Health and Social Networks in the Context of Network Analysis

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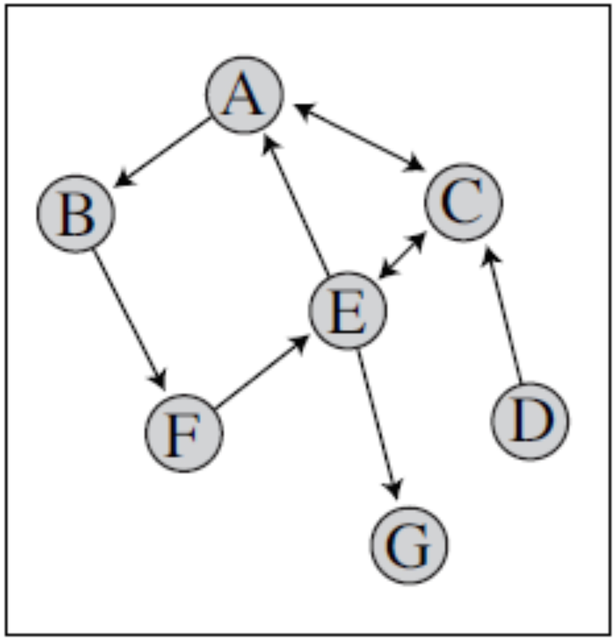
Outline

1. Basics of networks and social network analysis
2. Analysis 1: Utilizing nationwide networks to explain variation in health outcomes following medical procedures
3. Analyses 2 (if time permits): Using networks to study peer-effects in the treatment intensity of end-of-life health care of cancer patients
4. Relevant references

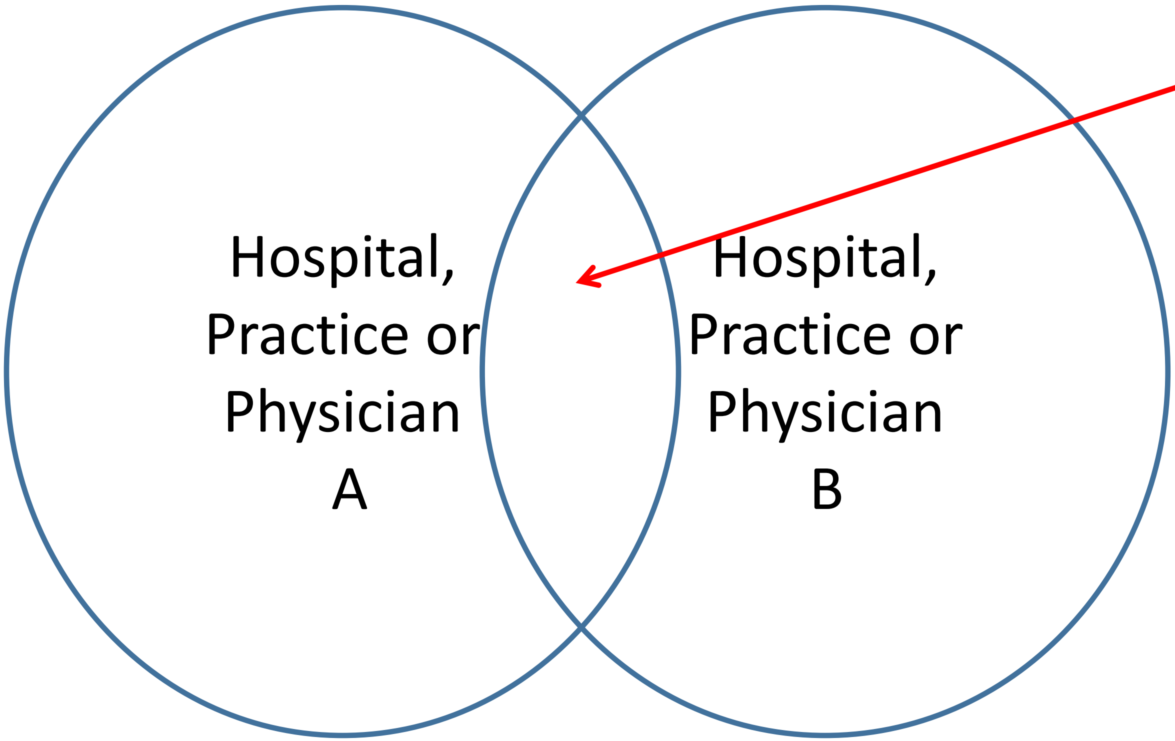
Definition of a social network

- A social network consists of one or more sets of actors—also known as "units," "nodes," or "vertices"—together with the possibly directed relationships or social ties among them



