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Comment

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3. A CLARIFICATION ON GROUP INTERACTIONS

Most existing studies of peer effects assume that peer groups partition the sample, as in Manski (1993). This is an important special case with specific features and properties. Goldsmith-Pinkham and Imbens note that under group interactions $\mathbf{GG} = \mathbf{G}$. In this case, Proposition 1 in Bramoullé, Djebbari, and Fortin (2009) confirms Manski (1993)'s earlier result. The linear-in-means model is not identified because of the reflection problem.

However, the property that $\mathbf{GG} = \mathbf{G}$ only holds when the mean is inclusive and is computed over everyone in the peer group including i. Assuming that an individual is one of his own peers seems a bit strange, and applied researchers typically consider *exclusive means*, where the average is computed over everyone in the peer group except i. As it turns out, this minor distinction has key implications for identification. Lee (2007) show that a linear-in-exclusive means model with group fixed effects is generally identified if there is variation in group sizes. Boucher et al. (in press) provide the first empirical application of this result and clarified the intuition behind identification. In essence, identification relies on mechanical effects. Better students have worse peers; this reduces the dispersion in outcomes, and this dispersion reduction decreases with group size at a decreasing rate. These mechanical effects hold in nonlinear models as well. Given the paucity of network data and the importance of the issue, I think that this idea deserves to be further investigated.

4. WHAT IF THE OUTCOME ALSO AFFECTS THE NETWORK?

To conclude, let me highlight a limitation of Goldsmith-Pinkham and Imbens' model, which is common to all studies on the topic. Here, outcome at t is affected by the network at t but the network at t is not affected by outcome at t. This asymmetry may not hold in reality, and the way social links are formed during period t may well be affected by the outcome of interest. To capture this possibility, we would need to develop an econometric model with simultaneous determination of outcome and links. This would undoubtedly raise interesting econometric challenges.

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Comment

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Consider a group of three, potentially connected, individuals ($i = 1, 2, 3$). Available is a large random sample of such groups. For each group sampled, we observe all social ties among its constituent members in each $t = 0, 1, 2, 3$ periods. Let $D_{ijt} = 1$ if individual i is "friends" (i.e., connected) with individual j in period t and zero otherwise. Ties are undirected so that $D_{ij} = D_{ji}$ for $i \neq j$. We rule out self-ties so that $D_{ii} = 0$. The network adjacency matrix in period t is denoted by $\mathbf{D}_t$ with typical element D_{ijt}. The sampling process asymptotically reveals

$$f(\mathbf{d}_3, \mathbf{d}_2, \mathbf{d}_1, \mathbf{d}_0) = \Pr(\mathbf{D}_3 = \mathbf{d}_3, \mathbf{D}_2 = \mathbf{d}_2, \mathbf{D}_1 = \mathbf{d}_1, \mathbf{D}_0 = \mathbf{d}_0).$$

Let $F_{ijt} = 1$ if i and j have any friends in common during period t and zero otherwise. For example, if i and k, as well as

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j and k, are connected in period t, then i and j will share the common friend k such that $F_{ijt} = 1$. Note that i and j need not be direct friends themselves.

Let ν_i and ξ_i be individual-specific, time invariant, latent variables. The latent social distance between individuals i and j is measured by the distance function $g(\xi_i, \xi_j)$. This distance function (i) takes a value of zero if $\xi_i = \xi_j$, (ii) is symmetric in its arguments, and (iii) is increasing in $|\xi_i - \xi_j|$. Let the pair-specific unobserved heterogeneity term $A_{ij} = \nu_i + \nu_j - g(\xi_i, \xi_j) = A_{ji}$.

Let $\mathbf{1}(\cdot)$ denote the indicator function; individuals i and j form a link in periods t = 1,2,3 according to the rule

$$D_{ijt} = \mathbf{1}(\alpha + \beta D_{ijt-1} + \gamma F_{ijt-1} + A_{ij} - U_{ijt} > 0). \quad (1)$$

The term inside the indicator function in (1) is the net social surplus associated with a link between i and j. Agents form a link if the net utility from doing so is positive. Goldsmith-Pinkham and Imbens (2013) model utility at the individual level and require positivity of both candidate partner utilities in order for a link to form. If utility is transferable, rule (1) seems reasonable (see Graham 2011). When utility is nontransferable, the approach of Goldsmith-Pinkham and Imbens is most appropriate.

