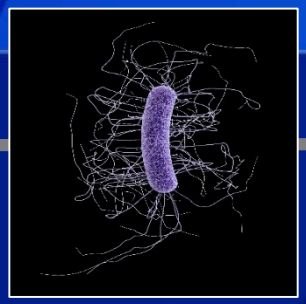
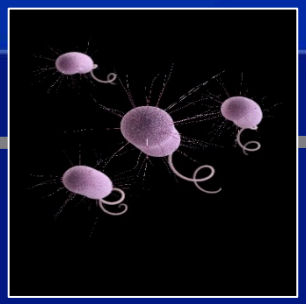





Making Health Care Safer
Stop Spread of Antibiotic Resistance

Building Momentum from CDC Vitalsigns™

Scott Fridkin
John Jernigan
Rachel Slayton
Kelly McCormick
Michael Ray (IL)
Erica Runningdeer (IL)
Marion Kainer (TN)
Zintars Beldavs (OR)

National Center for Emerging and Zoonotic Infectious Diseases
Division of Healthcare Quality Promotion

State HAI – Antibiotic Resistance Prevention Programs: Summary of Morning Presentation

- Organizational Framework

- Staffing Model (what expertise is ideal)

- **Key Functions of enhanced analytic capacity**
  - Access to data
  - Improve quality of data
  - Analyze the data for prevention

- Prevention activities

Improving Access to Data for Action
Access to Data Sources & Processing

State HAI/AR Prevention Programs should:

- **Increase availability of relevant data to inform program activities (key investment of time)**
  - Identify pathway to be conferred rights to NHSN data
    - HAI, CDI, MRSA BSI, NHSN Annual Survey, AUR module, Other
  - Identify additional data sources
    - Medicare, Hospital discharge data/HCUP, MDS
- **Promote and/or incentivize reporting from healthcare facilities to NHSN Antibiotic Use and Resistance Module and/or MDRO module**
- **Analyze to improve situational awareness***
  - Map out connectedness of communities of healthcare facilities
  - Target to prevent transmission, importation (present on admission)
  - Target to improve antibiotic use (CDI data, AU data)

Expand from morning presentation

HAI AR Session Overview

1. Review call to action for "Coordinated Approach to Regional AR Prevention" (J. Jernigan)

2. Illustrate analysis exploring ability to measure "connectedness" of healthcare facilities (R. Slayton)

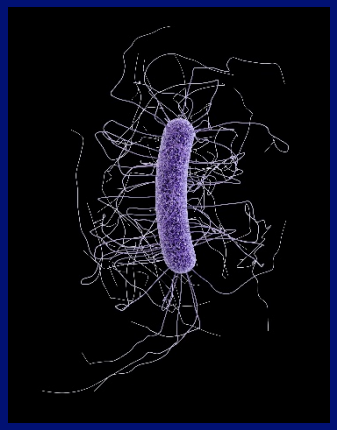
3. Present case-example of practical use of social network analysis in context of CRE in IL (M. Ray)

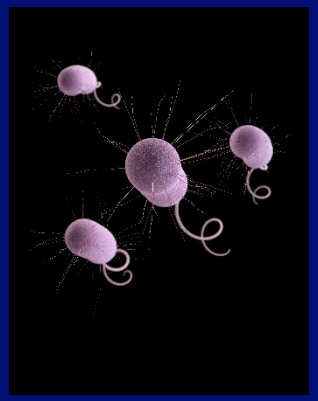
4. Outline potential use of "data in hand" to coordinate and target prevention of CDI within interconnected communities of healthcare (i.e., outside of the acute care hospital) (K McCormick)

- Wrap up and Panel – next practical steps to coordinate regional AR prevention and what DHQP should do to help state programs

Calls To Action

- In 2013 CDC Prioritized public health threats of AR
- White House activity (National Plan in 2014)
- CDC 2014 Vital Signs – call for universal antibiotic stewardship in acute care
- CDC 2015 Vital Signs Report shows that spread of drug-resistant and *Clostridium difficile (C. difficile)* germs will increase without immediate, nationwide improvements in infection control and antibiotic prescribing.

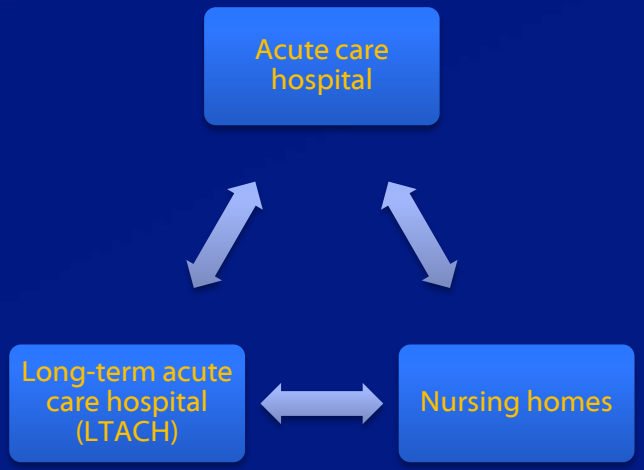


Antibiotic Resistance Control and Prevention

- **Improving antibiotic use across healthcare**
  - Acute care facilities
    - NHSN AU option
    - Antibiotic stewardship programs
  - Outpatient facilities
    - Understanding prescribing trends
    - Antibiotic stewardship activities
  - Long-term care facilities
- **Prevention of transmission**

Conceptual Framework for Preventing AR Transmission: Regional Approach to Controlling Healthcare-associated Multidrug-Resistant Organisms

- **Traditional approach to MDRO control**
  - Promotion of prevention efforts independently implemented by individual health care facilities
  - Does not account for inter-facility spread through movement of colonized/infected
- **Regional Approach**
  - Recognizes that individual facilities are components of integrated and dynamic networks connected via patient movement
    - Occurrences in one healthcare facility may affect many other healthcare facilities



Munoz-Price SL. Clin Infect Dis 2009;49:438-43
Lee et al, JAMIA 2013;20:e139

Emergence & Rapid Regional Spread of *K. pneumoniae* Carbapenemase-Producing Enterobacteriaceae

Hospital and Long-term Care Interrelations

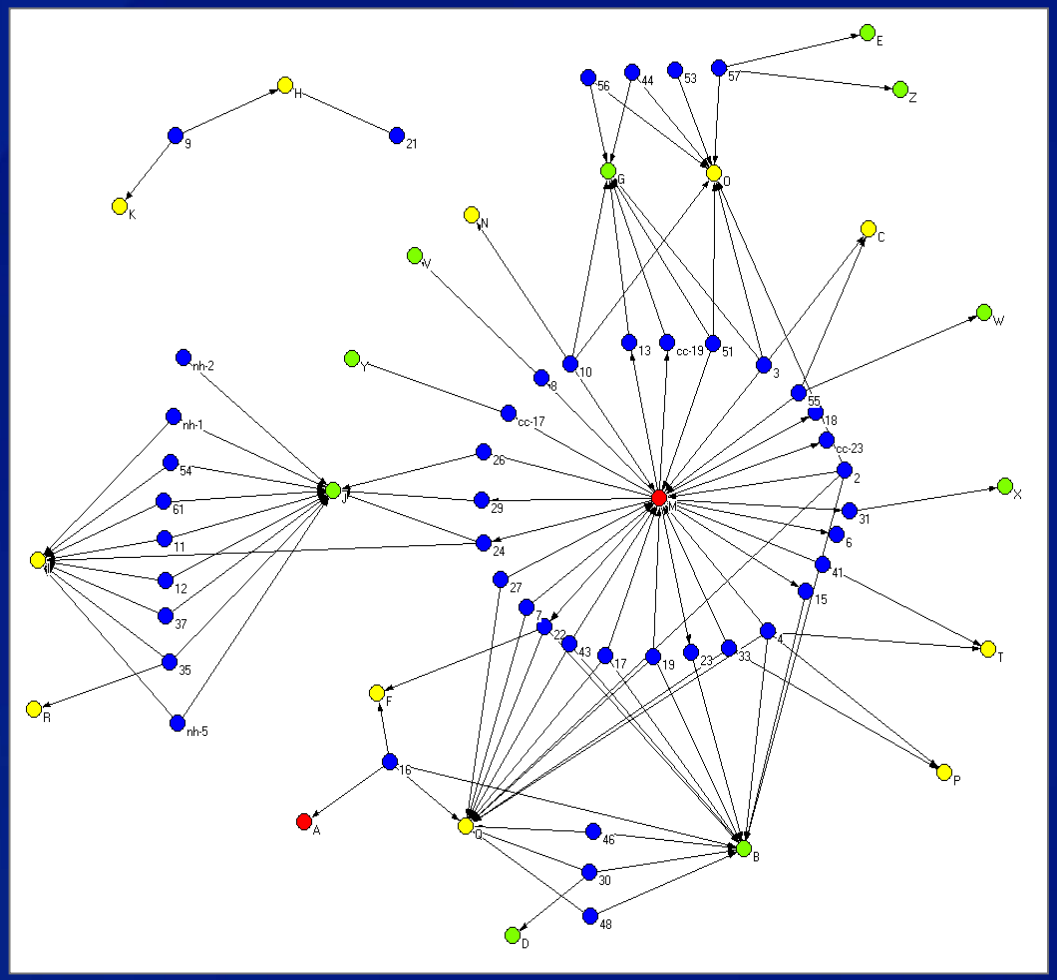
Social Network depiction of LTACH, Nursing Home, & Hospital spread of KPC (Carbapenem-resistant *Klebsiella pneumoniae)*