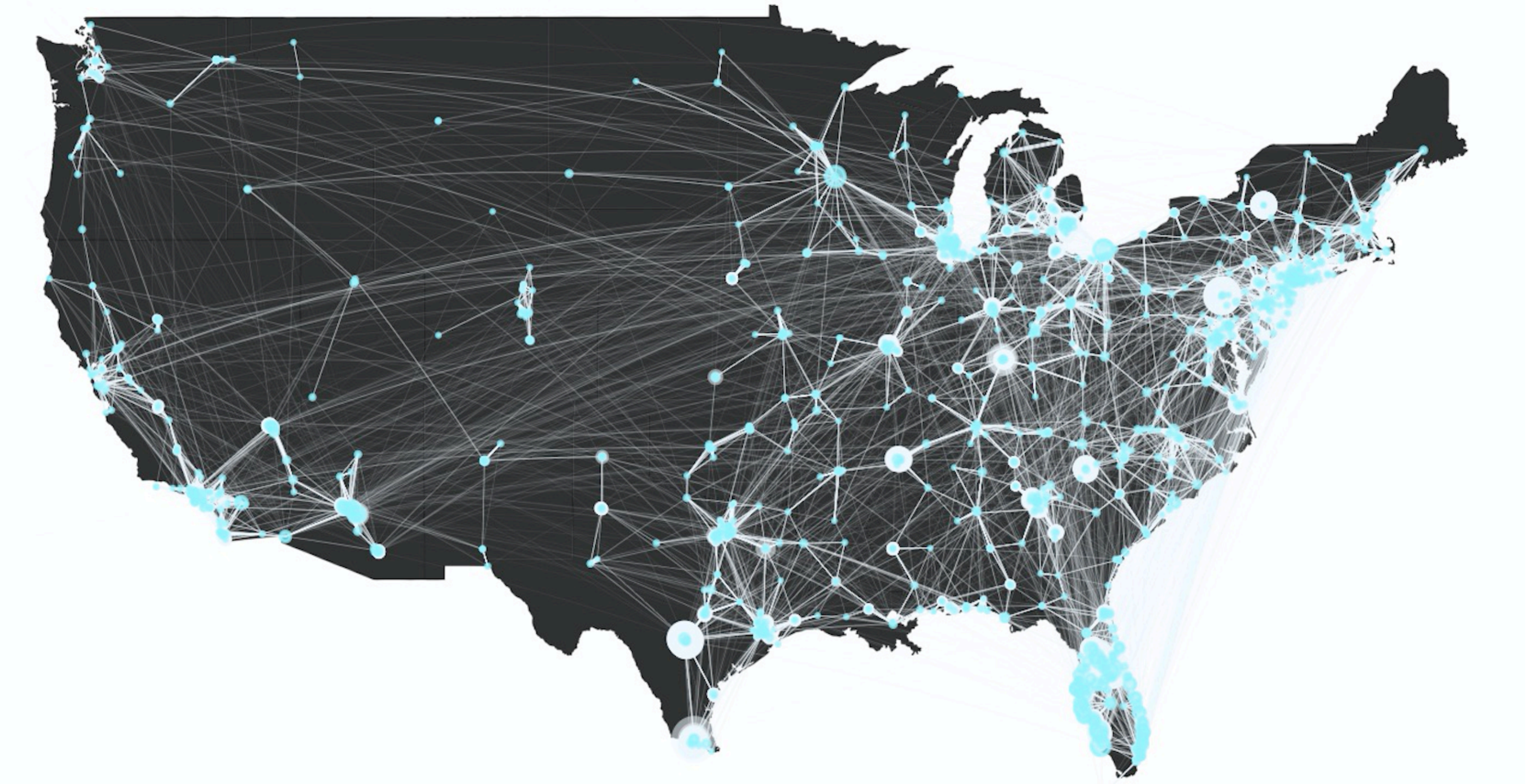
Patient-Sharing Network

Patients' utilization of services with two providers during a time-period (e.g., calendar year):



