# Using Network Data to Measure Social Returns and Improve Targeting of Crime-Reduction Interventions

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All opinions are those of the authors and do not represent the position of any government organization or data provider.

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# The high cost of crime and violence

- Acts of violence kill over 160 per day in the U.S. (CDC 2019)
  - And 2.3 million people live behind bars (Prison Policy Initiative 2020)
- Stark inequalities in who bears these costs
  - Violent-crime arrests 5 Xs higher for Black than White young people (OJJDP 2014)
  - With lifelong consequences on social & economic outcomes (Aizer & Doyle 2015, Mueller-Smith 2015, Nelson & Sheridan 2011)
- Social costs of gun violence alone at least \$100 billion/year, maybe $>$ \$500 billion (Cook & Ludwig 2000, Gobbo 2023)

# Randomized controlled trials (RCTs) and crime prevention

- Hundreds of RCTs over 4 decades have tested ways to address these problems
  - Policing strategies (e.g., Braga et al. 1999, 2006, 2017; Owens et al. 2018; Sherman & Berk 1984; Sherman & Weisburd 1995)
  - Employment & re-entry (e.g., Cook et al. 2015; MDRC 1980; Kemper et al. 1981; Valentine & Redcross 2015),
  - Urban environment (e.g., Branas et al. 2018; Chalfin et al. 2021)
  - Education and skill development (e.g., Armstrong et al. 2003; Dodge et al 2007; Schweinhart et al. 2007)
- Influential b/c convincingly isolate causal effect of treatment vs control condition
- Most assume one individual's behavior doesn't affect others (SUTVA)
  - Also true of many non-RCT quasi-experiments

# In fact, crime is social

- 50-85% of offenders offend with others, usually as youth when most crime occurs (Conway & McCord 2002; Sarnecki 2001)
- Peer effects in crime are well established
  - Exogeneous changes in exposure to A changes B's crime (Bayer et al. 2009; Bhuller et al. 2018; Billings et al. 2019; Damm & Gorinas 2020; Drago & Galbiati 2012; Dominguez 2021; Dustmann & Landersø 2021; Norris et al. 2021; Stevenson 2017; Philippe 2017)
- But existence of peer effects $\neq$ estimate of how an intervention's crime change spreads
  - Requires knowing how many people A affects, if effect varies with who A and B are/how they're connected, if changing A's behavior or just exposure to A matters

# Our paper: how do crime changes spread through networks?

- **Challenge 1: Measure social networks**
- Use administrative data on ~2m people $\rightarrow$ Chicago Police Department (arrests & reported victimizations 2005-21) and Chicago Public Schools records (2009-20)
- Co-arrest, co-victimization, same classes, same residence, geographic proximity
  - Clearly misses some strong friendship ties, but non-friend ties may matter (Granovetter 1983, Patacchini & Zenou 2008)
  - If these ties do matter, makes it feasible to look at crime spillovers retrospectively, at large scale

# Our paper: how do crime changes spread through networks?

- **Challenge 2: Overcome classic identification issues** $\rightarrow$ reflection problem, endogeneity of ties, common shocks (Manski 1993, Angrist 2014)
- Leverage 4 existing, large-scale RCTs of violence-reducing interventions in Chicago (Davis & Heller 2020, Heller 2014, Heller et al. 2017, Bhatt et al 2024)
  - Given baseline tie to RCT member, exposure to T is random with known probability
    - Aronow & Samii 2017$\rightarrow$ probability as IPW, conservative inference
  - Pooling RCTs may help solve challenges in handful of previous efforts to do this
    - Under-powered, potentially confounded (Abdul-Razzak et al, in progress, Dominguez 2023, Wood & Papachristos 2019)

# What we do

1. Today: Describe networks, estimate preliminary indirect exposure effects
    - Exposure = connected to at least one peer assigned to treatment (ITT)
        - *Within RCT exposure effect*: what initial ITTs missed for original samples
        - *Out of RCT exposure effect*: impact on those not in original RCTs
    - For now, 1st-degree peer + any exposure, no geography or overlapping networks yet
2. Future: Estimate counterfactual targeting mechanisms → optimal targeting
    - Use heterogeneity to tease out behavioral mechanisms
    - Build model incorporating effects on future tie formation, network position

