Leveraging Social Networks to Understand Behavioral and Biological Pathways in Substance Abuse and Dependence

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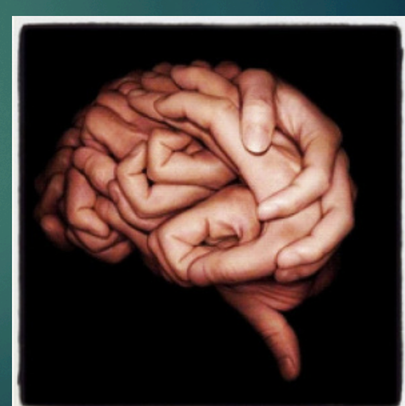
Social networks and health

How do social networks influence and moderate biological and behavioral pathways in health?

- Decision-making
- Access to resources
- Behavior
- Recovery
- Phenotypic expression



Ongoing projects in behavior genetics…

Genetic risk for disinhibition → Substance misuse and dependence

SOCIAL NETWORKS

Low social regulation
Permissive social norms
Access to drugs/alcohol

Exhibit A

Exhibit B

New projects…

Doctor Shopping for Controlled Substances: Insights from Two-Mode Social Network Analysis

Collaborators:

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- Trish Freeman, Clinical Associate Professor, Univ. of Kentucky
- Adam Jonas, LINKS Center, Univ. of Kentucky

Prescription drug abuse

- Prescription drug abuse "epidemic"
  - Opioid abuse increased by 4,680% between 1996 and 2011 in the U.S.
  - Prevalence of prescription drug abuse exceeds that for all other illicit drugs combined, except marijuana
  - Mortality from drug overdose is among the nation's leading preventable causes of death

Doctor shopping

Doctor shopping = obtaining controlled substances from multiple health care practitioners simultaneously, exceeding the recommended dosage (CDC, 2014)

Doctor shopping

- 12% of all prescriptions written for controlled substances
- Nearly 40% with prescription drug dependence obtain drugs through doctor shopping
- Indicator of escalating abuse, two-fold risk for fatal overdose
- Among most difficult drug seeking behaviors to identify and address

Existing gaps and limitations

- Poor measurement of doctor shopping
  - Usually "multiple provider episodes" (binary indicator) → Type I and Type II errors
  - Huge variation in measurement and estimates (ranging from 0.2% to 8%)
  - Difficult to identify doctor shopping and understand its etiology → impedes evaluation of prescription drug policies

Existing gaps and limitations

- Characteristics of patients involved
  - Doctor shopping used by a sub-group averse to illegal behavior
  - Women, older, higher SES, oral users
  - Harder to identify

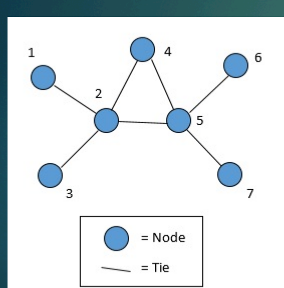
Existing gaps and limitations

- Two patterns that suggest SNA likely to provide insights:
  - Clustering: Physicians are systematically targeted on the basis of prescription behavior or other characteristics
  - Collusion: Knowledge of prescriber targets is shared amongst doctor shoppers

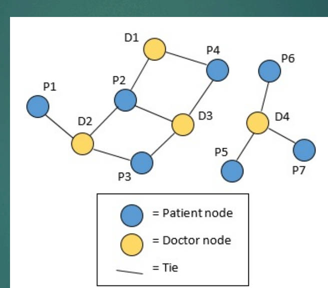
Social network analysis

- Why SNA?
  - Ideal when key mechanisms are relational processes or flow of resources or information between actors
  - SNA has been used to identify structural anomalies (e.g. fraud) in industry and financial markets, has not been applied to prescribing networks

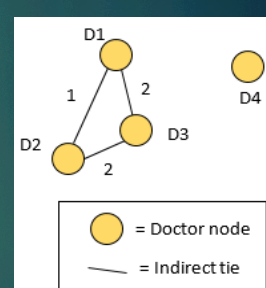
One mode versus two mode (affiliation) networks



Standard one mode network



Two mode affiliation network



Weighted one mode affiliation network

What can be done with two mode SNA?