Contribution to provider A – provider B professional relationship

US Cardiovascular Care Hospital-level Patient-sharing Network in 2011 (Top 25% Hospitals Based on Degree)

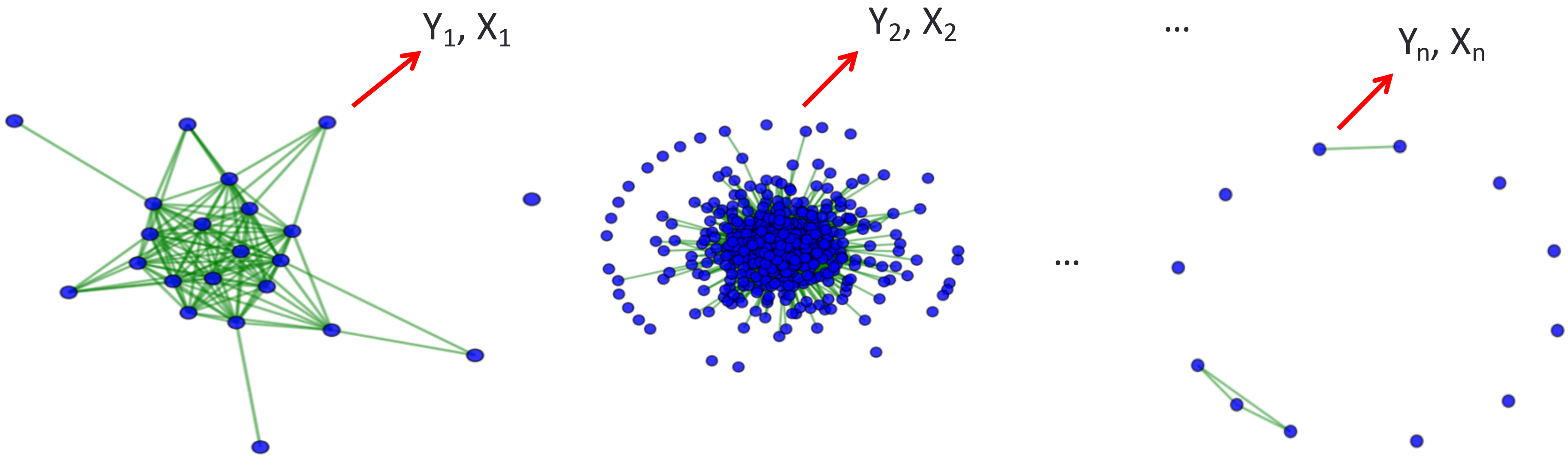


Node size corresponds to hospital's degree
Edge thickness reflects shared patient care

