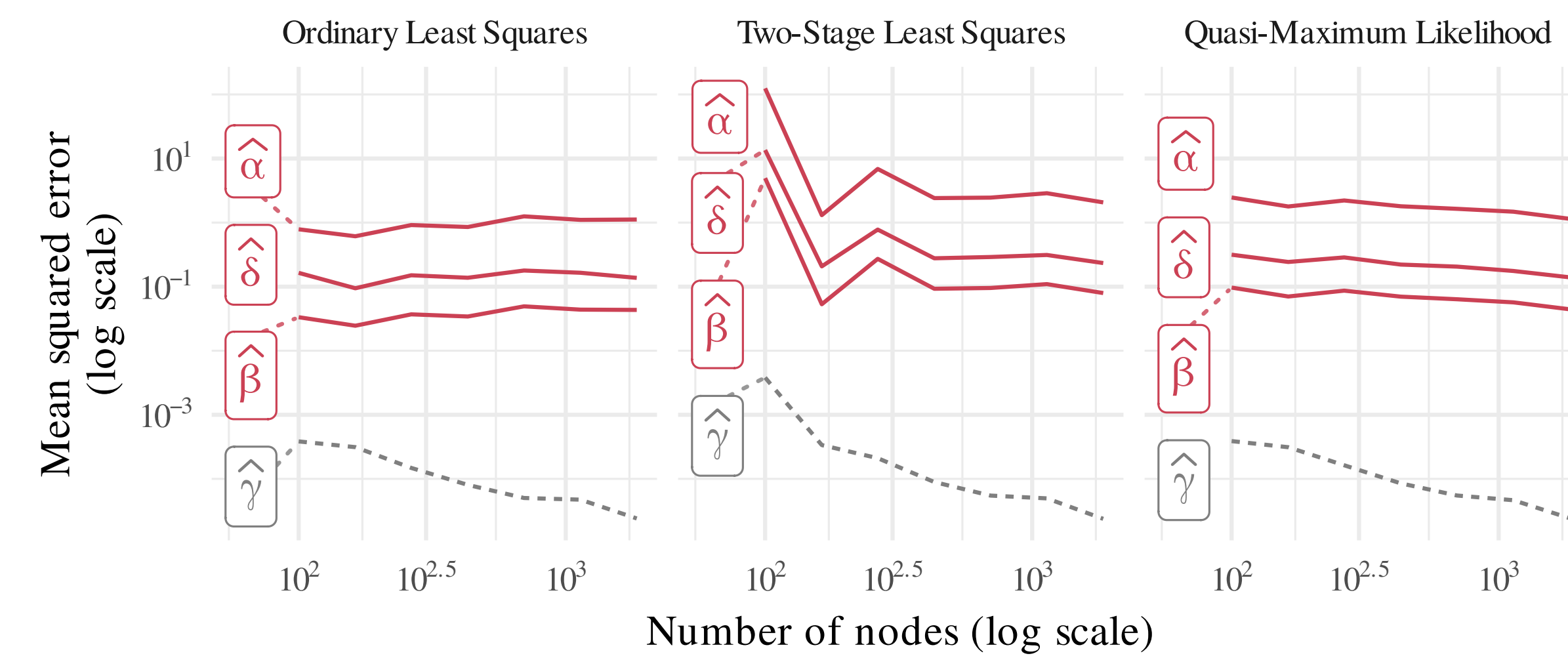
**Intuition:** Peer influence is identified when there are **open triangles** (“intransitivity”) in the network



Open:  $B \leftrightarrow C \leftrightarrow D \leftrightarrow B$   
Closed:  $A \leftrightarrow B \leftrightarrow C \leftrightarrow A$

## We show that peer effects can be inestimable even when identifying conditions hold

Three popular estimators all fail to estimate parameters at expected  $\sqrt{n}$  rates in simulations, even though half of all possible triangles in the network are open



## The problem is that peer effect terms become more and more colinear as the number of nodes in the network increases

**Intuition:** Imagine vaccination is a coin flip for every node (i.e., a Bernoulli design). As the network grows, the fraction of vaccinated friends  $\approx 0.5$  for every single node.

$$\lim_{d_i \rightarrow \infty} \underbrace{[GT]_i}_{\text{fraction vaccinated friends}} = \lim_{d_i \rightarrow \infty} \frac{1}{d_i} \sum_{j \in \mathcal{N}(i)} T_j = \frac{1}{2} \text{ almost surely.} \quad (1)$$