Legend

- LTACH
- Nursing Home
- Acute Hospital
- Patient

LTACH, Long term acute care hospital; MDRO, Multidrug resistant organism

Won et al, *Clin Infect Dis* 2011; 53(6):532-40



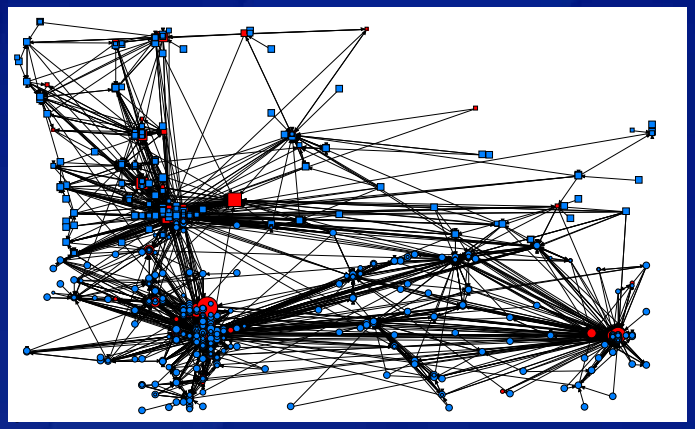
Hospital Transfers are a Significant Predictor of *Clostridium difficile* Burden

FIGURE 2 Map of hospitals (dots) and transfers (dark lines) on a map of California. The same connections from Figure 1 are projected onto a map of California. Major clusters are colored separately (San Diego in orange, Los Angeles in purple, and San Francisco and Northern California in green), and the map shows how transfers create closely connected hospitals, despite geographic distance.

"*Clostridium difficile* burden at a level can be better understood by knowing how a hospital is connected to other hospitals in terms of patient transfers"

Simmering et al, Infect Control Hosp Epidemiol 2015;36:1031-37

Is there an advantage to using a regional approach for CRE prevention across a healthcare network?



- **What would happen if health interventions to reduce MDRO transmission were based upon:**
  - Better situational awareness (i.e., timely information on incidence of MDROs from all facilities in a network)
  - Understanding of the "connectedness" of facilities within a region in terms of patient sharing
- **We estimated impact through mathematical modeling**

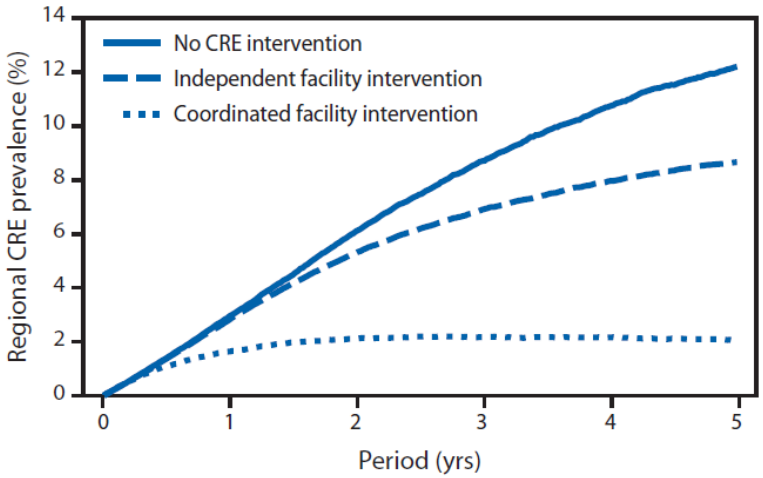
Centers for Disease Control and Prevention
MMWR
Morbidity and Mortality Weekly Report
Early Release / Vol. 64
August 4, 2015

Vital Signs: Estimated Effects of a Coordinated Approach for Action to Reduce Antibiotic-Resistant Infections in Health Care Facilities — United States

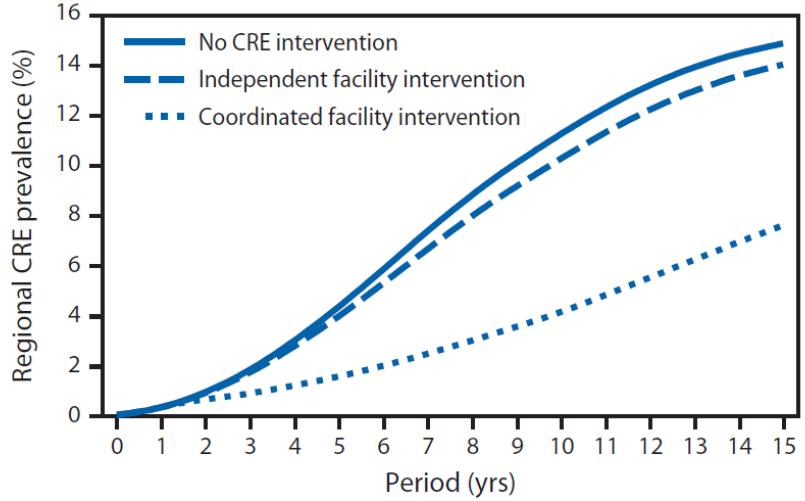
Rachel B. Slayton, PhD[1]; Damon Toth, PhD[2]; Bruce Y. Lee, MD[3]; Windy Tanner, PhD[2]; Sarah M. Bartsch, MPH[3]; Karim Khader, PhD[2]; Kim Wong, PhD[4]; Kevin Brown, PhD[2]; James A. McKinnell, MD[5]; William Ray[2]; Loren G. Miller, MD[6]; Michael Rubin, MD, PhD[2]; Diane S. Kim[7]; Fred Adler, PhD[8]; Chenghua Cao, MPH[7]; Lacey Avery, MA[1]; Nathan T.B. Stone, PhD[9]; Alexander Kallen, MD[1]; Matthew Samore, MD[2]; Susan S. Huang, MD[7]; Scott Fridkin, MD[1]; John A. Jernigan, MD[1]

- **Developed two complementary agent-based models**
  - Model 1: 10-facility model based upon VA data
  - Model 2: 102-facility model of Orange County, California
- **Simulated the spread of CRE among patients in**
  - Acute care hospitals, Long-term acute care hospitals (LTACs), Free-standing nursing homes
- **Three intervention scenarios:**
  - Common Approach: infection control activity currently in common use
  - Independent Efforts: augmented efforts implemented independently at individual subsets of facilities
  - Coordinated approach: coordinated augmented approach across a health care network

Projected Prevalence of CRE Based on Modeling



* Additional information available at http://www.cdc.gov/drugresistance/resources/publications.html. A video of the model simulations is available at http://www.cdc.gov/drugresistance/resources/videos.html.