The match-by-period specific utility shock, U_{ijt}, is independently and identically distributed across pairs and over time with distribution function $F(u)$. This distribution function may vary arbitrarily with $\mathbf{A} = (A_{12}, A_{13}, A_{23})'$, but I suppress any such dependence in what follows.[1]

An important feature of (1) is that it is backward-looking. This eliminates contemporaneous feedback, which can complicate identification (see Manski 1993). While i and j's decision to link or not *will* be influenced by the past link history of, say, agent k, it *will not* be influenced by any link decisions involving agent k in the current period.

Model (1) incorporates four types of network dependencies emphasized in prior research (see Snijders 2011). First, the $-g(\xi_i, \xi_j)$ component of A_{ij} in (1) increases the probability of ties across similar individuals. All other things equal, agents will assortatively match on ξ_j. Call this effect *homophily* (McPherson, Smith-Lovin, and Cook 2001; Jackson 2008). Goldsmith-Pinkham and Imbens (Section 7) choose $g(\xi_i, \xi_j) = \alpha_\xi |\xi_i - \xi_j|$ for their empirical model of network formation. Second, the presence of ν_i and ν_j in A_{ij} allows for *degree heterogeneity* (see Krivitsky et al. 2009). If ν_i is high, then the net surplus associated with *any* match involving i will tend to be high (e.g., i might be a "good friend" generically). Goldsmith-Pinkham and Imbens do not incorporate degree heterogeneity into their model, but such heterogeneity appears to be an important feature of real world networks. Third the presence of F_{ijt-1} in (1) implies a taste for *transitivity* in link formation or "triadic closure." Specifically a link between i and j in the current period is, all things equal, more likely if they shared a common friend in the prior period. The strength of transitivity in link formation is indexed by the parameter γ. Finally, the parameter β captures *state-dependence* in ties: i and j are more likely to be friends in period t if they were friends in period $t-1$.

Discriminating between homophily/degree heterogeneity and transitivity in network formation is scientifically interesting and important from the perspective of the policymaker. To motivate this assertion, consider the following stylized example. Let groups correspond to schools and ξ_i an index of socioeconomic background. Due to the sorting of families across neighborhoods, the distribution of ξ_i within schools is likely to be considerably more compressed than that between schools. Consequently, we may observe, for reasons of homophily, a large number of triangles (i.e., networks where agents 1, 2, and 3 are all connected) across our sample of schools. A preponderance of triangles may occur even in the absence of any structural taste for transitivity in links. The structural source of clustering is nevertheless policy-relevant. In the presence of transitivity, a teacher or principle may be able to alter the network structure within a school by facilitating tie-formation or tie-dissolution across a small number of students.[2] In the absence of a taste for transitivity, such manipulations may be much more difficult to engineer.

While the *homophily* versus *transitivity* identification problem has been informally articulated in the literature on network formation (e.g., Goodreau, Kitts, and Morris 2009; Kitts and Huang 2011; Miyauchi 2012), I am aware of no systematic analysis of it.

The joint density attached to a specific realization of a sequence of network structures and social distances is given by

$$\begin{aligned} f&(\mathbf{d_3}, \mathbf{d}_2, \mathbf{d}_1, \mathbf{d}_0, \mathbf{a}) \\ &= \prod_{t=1}^{3} \Pr(\mathbf{D}_t = \mathbf{d}_t | \mathbf{D_{t-1}} = \mathbf{d_{t-1}}, \mathbf{A} = \mathbf{a})\, \pi(\mathbf{d_0}, \mathbf{a}) \\ &= \prod_{t=1}^{3} \prod_{\{i<j, i\neq k, j\neq k\}} \{F(\alpha + \beta d_{ijt-1} + \gamma d_{ikt-1} d_{jkt-1} + a_{ij})^{d_{ijt}} \\ &\quad \times [1 - F(\alpha + \beta d_{ijt-1} + \gamma d_{ikt-1} d_{jkt-1} + a_{ij})]^{1-d_{ijt}}\} \\ &\quad \times \pi(\mathbf{d_0}, \mathbf{a}), \end{aligned} \quad (2)$$