# Intervention spillovers and social networks

- Multiple literatures developed methods to analyze peer effects, network diffusion
  - In development: how innovations diffuse through social networks, change network structure (Banerjee et al. 2013, Beaman et al. 2020, Beaman & Magruer 2012, Bhattacharya et al. 2013, Breza & Chandrasekhar 2019, Cai et al. 2015, Comola & Prina 2014, Feigenberg et al. 2013, Miguel & Kremer 2007, Miller & Mobarak 2014, Oster & Thornton 2012)
  - In education: how exposure to different peers or treating peers matters for learning/behavior (Babcock & Hartman 2010, Chaisemartin & Navarrete 2020, Dinarte & Egana-del Sol 2022, Paluck et al. 2016, Sacerdote 2001, review in Sacerdote 2011)
- Empirical crime literature: more focused on *you* when someone you know/live with gets (un)incarcerated, your school peers or cellmates change, you move, etc.
  - Exception: bullying interventions via reported friend networks (Hu 2024; Paluck,Shepherd & Aronow 2016)

# What we are learning

- These networks capture many relationships
  - $\sim$550 people exposed for every 100 people treated
- Peers of study members are different
  - Both from the study population and across network types
- Spillovers concentrated among peers also in the original RCTs
  - Observable and unobservable selection into the RCTs
- Spillovers vary by type of network connection
  - Diffusion among denser networks, substitution among closer relationships
- Spillovers are large
  - Current estimates suggest original RCTs understated violence $\downarrow$ by 40-80%

# Random variation: 4 violence-reducing RCTs in Chicago

1. **Becoming a Man** (BAM 2009-10, n = 2,740)
   - School-based cognitive behavioral therapy (CBT) intervention for 7th-10th grade boys
   - ITT/LATE: Violent-crime arrests ↓ 21/45% in year 1

2 & 3. **One Summer Chicago Plus** (OSC+ 2012 n = 1,634, OSC+ 2013 = 5,216)
   - SYEP+CBT w/ school-based recruiting in 2012, broader reach into legal system in 2013
   - Violent-crime arrests ↓ 21-41% / 32-42% in year 1
   - Not just incapacitation, continued decline post-program

4. **Rapid Employment & Development Initiative** (READI 2016-21, n = 2,456)
   - 18m job, CBT, wraparound services for men (18+) at highest risk of shooting/being shot
   - After 20m, 45/65% ↓ shooting & homicide arrests (adj. p=0.13), 38/48% ↓ S&H victimization for pre-specified subgroup

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# Outcomes

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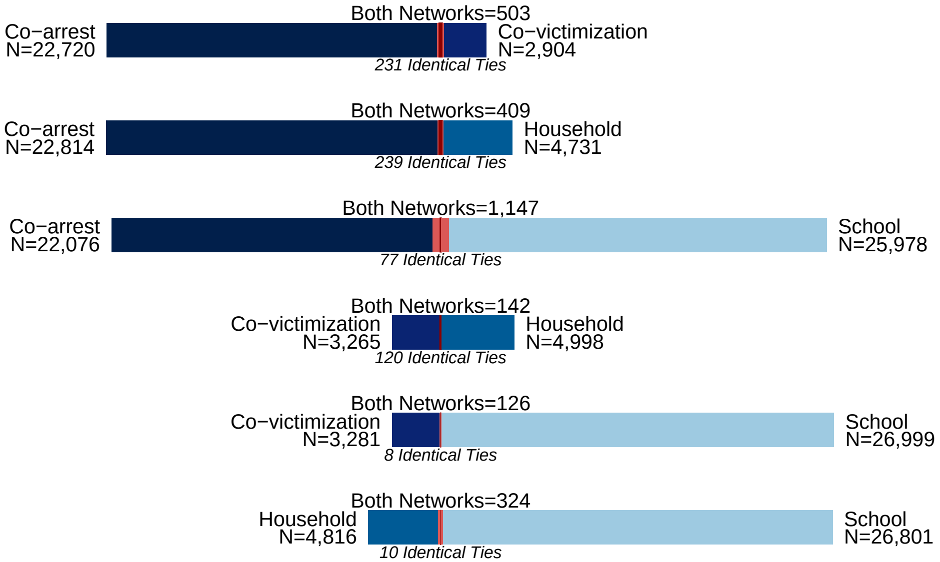
# Why a shock to criminal behavior might spill over