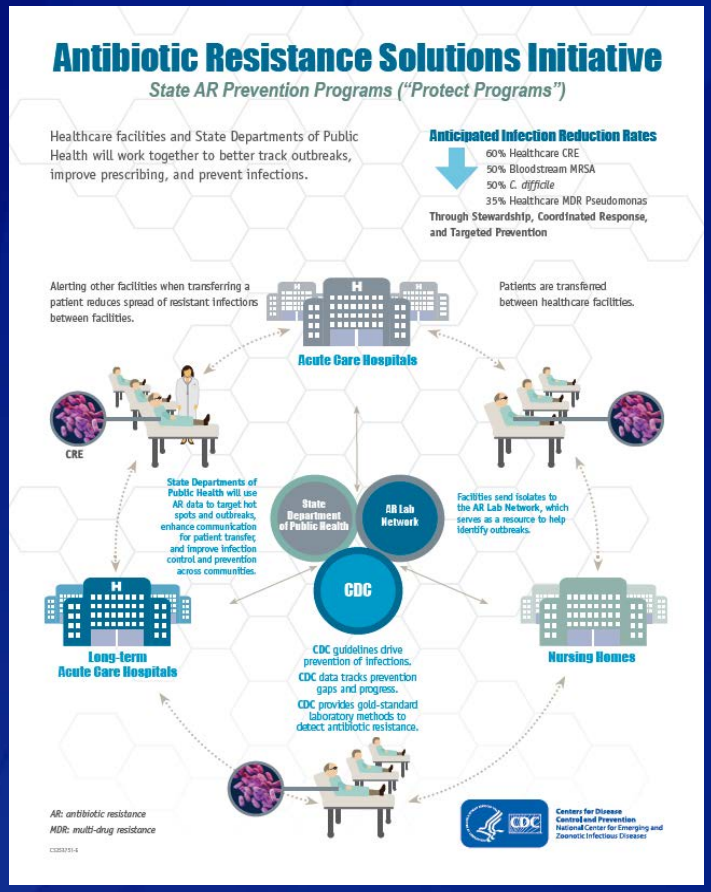
* Additional information available at http://www.cdc.gov/drugresistance/resources/publications.html.

Projected regional prevalence of CRE over a 5-year period under three different intervention scenarios 10 facility model, United States

Projected countywide prevalence of CRE over a 15-year period under three different intervention scenarios — 102 facility model, Orange County, California

Conclusion: Coordinated prevention approaches assisted by public health agencies have the potential to more completely address emergence and dissemination of MDROS and in comparison to independent facility based efforts

Support for Action Through State HAI-AR Prevention (Protect) Programs

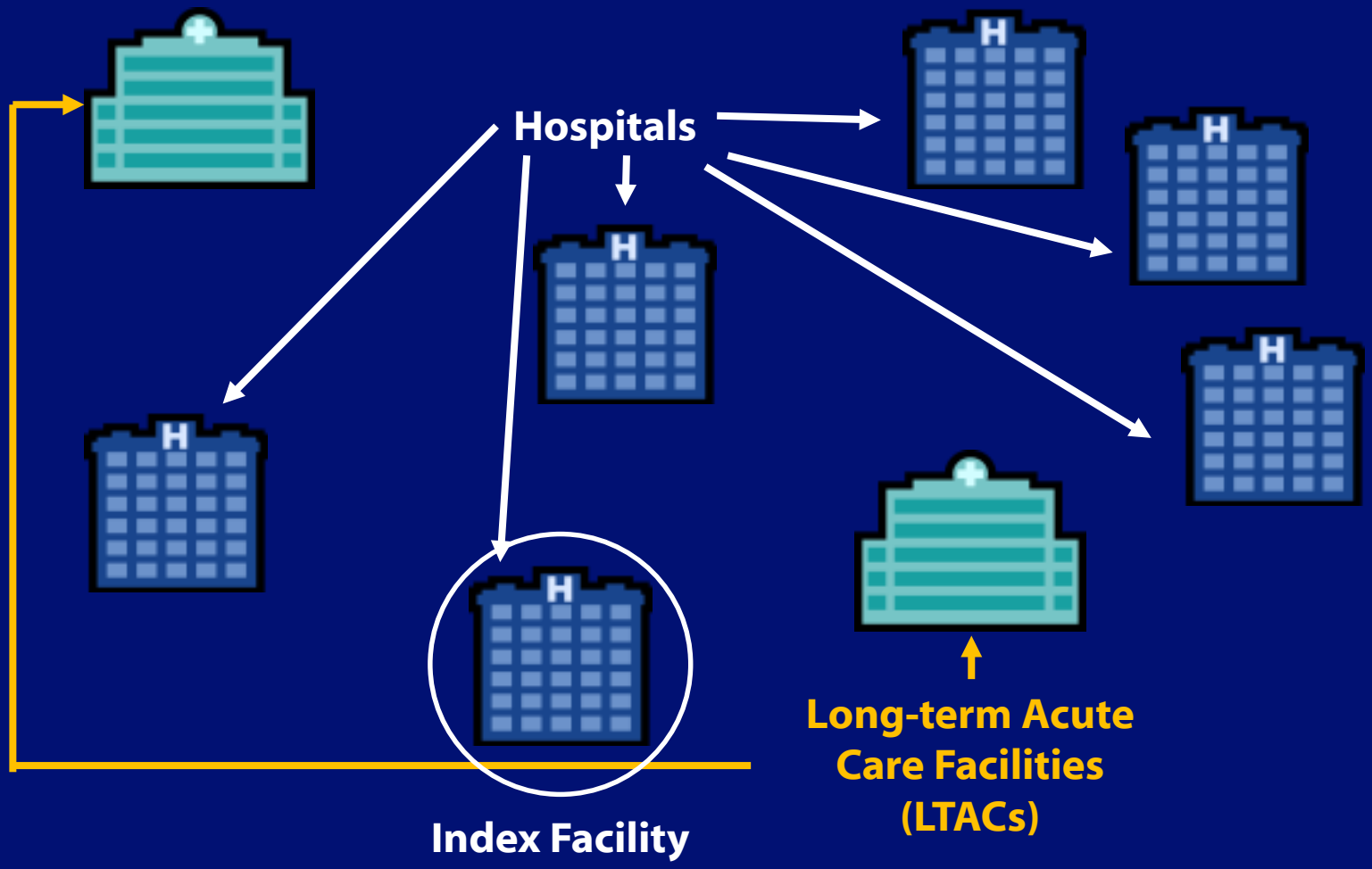


- **FY16 Budget Proposal calls for state-based programs**
- **Supporting states through the ELC cooperative agreement**
- **State Programs develop situational awareness across healthcare networks for targeted prevention**
  - Identify and target problems
  - Maximize use of NHSN data: MDRO module, AUR module, survey
- **Implement and coordinate solutions**
- **Leverage local partnerships**
- **Technical assistance from CDC on guidance and prevention**