where $\pi(\mathbf{d_0}, \mathbf{a})$ is the joint density of the initial network structure and vector of pair-specific heterogeneity terms (I have used the fact that $F_{ijt} = D_{ikt} D_{jkt}$). Goldsmith-Pinkham and Imbens assume independence of $\mathbf{D_0}$ and $\mathbf{A}$. If the network under consideration began prior to the initial period of observation this assumption seems implausible. The link rule given in (1) induces dependence between network structure and $\mathbf{A}$ in later periods. The issues involved are related to those of the initial conditions problem in dynamic binary choice panel data models (e.g., Heckman 1981a,b,c). Goldsmith-Pinkham and Imbens further model the ξ_i as independent draws from a two-mass-point distribution with known mixing probabilities. This assumption in turn induces a distribution for $\mathbf{A}$. While their approach does result in some dependence across the elements of $\mathbf{A}$, it is of a highly structured form. The stylized example given above

[1]More precisely each sampled network may have its own distribution for U_{ijt}. However, the assumption that U_{ijt} is independently and identically distributed across potential ties and over time *within* a network is essential.

[2]In the education context, the manipulation of social cliques may be of special interest.

suggests that the dependence structure across the elements of **A** may be quite complex.[3] Experience drawn from the literature on discriminating between state dependence and heterogeneity using panel data suggests that Goldsmith-Pinkham and Imbens' modeling assumptions lead them to overstate the role of past network structure in explaining current link formation. This is, of course, only a conjecture. It nevertheless motivates the question of what can be learned without imposing strong assumptions on the form of $\pi(\mathbf{d_0}, \mathbf{a})$?

Here I wish to formally study identification of β and, especially, γ. In contrast to Goldsmith-Pinkham and Imbens my treatment will be "fixed effects" in nature—the joint distribution of $\mathbf{D}_0$ and $\mathbf{A}$ will be left unrestricted. Link decisions across pairs of agents are conditionally independent given the network structure in the prior period and the *unobserved* vector of latent social distances **A**. However, unconditional on **A**, the dependence across different link decisions is allowed to be quite complex. There is some connection between my question and that of identifying state dependence using panel data (e.g., Chamberlain 1985, 1995; Hahn 2001). However the analogy is incomplete; a network structure is induced by the interconnected decisions of multiple agents. Modeling a sequence of networks is considerably harder than modeling a sequence of discrete decisions made by a single agent.

As a preliminary analysis, I will study what can be learned by the observed sequence of link decisions between agents i and j conditional on the observed sequence of links between the remaining agents. The goal is to find features of (2) that do not depend on **A**.

Without loss of generality set $i = 1$ and $j = 3$ and consider what can be learned from the relative frequency of observing a specific member of the set of network histories

$$\mathbf{E}_{01} = \left\{ \mathbf{D}_0 = \begin{pmatrix} 0 & D_{120} & D_{130} \\ D_{120} & 0 & D_{230} \\ D_{130} & D_{230} & 0 \end{pmatrix}, \right.$$
$$\mathbf{D}_1 = \begin{pmatrix} 0 & D_{121} & 0 \\ D_{121} & 0 & D_{231} \\ 0 & D_{231} & 0 \end{pmatrix},$$
$$\mathbf{D}_2 = \begin{pmatrix} 0 & D_{121} & 1 \\ D_{121} & 0 & D_{231} \\ 1 & D_{231} & 0 \end{pmatrix},$$
$$\left. \mathbf{D}_3 = \begin{pmatrix} 0 & D_{121} & D_{133} \\ D_{121} & 0 & D_{231} \\ D_{133} & D_{231} & 0 \end{pmatrix} \right\}$$