1. **Diffusion of behavioral change**: information, changes in attitudes/beliefs/time use get transmitted $\rightarrow$ peer crime $\Downarrow$
   (e.g. Akerlof & Kranton 2010, Pattacchini & Zenou 2009)
2. **Key players**: lose key member of criminal team, social influencer $\rightarrow$ peer crime $\Downarrow$
   (e.g. Lindquist & Zenou 2014, Tankard & Paluck 2016)
3. **Crime as function of opportunity**: if one youth desists, another may take his place $\rightarrow$ peer crime $\Uparrow$ (e.g. Cook 1986)
4. **Skill complementarity**: co-offending improves productivity $\rightarrow$ peer crime $\Downarrow$, or perhaps substitution to new peer with similar skills $\Uparrow$
   (e.g. Tremblay 1993; Weerman 2003)

# Constructing networks

1. **Co-arrest**: Arrested together or for same incident in 5 years prior to randomization
   - 42% in network, 2.8 ties/RCT member $(6.8|co-arrest > 0)$
2. **Co-victimization**: Victimized in same incident in 5 years prior to randomization
   - 15% in network, 0.27 ties/RCT member $(1.8|co-victim > 0)$
3. **Household**: Share parent/guardian name, address & last name in CPS data
   - 29% in network, 0.44 ties/RCT member $(1.5|sibling > 0)$ Details
   - Limit to age $> 12$ for crime outcomes
4. **Shared classes**: Clustering algorithm $\rightarrow$ many shared courses in prior year
   - Schedule data currently only OSC 1 & 2, BAM coming, READI schooling often old
   - 48% in network, 6.7 ties/RCT member, $(13.9|sharedclass > 0)$ Details
   - Students in community share avg of 5 of 16 courses, 0.5 outside community
5. **Neighborhood** (not yet)
   - Using CPS and CPD addresses, live within m mile radius in prior year

# Size and overlap of the networks: first-degree peers



# RCT study sample descriptive statistics

| | BAM/OSC | READI |
|---|---|---|
| | In-RCT | In-RCT |
| N | 9,590 | 2,456 |
| Age | 17.4 | 25.7 |
| Black | 0.85 | 0.96 |
| Male | 0.90 | 1.00 |
| Prior Arrests | 2.5 | 16.7 |
| Share Co-Arrests | 0.21 | 0.32 |
| Degree | 2.23 | 5.02 |

# Subset in co-arrest network & tied to another study member

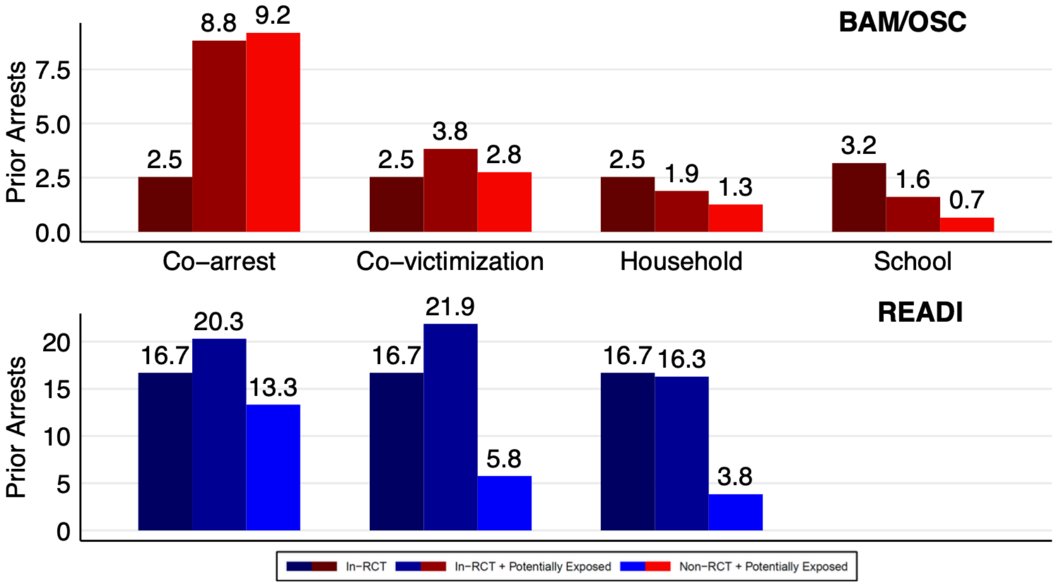
| | BAM/OSC | | READI | |
|---|---|---|---|---|
| | In-RCT | In-RCT + Potentially Exposed | In-RCT | In-RCT + Potentially Exposed |
| N | 9,590 | 1,396 | 2,456 | 975 |
| Age | 17.4 | 18.0 | 25.7 | 23.6 |
| Black | 0.85 | 0.91 | 0.96 | 1.00 |
| Male | 0.90 | 0.98 | 1.00 | 1.00 |
| Prior Arrests | 2.5 | 8.8 | 16.7 | 20.3 |
| Share Co-Arrests | 0.21 | 0.63 | 0.32 | 0.45 |
| Degree | 2.23 | 9.56 | 5.02 | 9.18 |