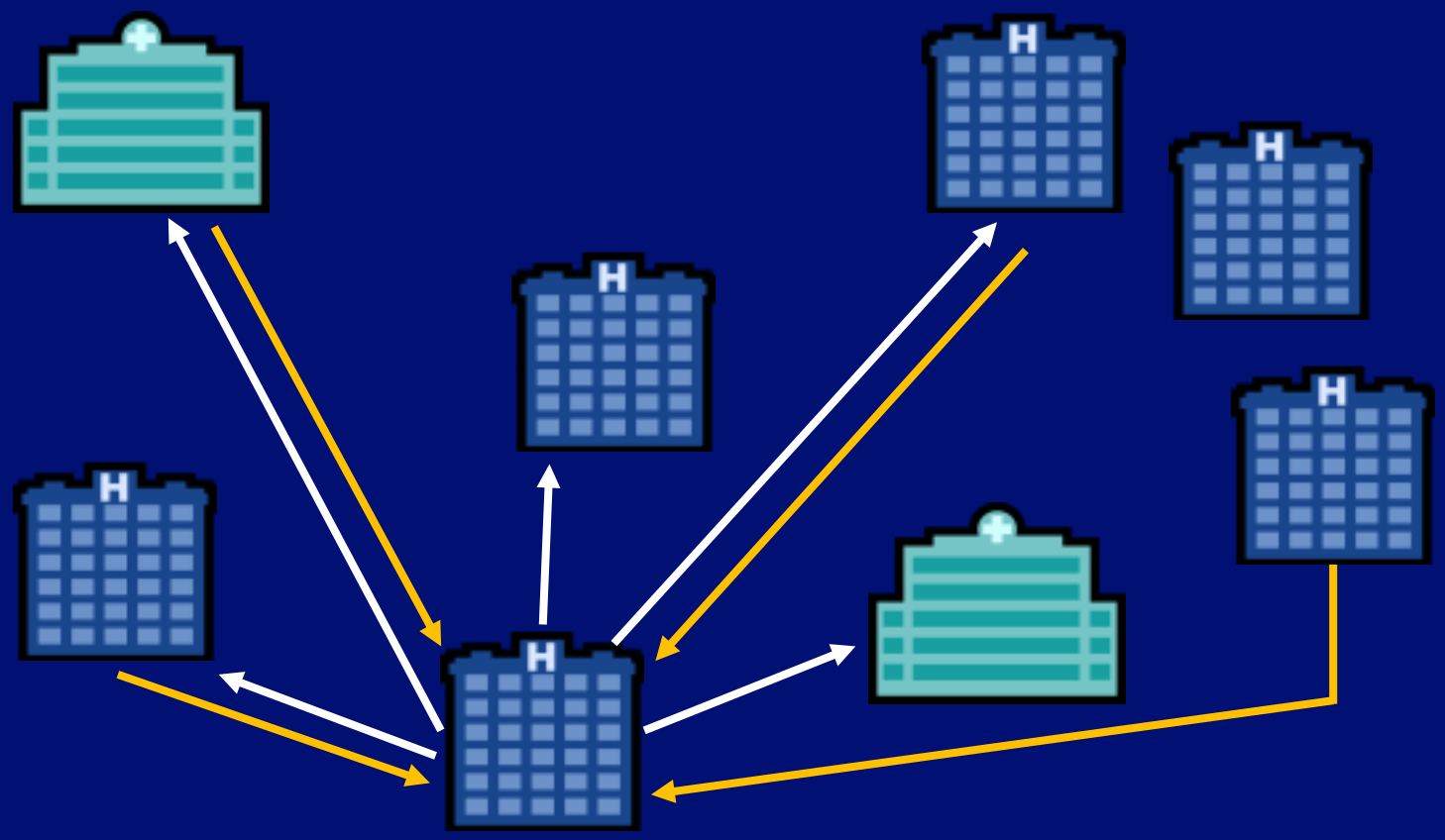
Overview of Social Network Analysis

- Framework in which to describe the relationships among entities in a system (e.g., relationships among individual people)
- Quantifies the connections among entities (i.e., nodes) using mathematical language to describe connections
- Used in many fields including physics, ecology, neurology, computer science, etc.
- Used in public health for understanding transmission of sexually transmitted infections

Social Network Measures: Facilities in a Region

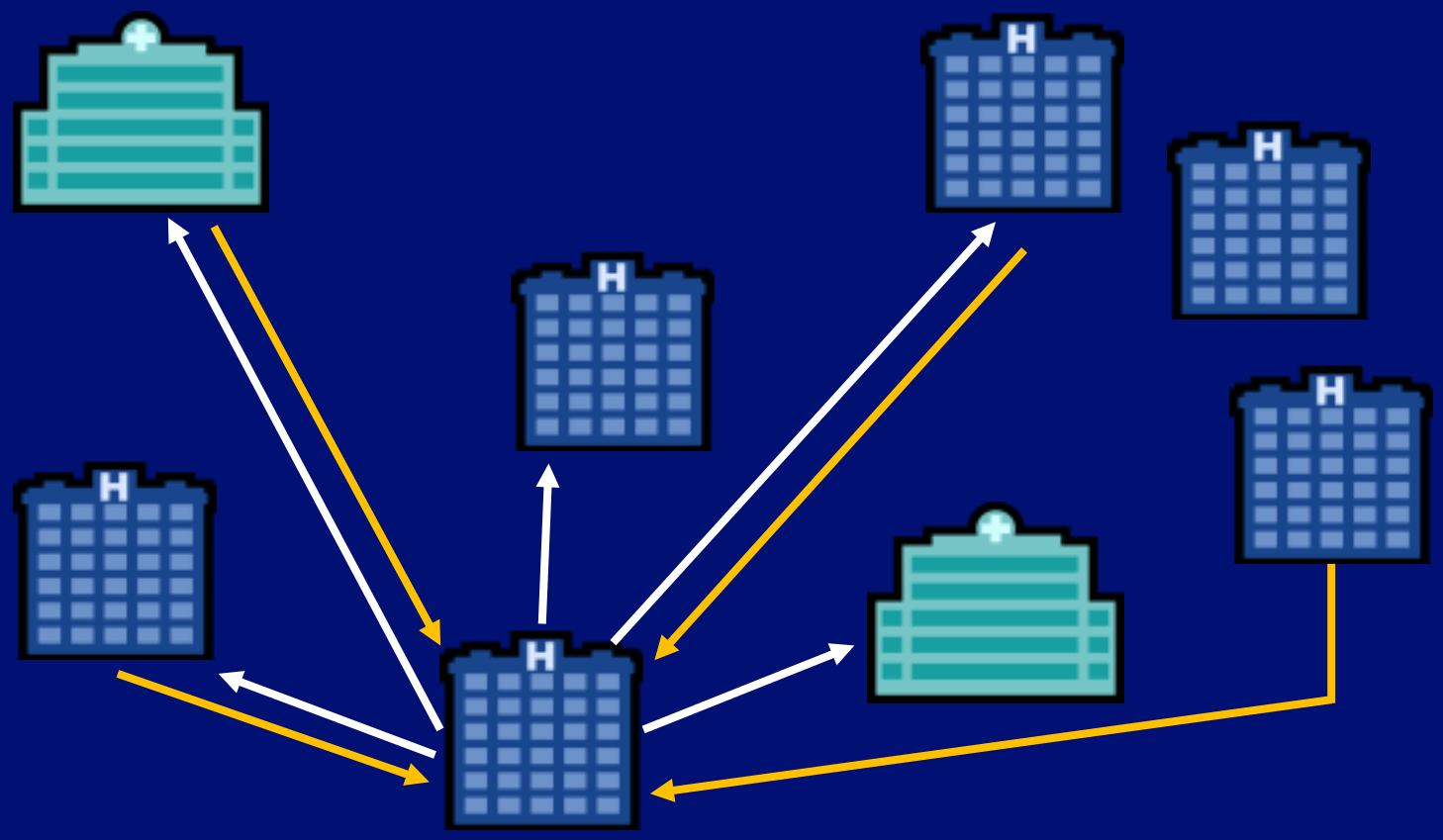


Social Network Measures: Patient Sharing



Yellow arrows: patients admitted to the index facility from other facilities
White arrows: patients discharged from the index facility to other facilities