- Examine prescribers linked indirectly through co-visitation by the same doctor shoppers, and vice versa
  - Clustering?
  - Develop SNA measures of doctor shopping
  - Identify characteristics of central actors
  - Link to prescription drug outcomes

Data

- Deidentified patient health claims info from a large commercially insured population from 2007-2009
  - 15 million patients annually, with private insurance and Medicaid
  - Nationally-representative of the US with regard to gender (50% men), regional distribution, and age

Data

- Analysis sample = any patient who filled one or more opioid or benzodiazepine prescriptions and every clinician who prescribed to one of these patients
- 5,197,238 patients; 718,146 prescribers

Preliminary analyses

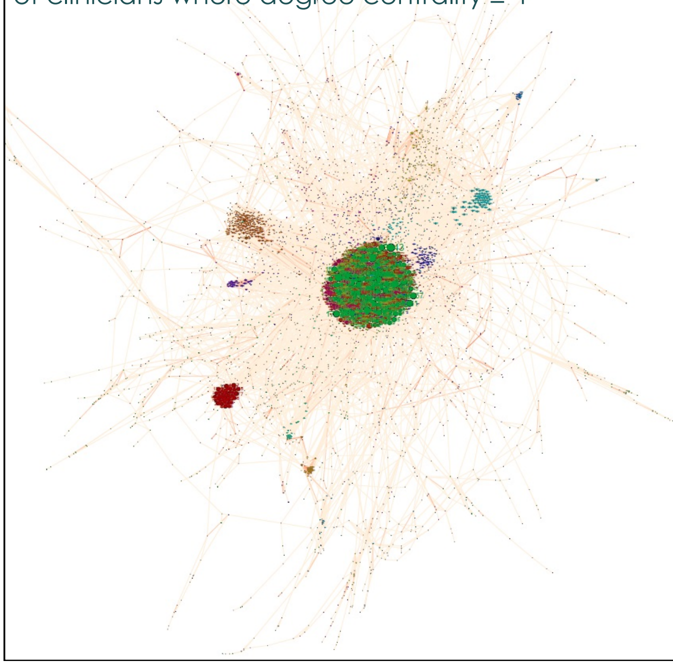
- A priori identification of doctor shopping (not deductive) = 4 prescriptions + 4 pharmacies criterion
- Only one mode weighted affiliation networks of clinicians
  - Degree centrality (# of ties to other clinicians through common doctor shopper)
  - Correlation of centrality to other measures
  - Visualization

Preliminary results

- 89,297 clinicians prescribed to at least one doctor shopper (12%)
- Mean degree centrality = 23.15
- Standard deviation = 61.48
- Range* = 0 – 995

*Most central prescriber in the network had been doctor shopped by 995 patients who also shopped another clinician in 1 year

Figure 1. Weighted one mode affiliation network of clinicians where degree centrality ≥ 4