# Co-arrest linkages: First degree peers are different

| | BAM/OSC | | | READI | | |
|---|---|---|---|---|---|---|
| | In-RCT | In-RCT + Potentially Exposed | Non-RCT + Potentially Exposed | In-RCT | In-RCT + Potentially Exposed | Non-RCT + Potentially Exposed |
| N | 9,590 | 1,396 | 14,257 | 2,456 | 975 | 6,595 |
| Age | 17.4 | 18.0 | 21.0 | 25.7 | 23.6 | 25.3 |
| Black | 0.85 | 0.91 | 0.86 | 0.96 | 1.00 | 0.95 |
| Male | 0.90 | 0.98 | 0.92 | 1.00 | 1.00 | 0.90 |
| Prior Arrests | 2.5 | 8.8 | 9.2 | 16.7 | 20.3 | 13.3 |
| Share Co-Arrests | 0.21 | 0.63 | 0.64 | 0.32 | 0.45 | 0.55 |
| Degree | 2.23 | 9.56 | 9.02 | 5.02 | 9.18 | 6.38 |

Co-Victims Households Classes

# Other networks



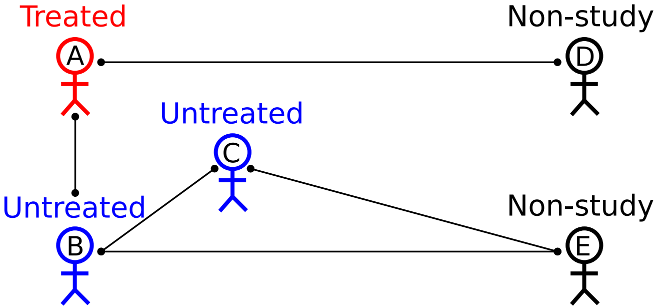
# Defining potential outcomes & treatment effects

- **If in original RCTs**: 4 potential outcomes for 4 exposure states ($\mathscr{E}$)
  $Y_{1,1}$: Directly treated, peer exposure
  $Y_{1,0}$: Directly treated, no peer exposure
  $Y_{0,1}$: Control, peer exposure
  $Y_{0,0}$: Control, no peer exposure
- Assume equal exposure effect for T and C (based on data and to help power)
  - $E(Y_{1,1}) - E(Y_{1,0}) = E(Y_{0,1}) - E(Y_{0,0})$

  $Exposure_{inRCT} = E(Y_{.,1}) - E(Y_{.,0})$
- **If not in original RCTs**: 2 potential outcomes for 2 exposure states
  $Y_1$: Peer exposure
  $Y_0$: No peer exposure