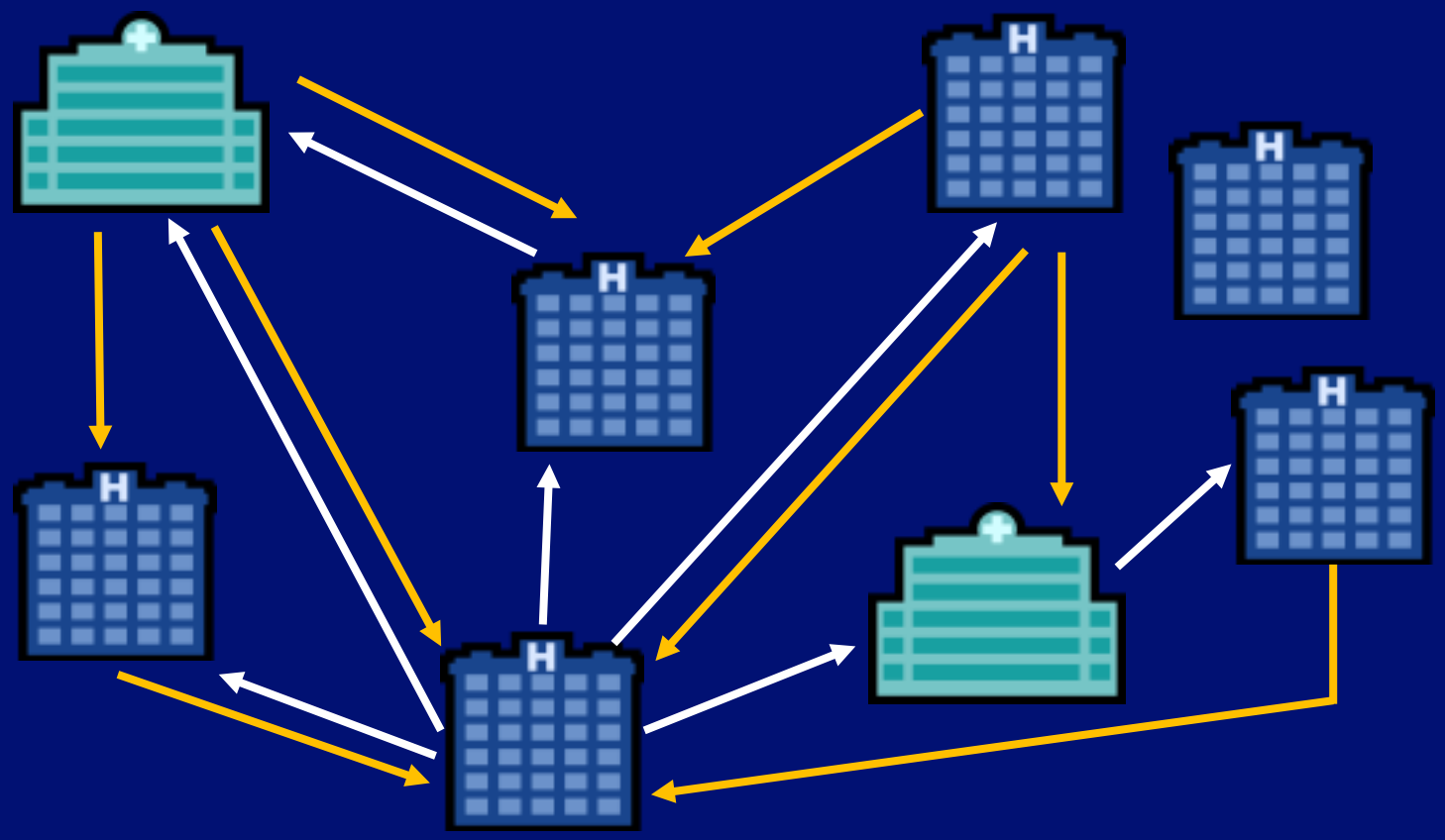
Social Network Measures: Indegree and Outdegree



Indegree: Sum of yellow arrows, from the perspective of the index facility

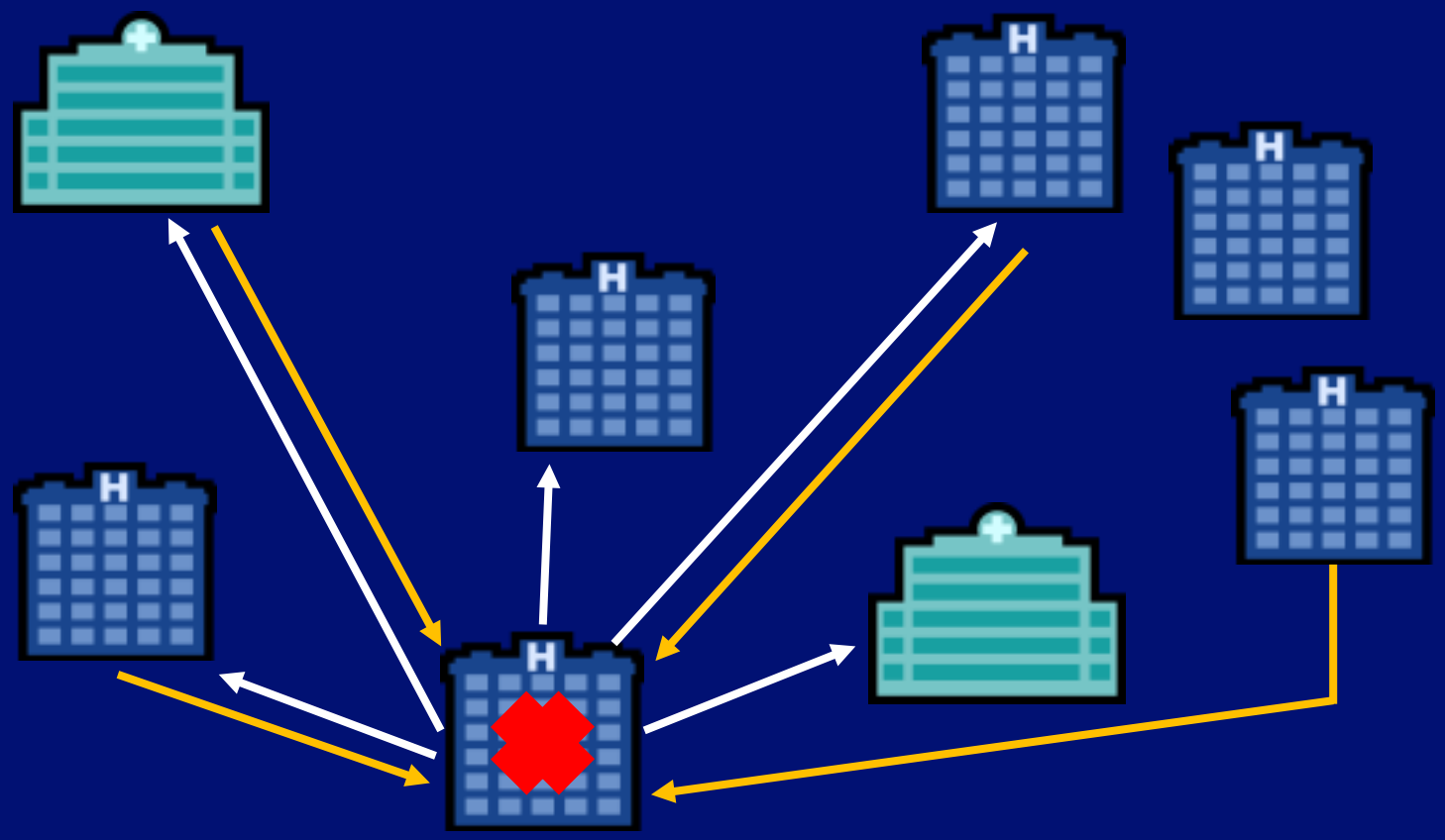
Outdegree: Sum of white arrows, from the perspective of the index facility

Social Network Measures: Eigenvector Centrality



Eigenvector Centrality: weighted sum the centralities of all facilities in the index facility's neighborhood

Social Network Measures: Ego Networks



Ego Network: a focal facility, the "ego" and the other facilities to whom the ego is directly connected