This also causes the contagion term to be near-colinear with the intercept, since  $GY$  is a repeated diffusion of  $T$  and  $GT$  over the network

$$\begin{aligned} Y &= \alpha 1_n + \beta GY + \gamma T + \delta GT + \varepsilon \\ &= (I - \beta G)^{-1} (\alpha 1_n + \gamma T + \delta GT + \varepsilon) \\ &= \sum_{k=0}^{\infty} \beta^k G^k (\alpha 1_n + \gamma T + \delta GT + \varepsilon) \end{aligned}$$

**Lemma:** Suppose that (1) the nodal covariates  $T_1, T_2, \dots$  are independent with shared mean  $\tau \in \mathbb{R}$ , and  $T$  is independent of  $A$ ; (2) the nodal covariates are sub-gamma random variables; (3) the regression errors  $\varepsilon_1, \varepsilon_2, \dots$  are independent subgamma random variables independent of  $T$ .

If the minimum degree of the network grows at a  $\omega(\log n)$  rate, then there exists  $\eta \in \mathbb{R}$  such that

$$\max_{i \in [n]} |[GT]_i - \tau| = o(1) \text{ and } \max_{i \in [n]} |[GY]_i - \eta| = o(1) \text{ almost surely.}$$

## Asymptotic colinearity leads to inconsistency because the signal-to-noise ratio gets worse with growing sample size

**Theorem:** Under the same conditions as the Lemma, let  $(\hat{\alpha}, \hat{\beta}, \hat{\gamma}, \hat{\delta})$  be the vector of ordinary least squares estimates of  $(\alpha, \beta, \gamma, \delta)$ . Suppose that the degrees of the network are such that  $\|G\|_F^2 = o(n)$ . Then if  $\beta = 0$ ,

$$\min\{|\hat{\alpha} - \alpha|, |\hat{\beta} - \beta|\} = \Omega_P(1)$$

and

$$|\hat{\delta} - \delta| = \Omega_P\left(\frac{1}{\|G\|_F}\right). \quad (2)$$

If  $\beta \neq 0$ ,

$$\min\{|\hat{\alpha} - \alpha|, |\hat{\beta} - \beta|\} = \Omega_P\left(\frac{1}{\|G\|_F}\right).$$

Under the stronger growth assumption  $\|G\|_F^2 = o(\sqrt{n})$ , eq. (2) holds for all values of  $\beta$ .

**Intuition:** In networks with growing minimum degree, ordinary least squares estimates of  $\alpha, \beta$  and  $\delta$  are either inconsistent, or at best consistent at  $\sqrt{n/d_{\min}}$  rates, where  $d_{\min} = \min_{i \in [n]} d_i$ .

## When nodal covariates are strongly associated with network structure, it is sometimes possible to avoid asymptotic colinearity

**Intuition:** the fraction of vaccinated peers in eq. (1) might not converge to a column of constants if treatment  $T$  depends on position in the network

**Random dot product graphs:** Let  $X_1, \dots, X_n \in \mathbb{R}^d$  be i.i.d. from a distribution  $F$  such that  $0 \leq x^T y < 1$  for all  $x, y \in \text{supp } F$  and put  $\mathbb{P}(A_{ij} | X_i, X_j) = X_i^T X_j$ .

**Theorem:** Suppose that  $(A, X)$  are sampled from a random dot product model where  $X \in \mathbb{R}^{n \times d}$  is full-rank with high probability. Let

$$Y = \alpha 1_n + \beta GY + X\gamma + GX\delta + \varepsilon \quad (3)$$

for  $\alpha, \beta \in \mathbb{R}$  and  $\gamma, \delta \in \mathbb{R}^d$ . Suppose that  $X$  has  $k \geq 2d$  distinct rows. Under suitable technical conditions, the columns of design matrix corresponding to  $(\alpha, \beta, \delta_1, \delta_2, \dots, \delta_d)$  are asymptotically colinear. If any two elements of  $(\alpha, \beta, \delta_1, \delta_2, \dots, \delta_d)$  are equal to zero, there is no asymptotic colinearity.

**Simulation:** In a network generated according to eq. (3) with no coefficients set to zero (*Unrestricted* model), there are still colinearity and estimation issues. However, when two coefficients from  $(\alpha, \beta, \delta_1, \delta_2, \dots, \delta_d)$  set to zero (*Restricted* model), popular estimators recover regression coefficients at expected  $\sqrt{n}$  rates.