  $Exposure_{outRCT} = E(Y_1) - E(Y_0)$

# Estimation: Aronow & Samii 2017

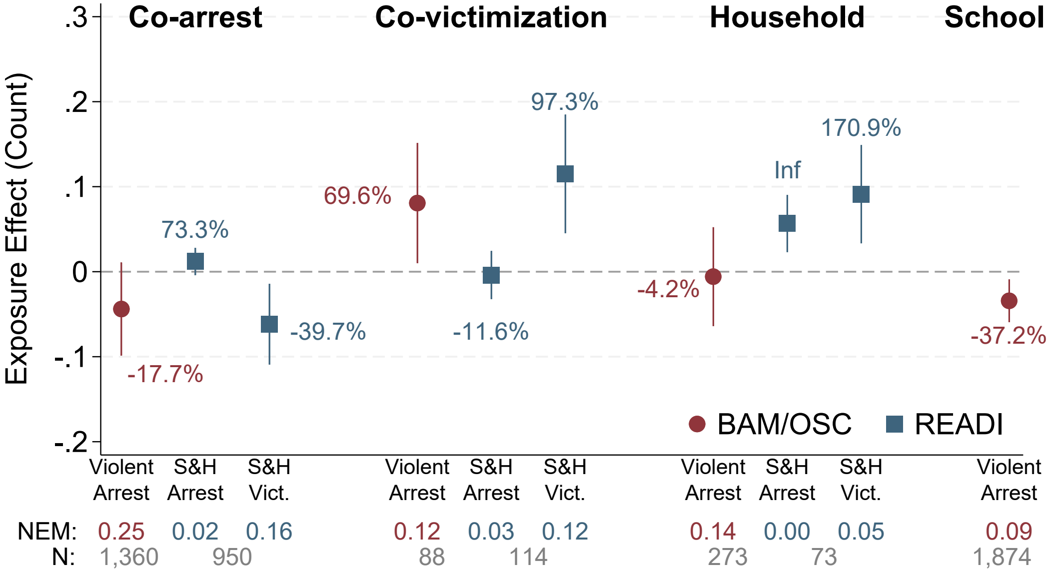



- Can calculate exact $p_{is}(j,k)$ or $p_{is}(k) = Pr(\mathscr{E} = e)$ for every exposure state