Research Question

- **Are hospitals that share more patients with other healthcare facilities more likely to have higher rates of *Clostridium difficile*?**

Data Sources

- **2012 CMS data**
  - Patient-level claims data with a unique ID for each Medicare beneficiary
  - Claims across healthcare settings
    - Acute care hospitals
    - Long-term acute care hospitals (LTACs)
    - Skilled nursing facilities (SNFs)
- **2013 NHSN data**
  - Facility-wide *Clostridium difficile* infection rates
  - Current reporting incentive for hospitals
  - Facility characteristics from the NHSN annual survey

Methods: Social Network Analysis

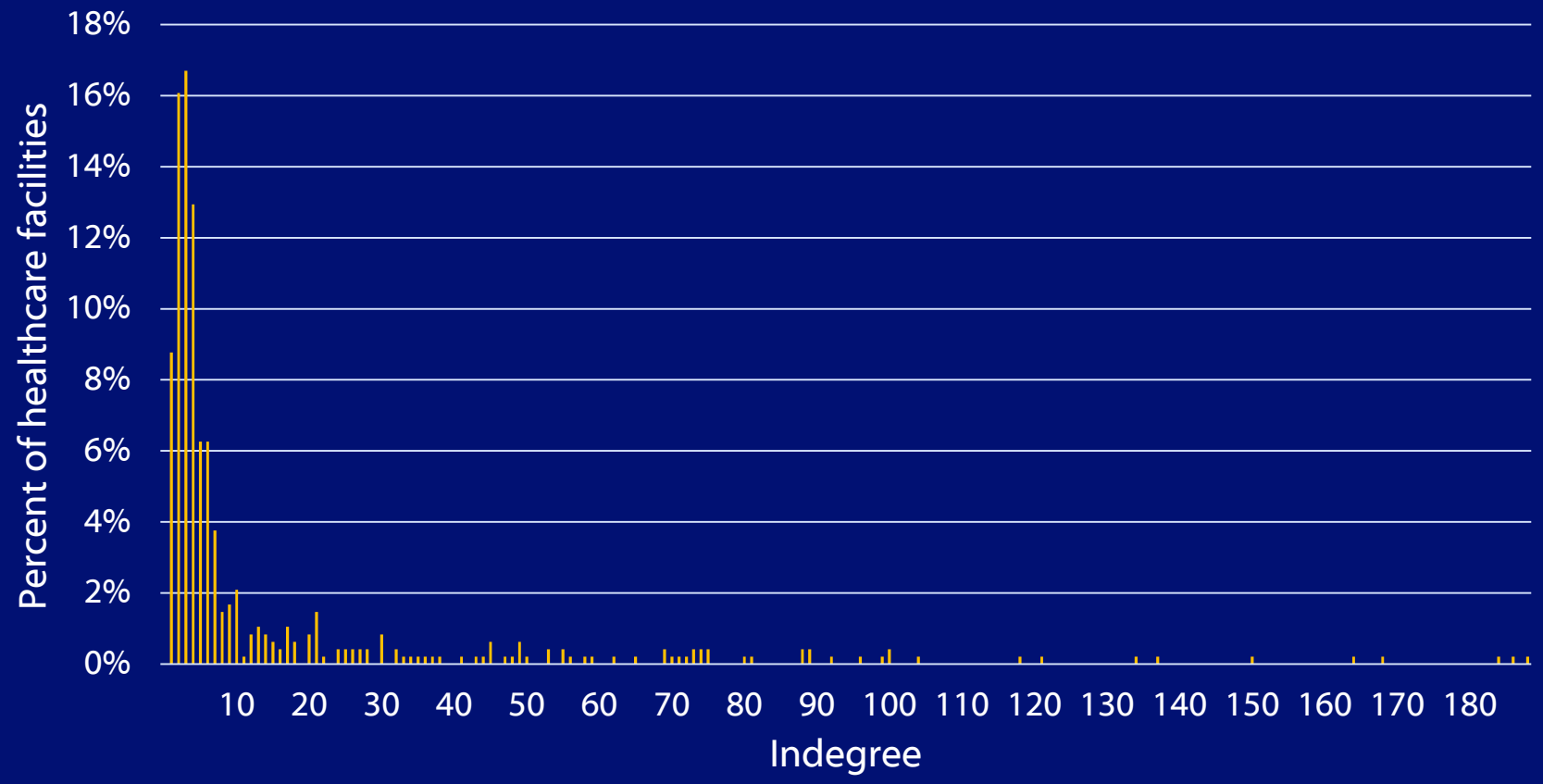
- **Initial analysis limited to states of Washington and Oregon**
  - Chosen because of population size, number of facilities, and population centers close to geographic boundaries
- **Calibrated transfer networks among facilities**
  - **Direct transfers**: Traditional transfers among healthcare facilities
  - **Indirect transfers**: Subsequent admissions to healthcare facilities ≤30 days after discharge from the index facility
- **Analysis excluded**
  - Outpatient claims
  - Psychiatric hospitals
- **Computed directed social network measures in UCINET**

Methods: Regression

- **Negative binomial regression using SAS 9.3**
  - Offset by log patient days
- **Facility-wide incident CDI as outcome**
- **Included covariates from NHSN HO-CDI risk adjustment**
  - CDI test type, facility bedsize, teaching status
- **Included in-degree in initial model**

http://www.cdc.gov/nhsn/PDFs/mrsa-cdi/RiskAdjustment-MRSA-CDI.pdf

Results: Histogram of Indegree: Medicare Patients, Washington and Oregon



Results: Facility-wide Incident CDI

Variable	Rate Ratio	95% CI	*P*-value
CDI Test Type (NAAT v. non-NAAT/EIA others)	1.1041	(0.7222-1.6878)	0.6475
CDI Test Type (EIA v. non-NAAT/EIA others)	0.5555	(0.1576-1.9577)	0.3604
Facility Bedsize (>245 v. ≤100)	0.8135	(0.5349-1.2372)	0.3346
Facility Bedsize (101-245 v. ≤100)	0.9764	(0.6501-1.4667)	0.9085
Teaching v. Non-teaching	1.2493	(0.8611-1.8127)	0.2411
Indegree (Quartile 2 v. Quartile 1)	1.0232	(0.6165-1.6984)	0.9292
Indegree (Quartile 3 v. Quartile 1)	1.7864	(1.0500-3.0393)	0.0324
Indegree (Quartile 4 v. Quartile 1)	2.2008	(1.2934-3.7447)	0.0036

- **Independent of hospital size, teaching status, and CDI testing method, connectedness of hospitals to other healthcare facilities in the region was independently associated with facility-wide incident CDI**

Next Steps

- **Social network analysis of transfer patterns among healthcare facilities in a region may provide important insights for HAI prevention**
- **Expand analysis to other states with HAI outcomes data**
  - CDI initially chosen because of prevalence and data availability
- **Investigate the use of State Inpatient Databases (SIDs) for conducting these analyses**
  - Strength: Includes all payers
  - Limitation: Skilled Nursing Facilities are not included in most SIDs
- **Explore the utility of this kind of an analysis for preventing spread of HAI outbreaks across connected healthcare facilities**
  - Michael Ray from the Illinois DOH will present on their social network analysis of facilities and CRE transmission

What we are doing in Illinois:

- Facility-level modeling using social network variables as predictors for elevated CRE rates
- Analyzing the ego networks of hospitals that have previously experienced CRE outbreaks
- Incorporating network information into SaTScan for cluster detection in addition to geographic parameters

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Background – CRE in Illinois

- Role of LTACHs
- Illinois XDRO registry (www.xdro.org)
  - Implemented November 2013
    - ~ 1000 cases reported the first year
  - Hospitals, LTACHs, nursing homes, etc.
  - Inter-facility communication and surveillance