versus a member of the set

$$\mathbf{E}_{10} = \left\{ \mathbf{D}_0 = \begin{pmatrix} 0 & D_{120} & D_{130} \\ D_{120} & 0 & D_{230} \\ D_{130} & D_{230} & 0 \end{pmatrix}, \right.$$
$$\mathbf{D}_1 = \begin{pmatrix} 0 & D_{121} & 1 \\ D_{121} & 0 & D_{231} \\ 1 & D_{231} & 0 \end{pmatrix},$$
$$\mathbf{D}_2 = \begin{pmatrix} 0 & D_{121} & 0 \\ D_{121} & 0 & D_{231} \\ 0 & D_{231} & 0 \end{pmatrix},$$
$$\left. \mathbf{D}_3 = \begin{pmatrix} 0 & D_{121} & D_{133} \\ D_{121} & 0 & D_{231} \\ D_{133} & D_{231} & 0 \end{pmatrix} \right\}.$$

The networks contained in the sets $\mathbf{E}_{01}$ and $\mathbf{E}_{10}$ have two key features. First, any $(i, k) = (1, 2)$ and $(k, j) = (2, 3)$ ties are stable across periods 1, 2, and 3. If either agent i or j is linked to k in period 1, they are also linked in periods 2 and 3. Likewise, the absence of a period 1 link is associated with an absence of a period 2 and 3 link. The (i, k) and (k, j) pairs may switch their link status between periods 0 and 1, and it is essential that this occurs in some sampled networks, but they do not revise their link status in subsequent periods. This last feature of $\mathbf{E}_{01}$ and $\mathbf{E}_{10}$ ensures variation over time in the opportunity for agents i and j to engineer triadic closure by forming a link. We can say that the (i, j) is embedded in a stable neighborhood. Second, the sequence of (i, j) links differs across $\mathbf{E}_{01}$ and $\mathbf{E}_{10}$. In the first set of histories, (i, j) are linked in period 2, but not 1, while in the second this ordering is reversed. We require that agents i and j switch their link status between periods 1 and 2.

The sets $\mathbf{E}_{01}$ and $\mathbf{E}_{10}$ were selected by a combination of educated guessing, inspired by the work of Cox (1958), Chamberlain (1985), and Honoré and Kyriazidou (2000) on the identification of dynamic binary choice panel data models, and trial and error. Let $\mathbf{D} = (\mathbf{D}_3, \mathbf{D}_2, \mathbf{D}_1, \mathbf{D}_0)$ denote the full sequence of network structures and $\mathbf{e}_{01}$ a specific element of the set $\mathbf{E}_{01}$ (and similarly for $\mathbf{e}_{10}$). A straightforward, albeit tedious, calculation gives (see the Appendix)

$$\frac{\Pr(\mathbf{D} = \mathbf{e}_{01} | \, \mathbf{A} = \mathbf{a})}{\Pr(\mathbf{D} = \mathbf{e}_{10} | \, \mathbf{A} = \mathbf{a})} = \frac{1 - F(\alpha + \beta d_{130} + \gamma d_{120} d_{230} + a_{13})}{F(\alpha + \beta d_{130} + \gamma d_{120} d_{230} + a_{13})} \times \frac{F(\alpha + \beta d_{133} + \gamma d_{121} d_{231} + a_{13})}{1 - F(\alpha + \beta d_{133} + \gamma d_{121} d_{231} + a_{13})}.$$

Monotonicity of F then implies that (see Manski 1987; Honoré and Kyriazidou 2000; Graham 2011, sec. 4.3):

$$\begin{aligned} &\operatorname{sgn}(\Pr(\mathbf{E}_{01} = \mathbf{e}_{01} | \, \mathbf{a}) - \Pr(\mathbf{E}_{10} = \mathbf{e}_{10} | \, \mathbf{a})) \\ &\quad = \operatorname{sgn}(\beta(d_{133} - d_{130}) + \gamma(d_{121} d_{231} - d_{120} d_{230})). \end{aligned} \tag{3}$$

By separately considering the subset of networks with, respectively, $d_{133} \neq d_{130}$ and $d_{121}d_{231} = d_{120}d_{230}$ and $d_{133} = d_{130}$ and $d_{121}d_{231} \neq d_{120}d_{230}$, we can show that the signs of β and γ are separately identified. Consequently, the presence of transitivity is identifiable without imposing any restrictions on the joint distribution of $\mathbf{D}_0$ and **A**. To my knowledge, this is a new result. In ongoing work, I have shown that this result may be extended to networks of arbitrary size (Graham 2012).