Prepared by
Erika Moen

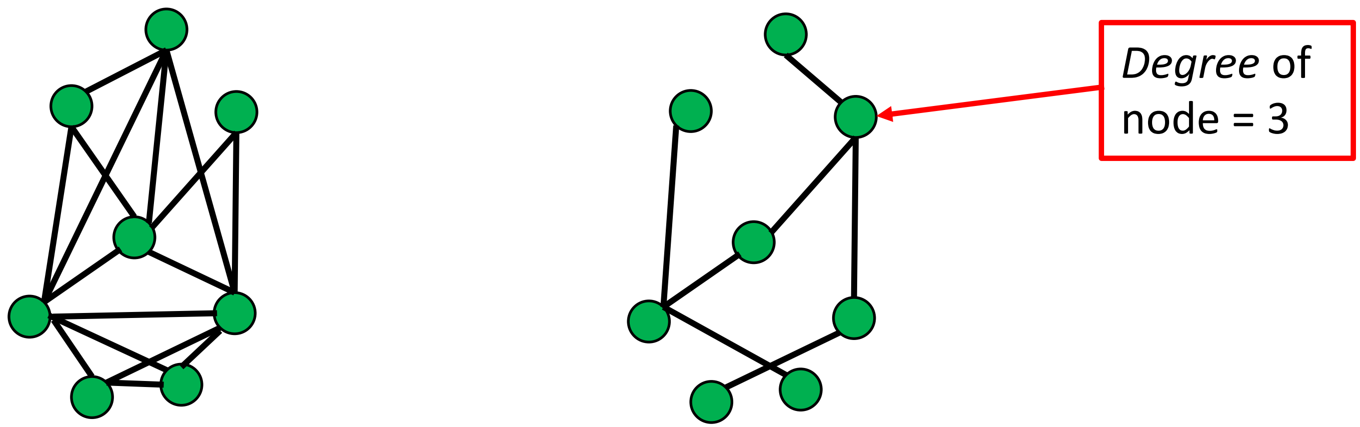
Utilizing Multiplicity of Sub-Networks

- Multiple hospital and regional networks
- Do features of these networks and actors positions in them correlate with important health variables?
- Summary network features:
  - Network-level; e.g., proportion of connections present
  - Actor (within network) level; e.g., number of connections



Network-level feature: Density

Density – number of edges divided by the maximum possible number of edges (the proportion of connections present)
∝ *average degree of nodes*



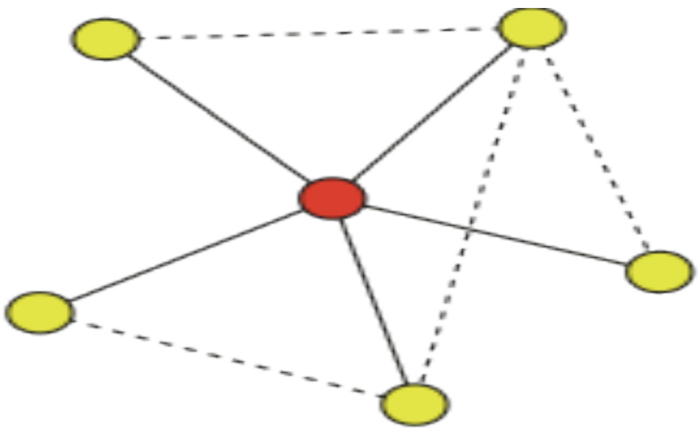
Density = 16/28 = 0.57 | Density = 7/28 = 0.25

Hospital density and variation in care

- Hospitals with a higher density of physician ties have higher costs and more intensive care (Barnett et al, 2012)

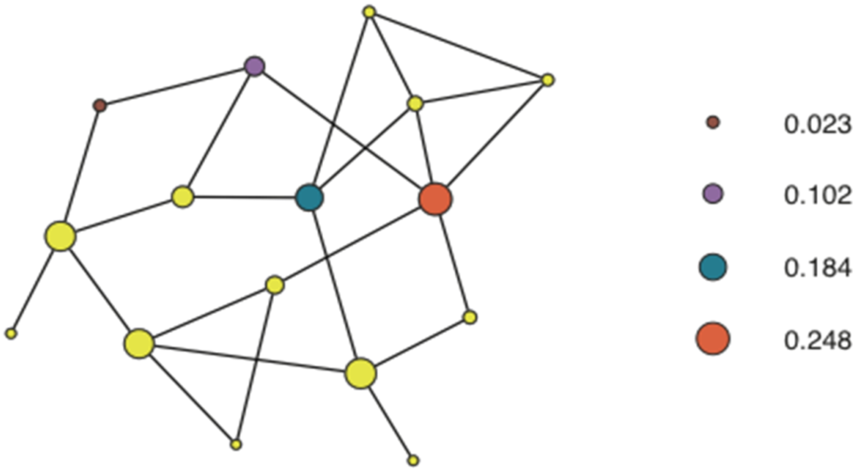
Within-network (positional) features

Clustering coefficient



Fraction of connections among neighbors of given actor (e.g., physician). In this example Clust. Coef. = 4/10

Betweenness centrality



Fraction of geodesic (shortest) paths between other actors (e.g., physicians) that pass through given actor; bigger = more central actor