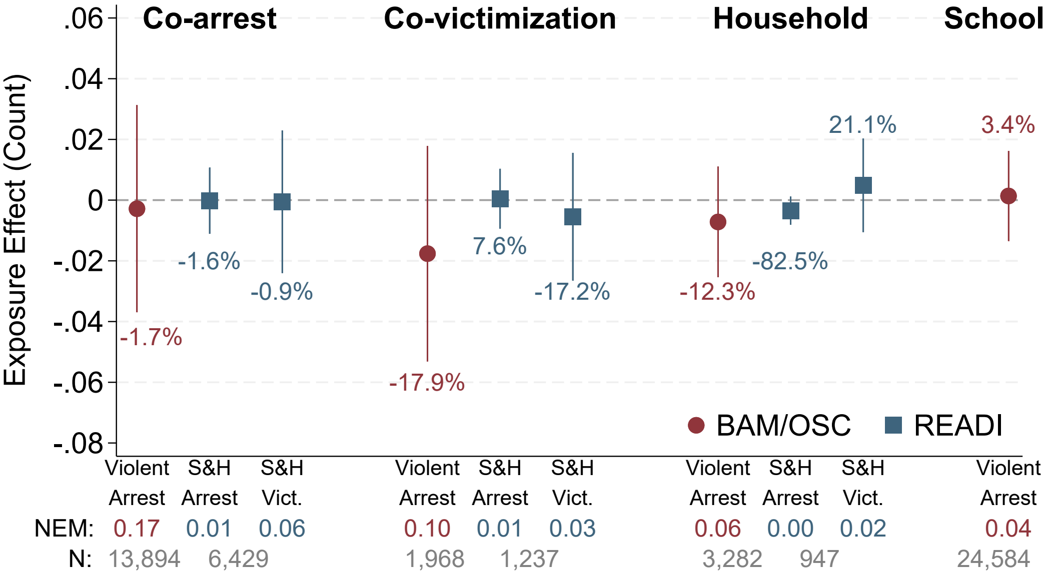
# Estimation: Aronow & Samii 2017

- IPW: $E(\tilde{Y}_e) = \frac{1}{N}\sum_i \frac{\mathbb{1}(\mathscr{E}=e)Y_i}{p_{is}(\mathscr{E}=e)}$ $\forall\, i$ where $p_{is}(\mathscr{E} = e) > 0$
- Estimate exposure effect$= E(\tilde{Y}_{.,1}) - E(\tilde{Y}_{.,0})$ or $E(\tilde{Y}_1) - E(\tilde{Y}_0)$
  - We do not constrain exposure effect to be the same in- and out-of-RCTs
  - Out-of-RCT peers look very different $\rightarrow$ allows for heterogeneity
  - And solves estimation problem $\rightarrow$ $Pr(\mathscr{E} = j, k) = 0$ for out-of-RCT sample
- Residualize covariates (Aronow & Samii 2017, Särndal et al. 1992)
  - Assume $E(Y_{1,1}) - E(Y_{1,0}) = E(Y_{0,1}) - E(Y_{0,0})$ $\rightarrow$ residualize direct treatment
- A & S derive asymptotic standard errors accounting for interdependence & covariates, estimates are conservative
  - Assumes exposure states are correctly specified

# Violence spillovers, within RCT sample



# Violence spillovers, non-RCT sample



# What could explain the heterogeneity?

- In-RCT sample observably different in at least 3 ways:
  - Higher risk of violence → non-exposed means 2-3 times those for non-RCT peers
  - More exposures → 26 vs 11% have multiple exposures, avg 1.6 vs 1.3 $|$ exposure
  - Peers with higher take-up → 25-50% more likely to have peer who participated
- In-RCT sample unobservably different
  - RCT sample selection may succeed in identifying those responsive to change
  - Could use differences in selection across RCTs to assess

# How big are these effects?

- Using estimates with $p \leq 0.1$, assume exposure effects are additive & re-calculate social impact of RCTs
- BAM/OSC: 48 RCT members indirectly exposed (in-study 1st degree peer in any network) per 100 treated people
  - Stacked ITT estimate: -2 violent-crime arrests per 100 treated (-22%)
  - Indirect exposure, all networks = -0.8 arrests per 100 treated (-20%)
  - Accounting for spillovers, average decline in violence from RCTs 40% higher
- READI: 63 exposed per 100 treated via co-arrest, co-victim, household
  - Net RCT impact shifts from -2.2 to -2.0 per 100 T for shooting & homicide arrests
  - From -1.3 (insig) to -4.0 per 100 T for shooting & homicide victimization
  - Together ~80% larger shooting & homicide decline

# Summary and next steps

- Networks dense enough to really matter
  - Current estimates: original RCTs may understate net violence decline by 40-80%
- Spillovers seem limited to those in original studies
  - Maybe programs successfully targeted those at risk of violence + responsive?
- Type of social relationship seems to matter
  - Violence $\downarrow$ diffuses via denser networks, weaker ties. Closer ties $\rightarrow$ viol. substitutes
  - Potentially important lessons about joint crime decisions here
- Much work left to do
  - Geography, other exposure definitions, ties via multiple networks, school outcomes
  - Heterogeneity to inform why peer behavior matters
  - Use results, treatment effects on future tie formation to build model
  - Optimal targeting

# Appendix Slides

## Appendix

# Household network

- Observe address and parent/guardian in CPS data once/year while a student
  - 96% of RCT members linked to non-missing info
- At any point in 2008/09 data (back to 90s) - randomization date, link anyone who shares:
  - Parent/guardian name, address, and last name
  - Drop co-habitants $<$ age 12 at randomization
  - $\sim$90% linked peers are ages 6-25, some older co-residents
- Among RCT members in CPS data, 31% have sibling/co-habitant

# Shared class network

- Use clustering algorithm (modularity blocking + stochastic block model) to identify "academic communities"
  - In year prior to randomization at school with most days present
- Maximizes likelihood of shared community given shared courses Details
  - Students linked if in shared academic community, not if otherwise
- Have experimented with threshold definitions (at least X shared courses)
- Schedule data currently available for OSC 1 & 2 in regular public schools (BAM coming, READI school involvement often old)

# What academic communities look like

| | Mean | SD | 10th | 90th |
|---|---|---|---|---|
| Community size | 13.7 | 8.3 | 6 | 24 |
| Total classes enrolled | 15.7 | | | |
| **Classes shared** | | | | |
| within community | 4.8 | 3.4 | 1.4 | 9.6 |
| outside community | 0.5 | 0.4 | 0.2 | 0.9 |

Community-level observations, N = 2,072.