If we additionally assume that U_{ijt} is logistically distributed, as in Goldsmith-Pinkham and Imbens (2013), we have

[3]Specifically, cross-group sorting suggests that ξ_1, ξ_2, and ξ_3 covary, which, in turn, induces dependence across the elements of **A**.

identification up to scale with

$$\Pr(\mathbf{D}=\mathbf{e_{01}}\,|\,\mathbf{A}=\mathbf{a},\mathbf{D}\in\{\mathbf{e}_{01},\mathbf{e}_{10}\}) = \frac{\exp\left(\frac{\beta(d_{133}-d_{130})+\gamma(d_{121}d_{231}-d_{120}d_{230})}{\sigma}\right)}{1+\exp\left(\frac{\beta(d_{133}-d_{130})+\gamma(d_{121}d_{231}-d_{120}d_{230})}{\sigma}\right)}, \quad (4)$$

where σ is the scale parameter for U_{ijt} (typically normalized to 1).

That, in the context of a simple dynamic model of network formation, it is possible to discriminate between transitivity and homophily/degree heterogeneity while leaving the joint distribution of $\mathbf{D}_0$ and $\mathbf{A}$ unrestricted is an encouraging result. Goldsmith-Pinkham and Imbens make very strong assumptions on this joint distribution and I suspect their conclusions may be sensitive to them.

While I have presented a simple "fixed effect" identification result, I remain sympathetic to the "(correlated) random effects" modeling strategy of Goldsmith-Pinkham and Imbens (i.e., an approach that does impose restrictions on the joint distribution of $\mathbf{D}_0$ and $\mathbf{A}$). As in nonlinear panel data analysis, the two approaches are complementary. Goldsmith-Pinkham and Imben's application, however, indicates that working with the integrated likelihood is numerically challenging. Some of their choices regarding the joint distribution of $\mathbf{D}_0$ and $\mathbf{A}$ appear to be driven by computational concerns. It would be useful to construct parsimonious parametric models for this distribution that incorporate richer forms of dependence. Of course, continued study of "fixed effects" approaches is also warranted.

APPENDIX

We begin by evaluating (2) at $\mathbf{E}_{01}=\mathbf{e}_{01}$ and $\mathbf{E}_{10}=\mathbf{e}_{10}$. We get

$$\begin{aligned}
&\Pr(\mathbf{D}=\mathbf{e}_{01}\,|\,\mathbf{A}=\mathbf{a})\\
&\quad=\pi(\mathbf{d_0},\mathbf{a})\\
&\qquad\times F(\alpha+\beta d_{120}+\gamma d_{130}d_{230}+a_{12})^{d_{121}}\\
&\qquad\times[1-F(\alpha+\beta d_{120}+\gamma d_{130}d_{230}+a_{12})]^{1-d_{121}}\\
&\qquad\times[1-F(\alpha+\beta d_{130}+\gamma d_{120}d_{230}+a_{13})]\\
&\qquad\times F(\alpha+\beta d_{230}+\gamma d_{120}d_{130}+a_{23})^{d_{231}}\\
&\qquad\times[1-F(\alpha+\beta d_{230}+\gamma d_{120}d_{130}+a_{23})]^{1-d_{231}}\\
&\qquad\times F(\alpha+\beta d_{121}+a_{12})^{d_{121}}[1-F(\alpha+\beta d_{121}+a_{12})]^{1-d_{121}}\\
&\qquad\times F(\alpha+\gamma d_{121}d_{231}+a_{13})\\
&\qquad\times F(\alpha+\beta d_{231}+a_{23})^{d_{231}}[1-F(\alpha+\beta d_{231}+a_{23})]^{1-d_{231}}\\
&\qquad\times F(\alpha+\beta d_{121}+\gamma d_{231}+a_{12})^{d_{121}}\\
&\qquad\times[1-F(\alpha+\beta d_{121}+\gamma d_{231}+a_{12})]^{1-d_{121}}\\
&\qquad\times F(\alpha+\beta+\gamma d_{121}d_{231}+a_{13})^{d_{133}}\\
&\qquad\times[1-F(\alpha+\beta+\gamma d_{121}d_{231}+a_{13})]^{1-d_{133}}\\
&\qquad\times F(\alpha+\beta d_{231}+\gamma d_{121}+a_{23})^{d_{231}}\\
&\qquad\times[1-F(\alpha+\beta d_{231}+\gamma d_{121}+a_{23})]^{1-d_{231}}
\end{aligned}$$