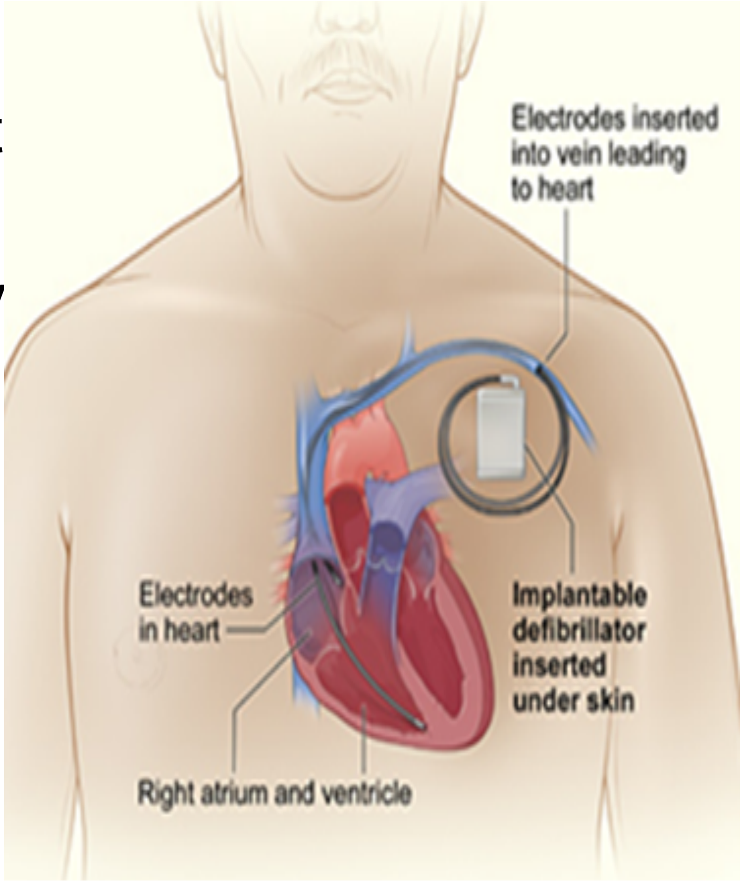
Hospitals with high centrality of primary care physicians have lower costs and care intensity (Barnett et al, 2012)

Analysis 1: Utility of Nationwide Network data

- There is substantial unexplained variation in health care outcomes (and utilization and cost) in the United States
- A nationwide network of physicians facilitates evaluation of new research questions
  - Overcomes fact that network studies are often hindered by arbitrary network boundaries
- Case Study: Do the within-hospital and the nationwide (across hospital) network positions of the physician implanting an Implantable Cardiac Defibrillator (ICD) in a patient associate with patient outcomes?
- Outcome event: Death within two years following an Implantable Cardiac Defibrillator (ICD)
- Key predictors: Within-hospital and National Across-hospital physician degree

Implantable Cardiac Defibrillators (ICDs)

- ICDs use electrical pulses or shocks to control potentially life-threatening ventricular arrhythmias in patients with heart failure
- Surgery is primarily performed by electrophysiologists, cardiologists, and thoracic surgeons
- Disagreement on appropriateness; therapeutic benefit versus quality of life
- Benefits depend on patient characteristics
- High cost of device