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Facility-level Modeling

- CRE case information – Illinois XDRO registry
- Facility characteristics – IDPH Annual Hospital Questionnaire (similar info in NHSN survey)
- Social Network Analysis – IDPH Hospital Discharge dataset (administrative data like HCUP)
- Centrality Measures – Degree and Eigenvector
- Adjust *a priori* for number of beds and proximity to Chicago

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Results

Variable	Absolute Rate difference	95% CI		p-value
No. of patients shared with an LTACH		**Lower**	**Upper**	
0	ref		--	
1 to 3	0.0	-0.6	0.7	0.94
4 to 6	1.2	0.1	2.3	0.03
6 to 9	1.2	0.0	2.4	0.05
10+	1.3	0.5	2.2	0.002
Eigenvector (Quintiles)[k]				
1	ref		--	
2	-0.23	-0.99	0.53	0.56
3	-0.17	-0.92	0.59	0.66
4	-0.25	-1.03	0.52	0.52
5	1.51	0.75	2.29	0.0001

↑ Eigenvector = connected to others that are well-connected

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Results

Model [a]	Covariate	RR	95% CI	P-value
Entire state of Illinois	Eigenvector[b]	2.3	1.2 to 4.7	0.02
	LTACH	1.7	0.8 to 3.5	0.16
Chicago region	Eigenvector	3.0	1.6 to 5.3	<0.001
	LTACH	2.0	1.1 to 3.7	0.03

Abbreviations: RR, rate ratio; LTACH, long-term acute care hospital.

[a] Both models adjusted for total number of beds and distance from the center of Chicago.

[b] Highest quintile of eigenvector values.

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Summary of findings

- Elevated CRE rates are independently associated with higher network centrality and sharing patients with LTACHs for both the Chicago and statewide models
- We can identify the facilities that are predicted to have high CRE rates for targeted intervention (i.e. increased screening, automated alerts)
- We can identify which facilities might act as a bridge to low CRE regions to prevent spread

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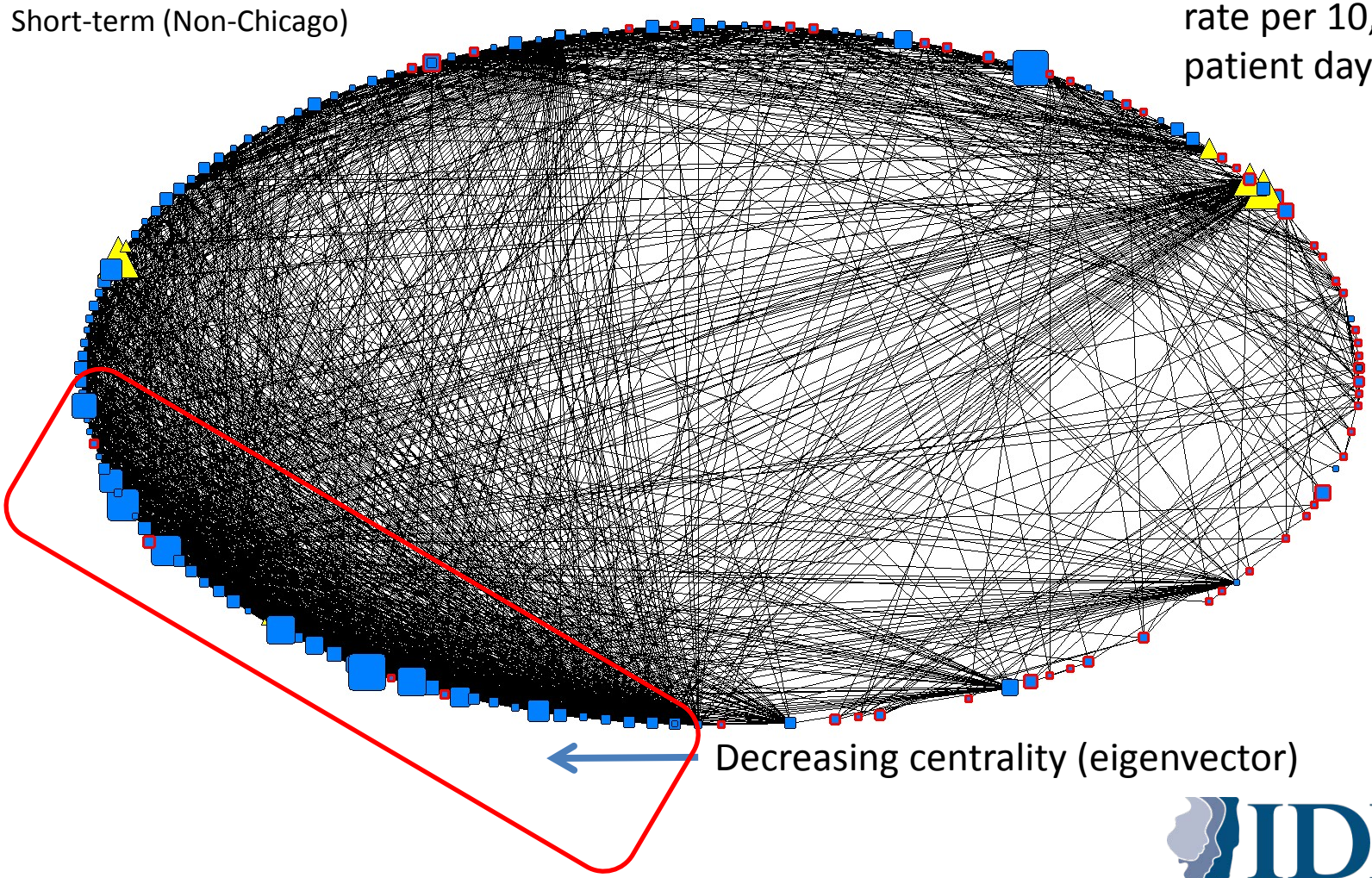
Illinois Sociogram – A dense network

LTACH

Short-term (Chicago)

Short-term (Non-Chicago)

*Node size is proportional to CRE rate per 10,000 patient days



Decreasing centrality (eigenvector)

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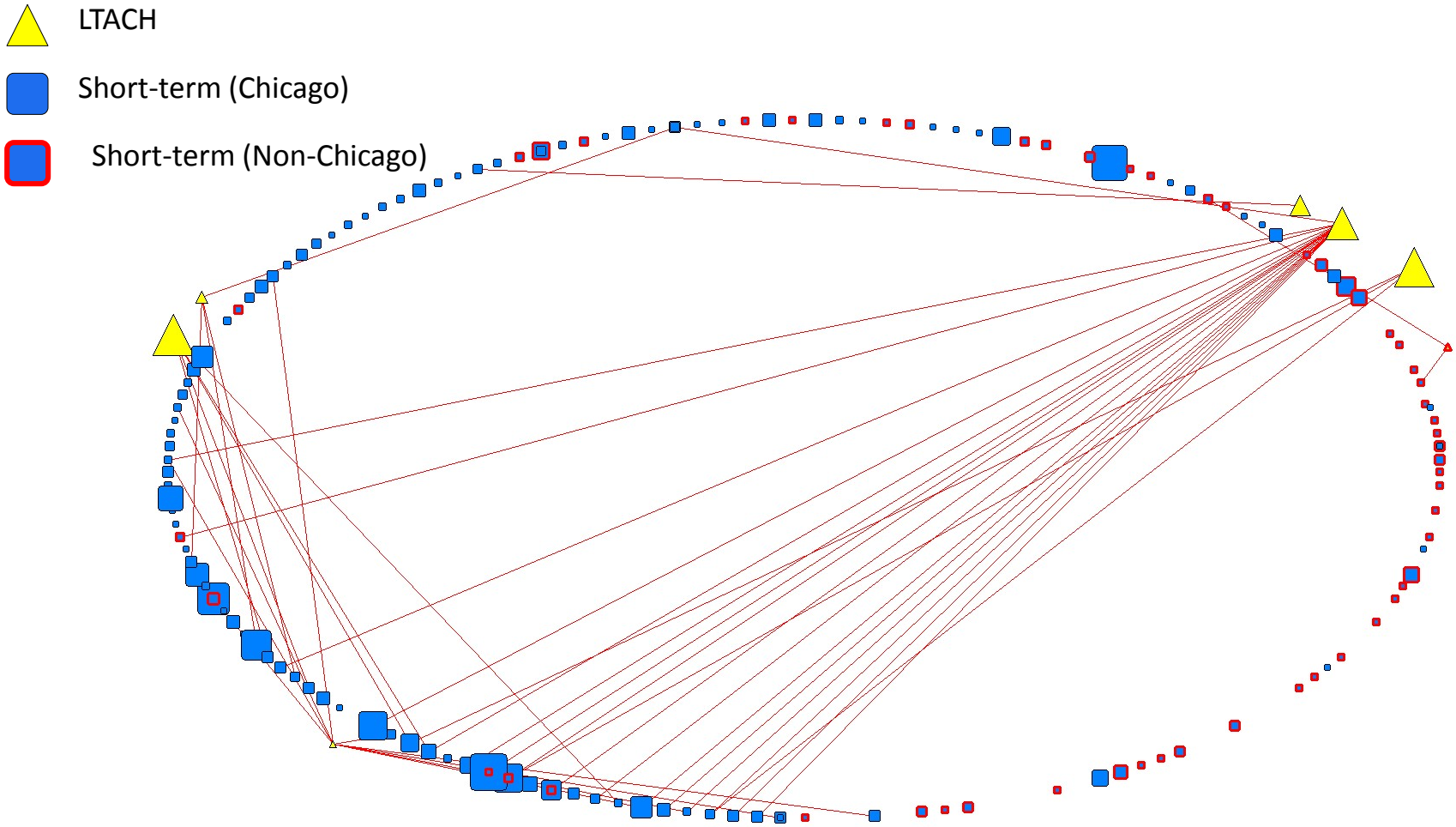
LTACH sharing (4 patient threshold)