and

$$\begin{aligned}
&\Pr(\mathbf{D}=\mathbf{e}_{10}\,|\,\mathbf{A}=\mathbf{a})\\
&\quad=\pi(\mathbf{d_0},\mathbf{a})\\
&\qquad\times F(\alpha+\beta d_{120}+\gamma d_{130}d_{230}+a_{12})^{d_{121}}\\
&\qquad\times[1-F(\alpha+\beta d_{120}+\gamma d_{130}d_{230}+a_{12})]^{1-d_{121}}\\
&\qquad\times F(\alpha+\beta d_{130}+\gamma d_{120}d_{230}+a_{13})\\
&\qquad\times F(\alpha+\beta d_{230}+\gamma d_{120}d_{130}+a_{23})^{d_{231}}\\
&\qquad\times[1-F(\alpha+\beta d_{230}+\gamma d_{120}d_{130}+a_{23})]^{1-d_{231}}\\
&\qquad\times F(\alpha+\beta d_{121}+\gamma d_{231}+a_{12})^{d_{121}}\\
&\qquad\times[1-F(\alpha+\beta d_{121}+\gamma d_{231}+a_{12})]^{1-d_{121}}\\
&\qquad\times[1-F(\alpha+\beta+\gamma d_{121}d_{231}+a_{13})]\\
&\qquad\times F(\alpha+\beta d_{231}+\gamma d_{121}+a_{23})^{d_{231}}\\
&\qquad\times[1-F(\alpha+\beta d_{231}+\gamma d_{121}+a_{23})]^{1-d_{231}}\\
&\qquad\times F(\alpha+\beta d_{121}+a_{12})^{d_{121}}[1-F(\alpha+\beta d_{121}+a_{12})]^{1-d_{121}}\\
&\qquad\times F(\alpha+\gamma d_{121}d_{231}+a_{13})^{d_{133}}\\
&\qquad\times[1-F(\alpha+\gamma d_{121}d_{231}+a_{13})]^{1-d_{133}}\\
&\qquad\times F(\alpha+\beta d_{231}+a_{23})^{d_{231}}[1-F(\alpha+\beta d_{231}+a_{23})]^{1-d_{231}}.
\end{aligned}$$

Taking the ratio of these two probabilities yields, after some obvious cancellations:

$$\begin{aligned}
&\frac{\Pr(\mathbf{D}=\mathbf{e}_{01}\,|\,\mathbf{A}=\mathbf{a})}{\Pr(\mathbf{D}=\mathbf{e}_{10}\,|\,\mathbf{A}=\mathbf{a})}\\
&\quad=\frac{1-F(\alpha+\beta d_{130}+\gamma d_{120}d_{230}+a_{13})}{F(\alpha+\beta d_{130}+\gamma d_{120}d_{230}+a_{13})}\\
&\qquad\times\frac{F(\alpha+\gamma d_{121}d_{231}+a_{13})}{1-F(\alpha+\beta+\gamma d_{121}d_{231}+a_{13})}\\
&\qquad\times\{F(\alpha+\beta+\gamma d_{121}d_{231}+a_{13})^{d_{133}}\\
&\qquad\quad\times[1-F(\alpha+\beta+\gamma d_{121}d_{231}+a_{13})]^{1-d_{133}}\}\\
&\qquad/\{F(\alpha+\gamma d_{121}d_{231}+a_{13})^{d_{133}}\\
&\qquad\quad\times[1-F(\alpha+\gamma d_{121}d_{231}+a_{13})]^{1-d_{133}}\}.
\end{aligned}$$