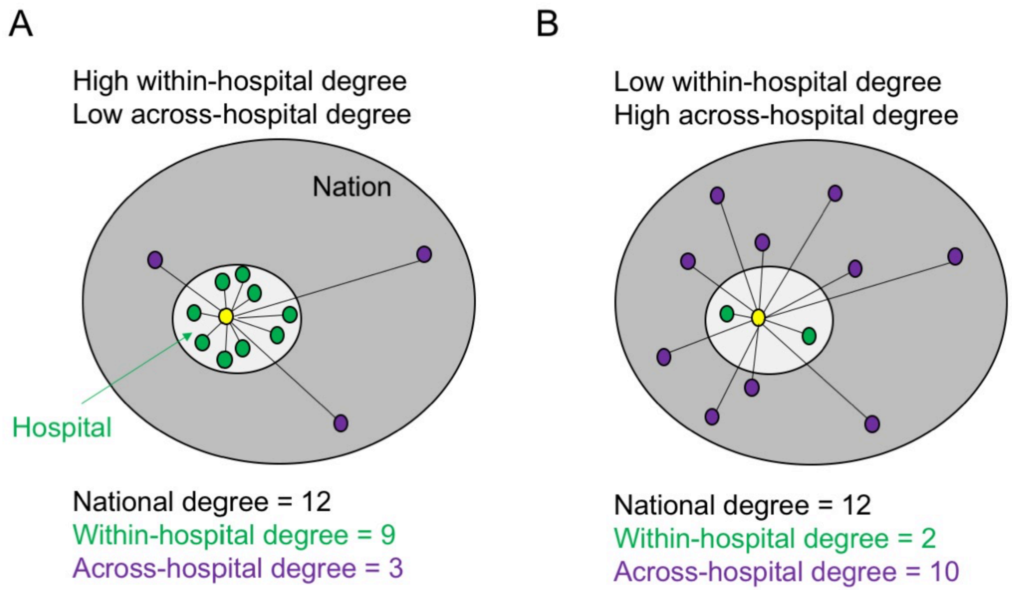
Physician Degree Decomposition

- Let A denote the network adjacency matrix and let *i*, *j* denote two physicians (a “dyad”)
- The degree of a physician in the network may be expressed as

$$Degree_i = \sum_{i \neq j}^{N} A_{ij}$$

$$= \sum_{i \neq j}^{N} A_{ij} I\left(Hosp_i = Hosp_j\right) + \sum_{i \neq j}^{N} A_{ij}\, I(Hosp_i \neq Hosp_i)$$

$$= WithinHospitalDegree_i + AcrossHospitalDegree_i$$



Data and Descriptive Analysis

- 105,109 ICD therapy patients treated by 3,474 implanting physicians within 1,280 hospitals over 2008-2011
- Pearson correlation of physician within- and across-hospital degree = 0.25
  - Across-hospital degree has potential to capture unique variation
- Adjust for physician and hospital volume to isolate the effects of the physician degree measures
  - Volume measures only modestly correlated with physician degree measures
  - May allow the network-effects to be modified by volume measures

Statistical Model

- Let Y_{it} denote the death within two years (1 = death, 0 = survived)
- Hierarchical (mixed-effect) logistic regression model of patient outcome on prior years network and other predictors:

$$logit\left(Y_{i(t+1)}|Deg_{it}\right) = \beta_0 + \beta_1 Deg(Within)_i + \beta_2 Deg(Across)_i$$
$$+\beta_3 Pat_{it} + \beta_4 Phys_{it} + \beta_4 Hosp_{it} + \theta_{HRR,i} + \gamma_{Hosp,i} + \delta_{Phys,i}$$

- where *Deg* = degree; *Pat*, *Phys*, and *Hosp* denote control predictors of the patient, physician, and health referral region (HRR); θ_{HRR}, θ_{Hosp} and δ_{Phys} are independent random effects for HRR, hospital and physician each assumed to be drawn from normal distributions with mean 0 and unknown variances

Main Effect Results

Characteristic	Estimate (std err)	p-value
Physician variables		
Within-hospital degree	-4.94e-4 (2.35-4)	0.04
Across-hospital degree	2.91e-4 (7.56e-5)	<0.001
ICD procedure volume	-1.46e-3 (5.47e-4)	0.008
Specialty: cardiology	-2.39e-1 (4.93e-2)	<0.001
Publishing record	-2.94e-2 (2.05e-2)	0.15
Clinical trial participation	-6.88e-2 (2.45e-2)	0.005
Hospital variables		
ICD procedure volume	-4.05e-4 (2.34e-4)	0.08
Degree	3.51e-5 (3.91e-5)	0.37
HHI	1.35e-1 (8.30e-2)	0.1
Teaching status	-2.29e-2 (2.95e-2)	0.44
Patient controls		
Lots of them!		