# Class network: stochastic block model

- Number of shared classes $c$ between 2 students $i, j$ function of unobserved academic network $A$
- Want to use data to identify peers in same academic network
- Can write down joint distribution of network membership and avg classes shared, where q is number of academic communities
  - $logp(\mathbb{C}, \mathbb{A}) = \sum_i \sum_q A_{iq} log \alpha_q + \sum_{i<j} \sum_{q,l} A_{iq} A_{jl} logf_{\lambda_{ql}}(C_{ij})$
- If we knew $A$, could estimate $\alpha, \lambda$ via maximum likelihood
  - Instead, need to add some structure with distributional functional forms (factorized multinomial)
  - Then jointly estimate community membership and distributional parameters

# Class network: stochastic block model

- Too complex to do for full data: restrict size of networks within schools
- 2/3 students take at least 2/3 of courses with students in other grades
  - So grade blocking is limiting
- Use modularity clustering algorithm – very fast (Clauset et al 2004)
  - Finding groups that maximize the difference between actual ties and what ties would look like if random
- Right now, 5% of communities have $<1$ shared classes with each other
  - Will likely eventually trim some "weak" communities

# Non-RCT estimation in regression form

1. Control for $p_{is}$ directly, propensity-score style:

$$Y_{is} = \tau Exposed_{is} + \delta_s p_{is} + \gamma_s + \theta X_{is} + \varepsilon_{is}$$

2. Borusyak & Hull 2021 improvement: Recenter indirect treatment by using $Exposed_{is} - p_{is}$ + randomizaton inference

   - BUT: when 2 kinds of treatments (direct, indirect), correct inference is on other side of frontier (not a sharp null)
   - Athey et al (2018): Fix direct T for subset & re-randomize for others – large power reductions + estimates can vary depending on whose direct T is fixed

# Co-victim first-degree peers

| | BAM/OSC | | | READI | | |
|---|---|---|---|---|---|---|
| | In-RCT | In-RCT + Potentially Exposed | Non-RCT + Potentially Exposed | In-RCT | In-RCT + Potentially Exposed | Non-RCT + Potentially Exposed |
| N | 9,590 | 88 | 1,968 | 2,456 | 114 | 1,237 |
| Age | 17.4 | 17.5 | 24.4 | 25.7 | 23.9 | 29.9 |
| Black | 0.85 | 0.98 | 0.93 | 0.96 | 1.00 | 0.91 |
| Male | 0.90 | 0.89 | 0.69 | 1.00 | 1.00 | 0.69 |
| Prior Arrests | 2.5 | 3.8 | 2.8 | 16.7 | 21.9 | 5.8 |
| Prior Victimizations | 0.6 | 2.2 | 3.2 | 1.5 | 2.3 | 3.4 |
| Degree | 0.22 | 1.85 | 2.55 | 0.46 | 2.25 | 2.10 |

# Household first-degree peers

| | BAM/OSC | | | READI | | |
|---|---|---|---|---|---|---|
| | In-RCT | In-RCT + Potentially Exposed | Non-RCT + Potentially Exposed | In-RCT | In-RCT + Potentially Exposed | Non-RCT + Potentially Exposed |
| N | 9,590 | 273 | 3,847 | 2,456 | 73 | 947 |
| Age | 17.4 | 17.0 | 16.9 | 25.7 | 23.7 | 22.8 |
| Black | 0.85 | 0.88 | 0.82 | 0.96 | 0.99 | 0.98 |
| Male | 0.90 | 0.86 | 0.50 | 1.00 | 1.00 | 0.50 |
| Prior Arrests | 2.5 | 1.9 | 1.3 | 16.7 | 16.3 | 3.8 |
| Degree | 0.44 | 1.62 | 1.90 | 0.43 | 1.82 | 2.00 |

# Classroom first-degree peers

| | OSC1/OSC2 | | |
|---|---|---|---|
| | In-RCT | In-RCT + Potentially Exposed | Non-RCT + Potentially Exposed |
| N | 6,850 | 1,923 | 25,202 |
| Age | 18.1 | 17.3 | 17.0 |
| Black | 0.92 | 0.96 | 0.74 |
| Male | 0.85 | 0.65 | 0.49 |
| Prior Arrests | 3.2 | 1.6 | 0.7 |
| Degree | 6.65 | 15.32 | 18.27 |