Now observe that if $d_{133}=1$, we have $F(\alpha+\beta+\gamma d_{121}d_{231}+a_{13})^{d_{133}}=F(\alpha+\beta d_{133}+\gamma d_{121}d_{231}+a_{13})$ and $1-F(\alpha+\beta+\gamma d_{121}d_{231}+a_{13})=1-F(\alpha+\beta d_{133}+\gamma d_{121}d_{231}+a_{13})$ which implies the simplification given immediately prior to Equation (3) of the main text. Similarly if $d_{133}=0$, we have $[1-F(\alpha+\gamma d_{121}d_{231}+a_{13})]^{1-d_{133}}=[1-F(\alpha+\beta d_{133}+\gamma d_{121}d_{231}+a_{13})]$ and $F(\alpha+\gamma d_{121}d_{231}+a_{13})=F(\alpha+\beta d_{133}+\gamma d_{121}d_{231}+a_{13})$ which gives the same result.

In the logistic case, we have

$$\frac{\frac{1-F(\alpha+\beta d_{130}+\gamma d_{120}d_{230}+a_{13})}{F(\alpha+\beta d_{130}+\gamma d_{120}d_{230}+a_{13})}}{\frac{1-F(\alpha+\beta d_{133}+\gamma d_{121}d_{231}+a_{13})}{F(\alpha+\beta d_{133}+\gamma d_{121}d_{231}+a_{13})}} = \exp\left(\frac{\beta(d_{133}-d_{130})+\gamma(d_{121}d_{231}-d_{120}d_{230})}{\sigma}\right),$$

from which (4) follows directly.

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Comment

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1. INTRODUCTION

Understanding peer effects is of first-order importance in a range of settings including education, labor markets, crime, voting, and consumer behavior. However, although casual introspection and some field experiments (e.g., Duflo and Saez 2003; Centola 2010) suggest that the influence of friends and acquaintances on behavior can be substantial, there are formidable challenges in establishing peer effects using (increasingly available) purely observational data that couple behaviors with social relationships.

The challenges in establishing that peer effects are truly present include:

- Identification: A model of peer effects must be specified in a manner such that the channels through which peers influence one's behavior can be identified as well as distinguished from other sources of influence (Manski 1993; Bramoullé et al. 2009; Blume et al. 2011).
- Endogenous networks and homophily: Linked individuals are likely to be similar not only in terms of observed characteristics but also in terms of unobserved characteristics that could influence behavior. By failing to account for similarities in (unobserved) characteristics, similar behaviors might mistakenly be attributed to peer influence when they simply result due to similar characteristics (Aral et al. 2009; Jackson 2008). This is complicated by the richness of the set of possible characteristics that could matter, which not only involve innate or exogenous ones that might influence preferences, but also correlated ones that include exposure to common stimuli (Manski 1993).
- Computation: The possible set of networks of peer relationships is generally exponential in the size of the population and so having a model that allows for endogenous peer relationships can face significant computational challenges (Chandrasekhar and Jackson 2012).
- Measurement error: Relationships can be difficult to observe and quantify. This can reduce the power of a test, especially with self-reported relationships that are easily unobserved (Chandrasekhar and Lewis 2011). In particular, this applies to data with caps on the numbers of friends that can be reported as in the Add Health dataset.
- Misspecification: Specifying the appropriate set of peers, which can be time- and context-dependent, is difficult, as in correctly specifying the ways in which they influence each other, including possible heterogeneity among a given individual's friends.

The difficulties of convincingly demonstrating peer effects are complicated by the fact that the biases introduced by the various issues mentioned above can push in different directions. For

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