Results: Model with Interaction Effects Added

Interaction model	Estimate (std err)	p-value
Within-hospital degree x physician volume	1.49e-05 (7.13e-06)	0.04
Across-hospital degree x physician volume	4.17e-06 (2.12e-06)	0.05

Interpretation of Results

- Patients have better outcomes when treated by physicians who are locally (within-hospital) prominent
- Within-hospital degree effect is offset by volume (main effect of within-hospital degree was negative)
- Across-hospital degree effect increases with volume

Summary

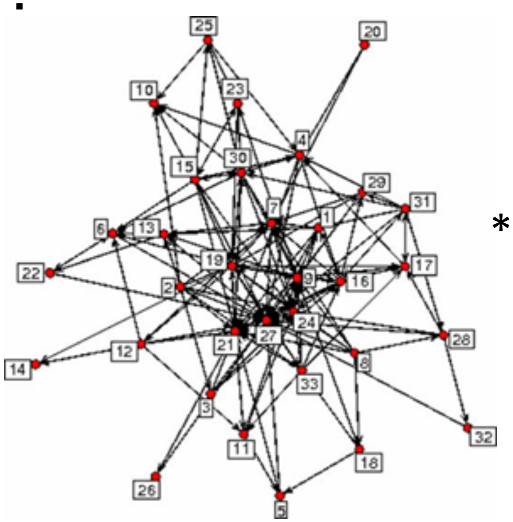
- Within-hospital degree could be interpreted as a marker for high quality care after accounting for volume
- Physicians with high across-hospital degree:
  - Might be being referred more complex patients than physicians with low external degree
  - Or may be treating a broader spectrum of cardiovascular disease patients and so are potentially less specialized in ICD therapy
- Potential policy implication: Patients undergoing select surgical procedures should be channeled to specific surgeons and hospitals to optimize outcomes

Analysis 2: Peer Effects of the Intensity of Physician End of Life Spending

- With Landon, Keating and Onnela at Harvard
- Research question: Does a physician's mean spending on cancer patients in their last month of life depend on the spending of their peer physicians' cancer care delivery?
  - Is the effect modified by whether physician peers work in the same medical practice?
- The key predictors are peer variables, which are evaluated on other physicians, not the focal physician
  - Associated regression coefficients termed "peer effects"

Background: Types of social influence analyses

- Endogenous peer effects
  - Does the behavior of my peers affect my own behavior?
  - The case considered today
- Exogenous peer effects
  - Does the treatment received by my peers affect my outcome?



* $Y, X = Y_{peer}, X_{peer}$

Evaluation of Peer Variable Predictors

- Denote the network strength (number of shared patients) between providers *i* and *j* by W_{ij}
  - By definition $W_{ii} = 0$
- The matrix of the shared patients is denoted, W
- Scale the rows of W to sum to 1 (a row-stochastic matrix)
- If Y denotes the outcome variable, *WY is the corresponding peer variable (averaged over peers)*
  - Interpret as the exposure to peers who exhibit the trait (health care spending, technology adoption, medical practice) being modeled

Analysis of Peer Effects of End-of-Life Spending

- Network ties reflect shared patients among physicians who cared for at least 30 Medicare patients within the same episode of care
  - Median degree = 7
- For all physicians who cared for a cancer patient who died, we then developed peer variables based on physicians in the same practice (identified via Tax ID) and separately for those outside of practice within the HRR
  - Organizational affiliation again allows decomposition of network variables and effects into components

Statistical Model

- Let y_{it} denote patient case-mix Medicare spending over the last 30-days of life for physician *i* in year *t*
- Key predictors: Prior year weighted average spending per patient over the peer physicians in the same practice and in different practices than physician *i*
- Statistical model for Medicare spending per patient year:

$$\mathrm{E}\left[log\left(y_{i(t+1)}\right)\middle|Y_t,\theta_i\right] = \beta_0 + \beta_1\bar{Y}(WithinPract)_i + \beta_2\bar{Y}(AcrossPract)_i + \beta_3^T x_{it} + \theta_{HRR,i} + \gamma_{Prac,i} + \delta_{Phys,i}$$

where x denotes control predictors and θ_{HRR}, θ_{Prac} and δ_{Phys} are independent random variables from normal distributions with mean 0 and unknown variances

Results: Peer Effect of End of Life Spending

Type of peer effect	Effect of peers outside of practice	Effect of peers in practice
For each $1000 increase in spending for peers' patients in prior year…		
Increase in spending in last 30 days of life	$72 ($35-110)‡	$27 ($6-$48)*