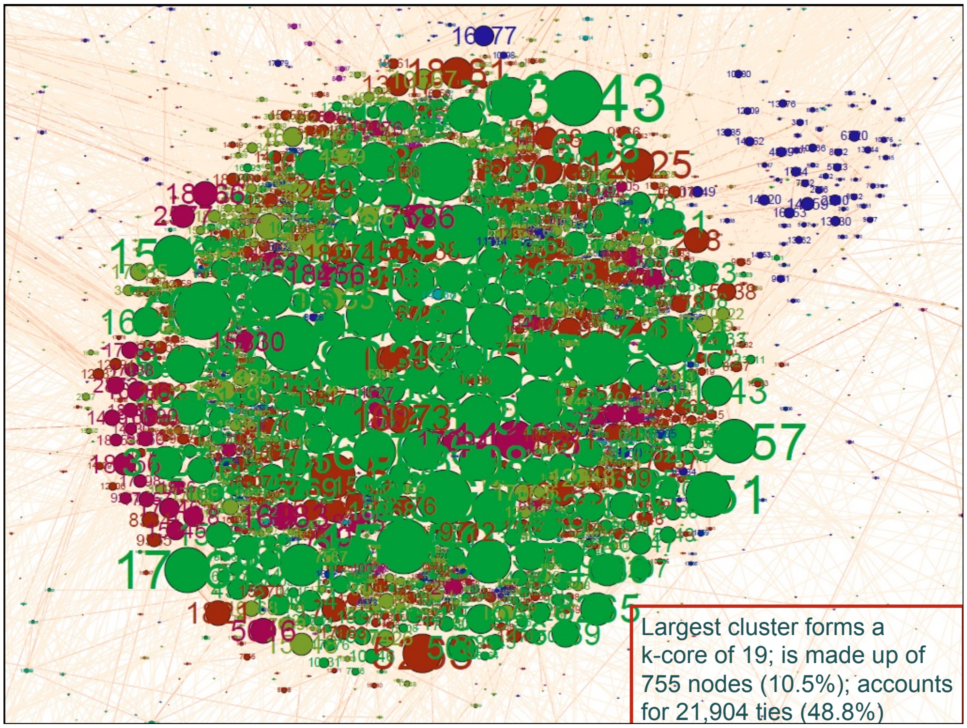


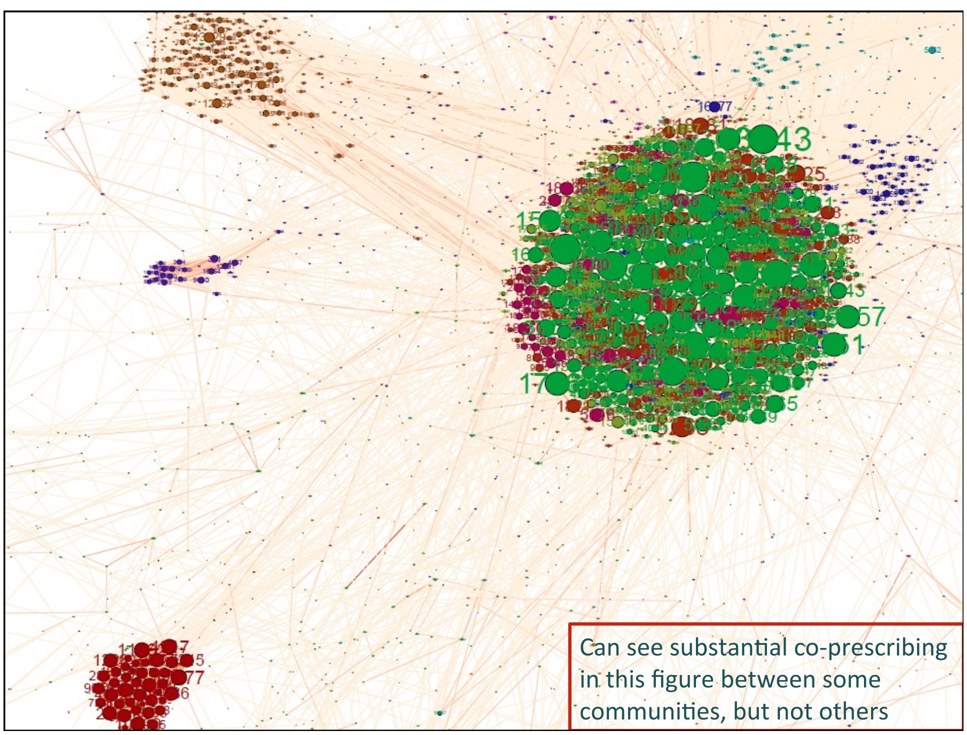
Result is a large network of 7,288 doctors tied by 45,181 co-prescribing relationships

About 76% of prescribers are connected in one main component that consists of 99.96% of all ties (Figure 1)

Node size = weighted degree centrality
Node color = Community
Line thickness = number of co-prescription ties

A strong 'core' of doctors and several subgroups clearly emerge


Largest cluster forms a
k-core of 19; is made up of
755 nodes (10.5%); accounts
for 21,904 ties (48.8%)


Can see substantial co-prescribing
in this figure between some
communities, but not others