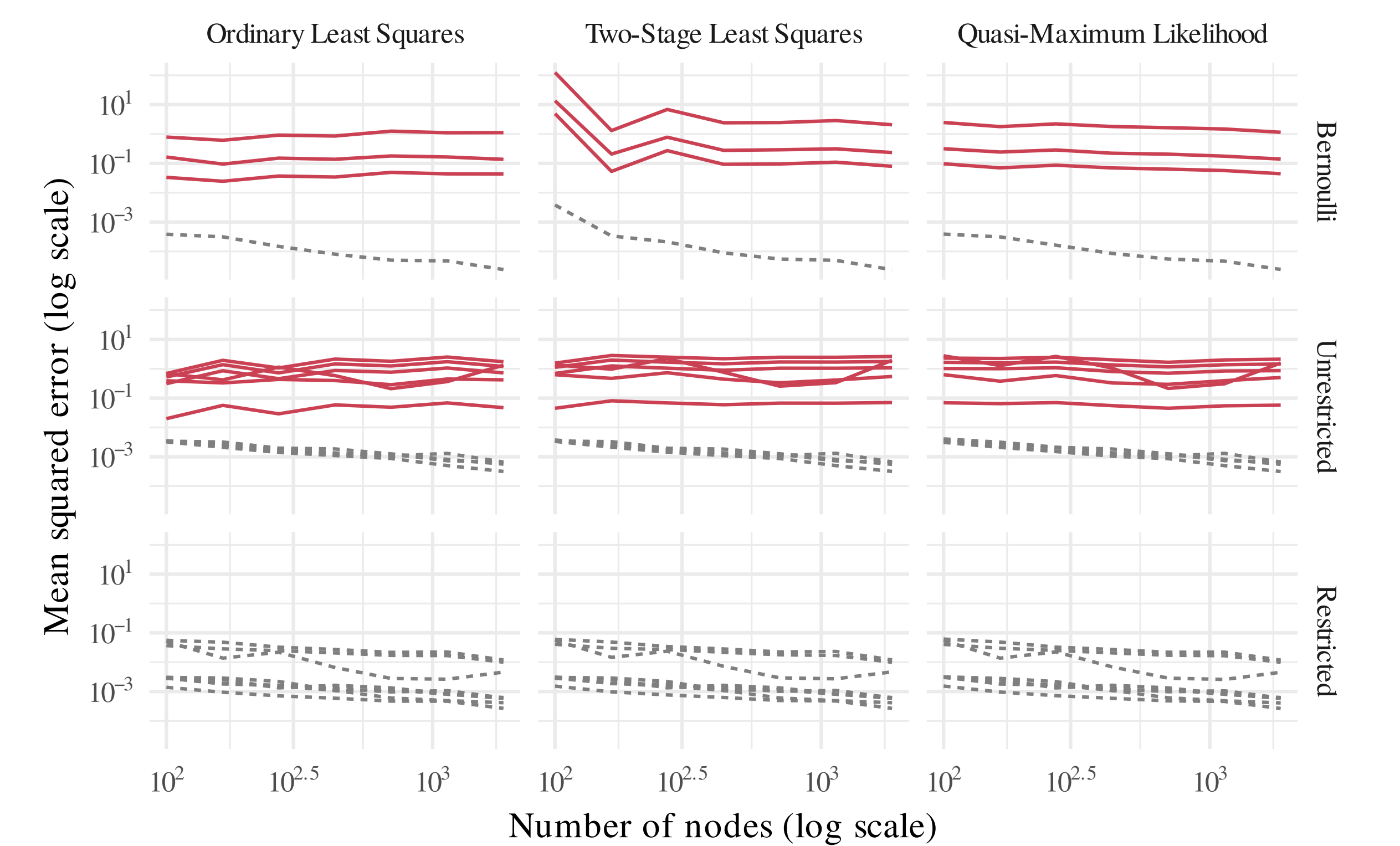


Figure 1. Solid red lines represent estimation error for asymptotically aliased regression coefficients, and dashed gray lines represent estimation error for asymptotically un-aliased coefficients.

## Takeaways

1. It can be impossible to estimate peer effects using linear-in-means models, even when all parameters in the model are identified.
2. Modeling homophily using random dot product graphs can help identify peer effects and avoid colinearity issues.

## Want to learn more? Have a comment? Pre-print & contact info

Hayes, Alex and Keith Levin (Oct. 2024). *Peer Effects in the Linear-in-Means Model May Be Inestimable Even When Identified*. arXiv: 2410.10772 [stat]. URL: <http://arxiv.org/abs/2410.10772> (visited on 10/15/2024).

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