*P<.05; †P<.01, ‡P<.001

- Mean (standard deviation) spending in the last month of life was $16,237 ($17,124)
- More of the peer effect was explained by peer physicians outside of the practice ($72 increase for each $1000 increase by peer physicians' patients, P<.001) than peer physicians in the practice ($27 for each $1000 increase by within-practice peer physicians' patients, P=.01)

Summary

- Exposure to peer physicians with higher end-of-life spending per patient may increase a physician's own spending
- Peer-effect analyses can help guide interventions on the health care system to help improve quality of care delivered and functioning
  - Strong peer effects motivate group interventions and educational interventions
  - Weak peer effects suggest that independently held physician beliefs may account for some of the unexplained geographic variation in health outcome variables

References for the two Examples

1. Moen EL, Bynum JL, Skinner JS, O’Malley AJ. Physician network position and patient outcomes following implantable cardioverter defibrillator therapy. In press: Health Services Research
2. Keating NL, O’Malley AJ, Onnela J-P, Gray SQ, Landon BE. Influence of Peer Physicians on Intensity of End-of-Life Care for Cancer Decedents. In Press: Medical Care

Other Dartmouth Group References

- Moen EL, Austin AM, Bynum JP, Skinner JS, O'Malley AJ. An analysis of patient-sharing physician networks and implantable cardioverter defibrillator therapy. Health Services and Outcomes Research Methodology, 2016,16(3), 132-153
- Moen EL, Bynum JP, Austin AM, Skinner JS, Chakraborti G, O'Malley AJ. Assessing variation in implantable cardioverter defibrillator therapy guideline adherence with physician and hospital patient-sharing networks. Accepted for publication in Medical Care
- An C, Rockmore D, O'Malley AJ: Nationwide Physician Networks determined from CMS's publically available Medicare data on physicians' overlap of care for the same patients. Accepted for publication in Statistics in Medicine
- An C, O'Malley AJ, Rockmore DN. Referral Paths in the U.S. Patient Referral Network. Applied Network Science, 2018, 3:20, https://doi.org/10.1007/s41109-018-0081-4
- An C, O'Malley AJ, Rockmore DN (2019) Walk Prediction in Directed Networks. In press: Applied Network Science

Other Harvard Group References

- Landon BE, Onnela JP, Keating NL, Barnett ML, Paul S, O'Malley AJ, Keegan T, Christakis NA. Using Administrative Data to Identify Naturally Occurring Networks of Physicians. Medical Care, 2013, 51 (8), 715-721. PMID: 23807593.
- Landon BE, Keating NL, Barnett ML, Onnela JP, Paul S, O'Malley AJ, Keegan T, Christakis NA. Variation in Patient-Sharing Networks of Physicians Across the United States. Journal of the American Medical Association, 2012, 308, 265-73. PMID: 22797644
- Barnett ML, Christakis NA, O'Malley AJ, Onnela J-P, Keating NL, Landon BE. Physician Patient-Sharing Networks and the Cost and Intensity of Care in US Hospitals. Medical Care 2012, 50, 152-60. PMID: 22249922.
- Barnett ML, Landon BE, O'Malley AJ, Keating NL, Christakis NA. Mapping physician networks with self-reported and administrative data. Health Services Research 2011, 46, 1592-1609. PMID: 21521213

Methodological References

- O’Malley AJ, Marsden PV. The Analysis of Social Networks. Health Services and Outcomes Research Methodology 2008, 8, 222-269
- Paul S, Keating NL, Landon BE, O’Malley AJ. Results from using a new dyadic-dependence model to analyze sociocentric physician networks. Social Science & Medicine, 125, 2015, 51-59
- O’Malley AJ, Paul S (2014). Using Retrospective Sampling to Estimate Models of Relationship Status in Large Longitudinal Social Networks. Computational Statistics and Data Analysis, 82, 35–46.
- Paul S, O'Malley A.J. (2013). Hierarchical longitudinal models of relationships in social networks. Journal of the Royal Statistical Society, Series C.
- O'Malley AJ, Christakis NA. (2011). Longitudinal Analysis of Large Social Networks: estimating the Effect of Health Traits on changes in Friendship Ties. Statistics in Medicine, 30, 9, 950-964
- Under revision: Viles WD, O’Malley AJ. External Information in Community Detection