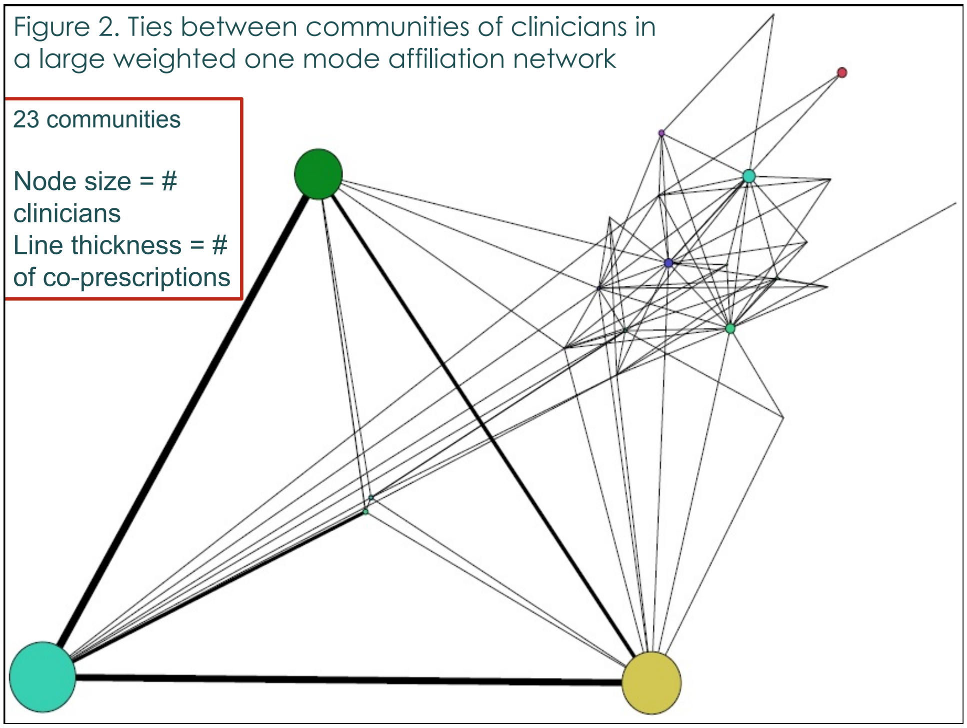


Table 1. Correlation between clinician degree centrality and aggregate patient characteristics

Patient characteristics	Pearson's r	p-value
Severity of doctor shopping		
Avg # pharmacies	0.28	>.001
Avg # prescriptions	0.21	>.001
Avg # MPEs	0.43	>.001
Avg # repeat visits	0.13	>.001
Socio-demographics		
% female	0.03	NS
% of patients on Medicaid	0.34	>.001
Avg net worth	-0.08	>.001
Avg age	-0.14	>.001
Quantity prescribed		
Avg # refills	-0.06	>.001
Avg days of medication	-0.08	>.001
Avg dose in mgs	-0.06	>.001

Summary of findings

- There is substantial nonrandom clustering
  - Several very active communities (Drug rings? Pain clinics?) with ties to each other and to outside communities
  - Suggests that clinicians may be systematically targeted
  - Suggests collusion on the part of doctor shoppers and/or prescribers

Summary of findings

- Clinicians who are active in networks have significantly different patient populations
  - Involved in more serious drug abuse or diversion
  - Lower SES and younger

Summary of findings

- Clinicians who are more active prescribe lower quantities per patient
  - May be suspicious and want to reduce harm
  - May be complicit and want to maintain demand

Insights from SNA

- May be able to reduce errors of classification using SNA measures
  - *Who* patients target may be just as important for identifying doctor shopping as *how many* prescribers they visit
  - Improve ability to detect early signs of prescription drug abuse, behavior that is intermittent or less intense, but still problematic

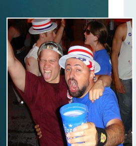
Future directions

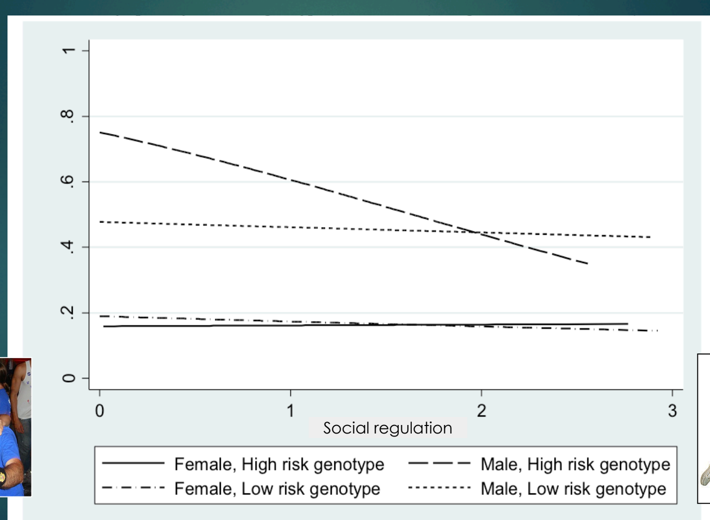
- Use SNA measures to establish doctor shopping criteria deductively
- Establish validity
  - Do SNA measures explain variance in drug abuse outcomes above and beyond MPEs?
  - Correlation with traditional criteria?
- Use social network informed criteria to examine characteristics of doctor shopping patients and their clinicians

THANK YOU!

Extra Slides

Ongoing projects in behavior genetics…





[1] n by group: Female, high-risk = 403; Female, low-risk = 873; Male, high-risk = 321; Male, low-risk = 684