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This hospital is 135 miles from Chicago

Chicagoland
Non-Chicago Urban
Rural

Patient sharing can span large distances. It is important that facilities are aware of these connections in the event of a possible outbreak.

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Ego network analysis: A retrospective look at a point source outbreak

- Ego Network – the part of the overall network that includes the "ego" on which we are focusing
- Dense network in Chicagoland: Decided on a 50-patient threshold to be included in ego network (2 years of discharge data)

Borgatti SP, Everett MG, Johnson JC. *Analyzing social networks.* SAGE Publications Limited; 2013.

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NDM Outbreak Background

- New Delhi metallo-β-lactamase
- 39 cases traced back to a single duodenoscope at a suburban tertiary hospital in northestern Illinois in 2013

- What if we would have known what we know now?

Epstein, L., Hunter, J. C., Arwady, M. A., Tsai, V., Stein, L., Gribogiannis, M., ... & Kallen, A. J. (2014). New Delhi metallo-β-lactamase–producing carbapenem-resistant Escherichia coli associated with exposure to duodenoscopes. *Jama*, *312*(14), 1447-1455.

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NDM Outbreak Hospital

31 unique patients entered into the XDRO registry from the NDM outbreak.

19 of those same patients visited **13** other facilities after the NDM outbreak.

9 facilities were defined to be in the NDM outbreak hospital's ego network at a threshold of 50 patients shared (22 total in ego net.)

5 facilities reported additional NDM cases other than the original index patients. 3 were within 1 year of the LGH outbreak (1 facility reported 4 cases, 1 reported 2 cases, the others reported 1 case).

4 were not in the ego network at the 50-patient threshold; however 2 more would have been in the ego network at a 25-patient threshold (37 total in ego network)

1 facility reported an NDM other than the original outbreak, and it would have been in the ego network at a 25-patient threshold

4 facilities that are neither part of LGH's ego network nor were visited by the index patients have reported NDM cases to the XDRO registry

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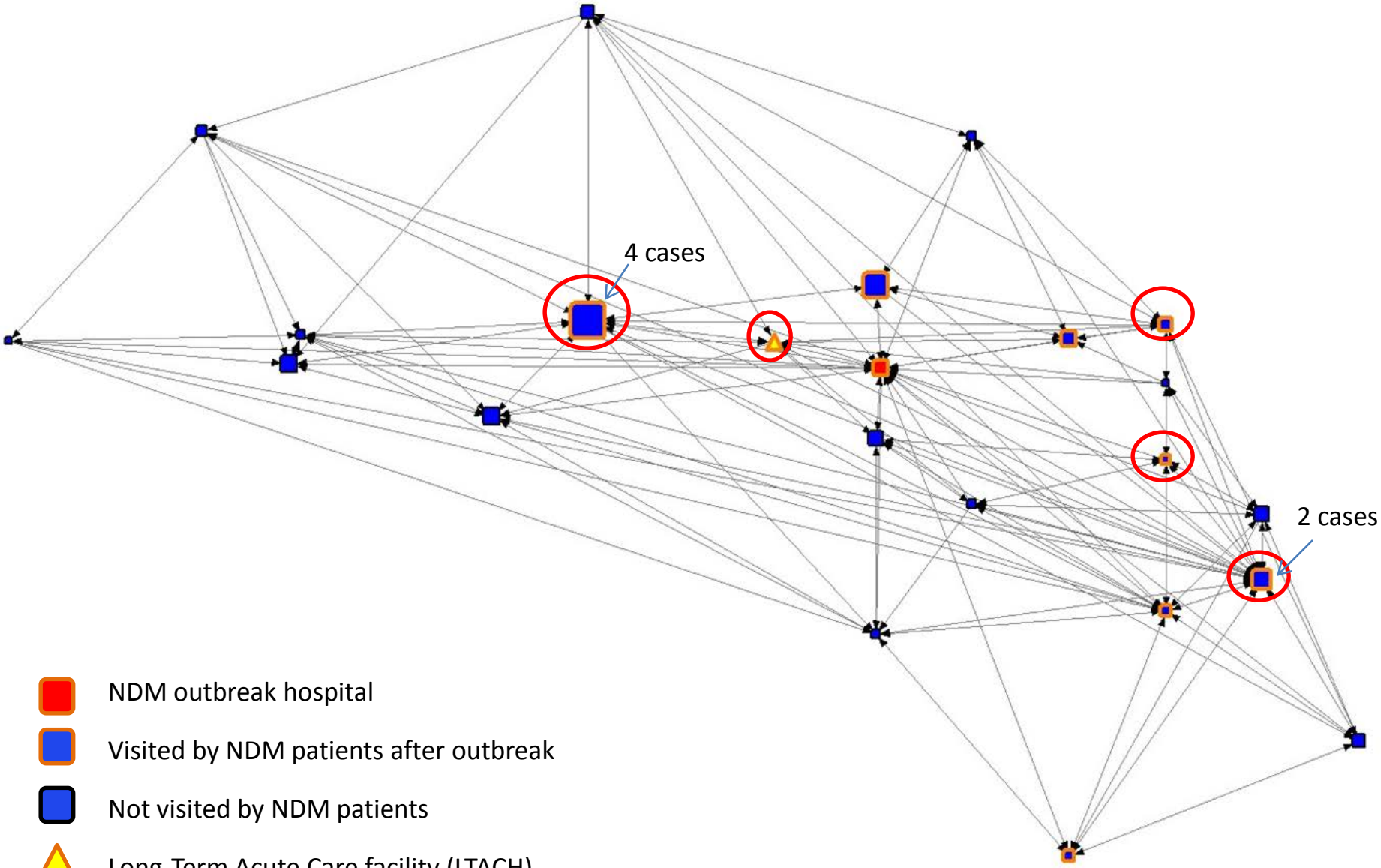

NDM outbreak hospital

Visited by NDM patients after outbreak

Not visited by NDM patients

Long-Term Acute Care facility (LTACH)

Additional facilities reporting NDM

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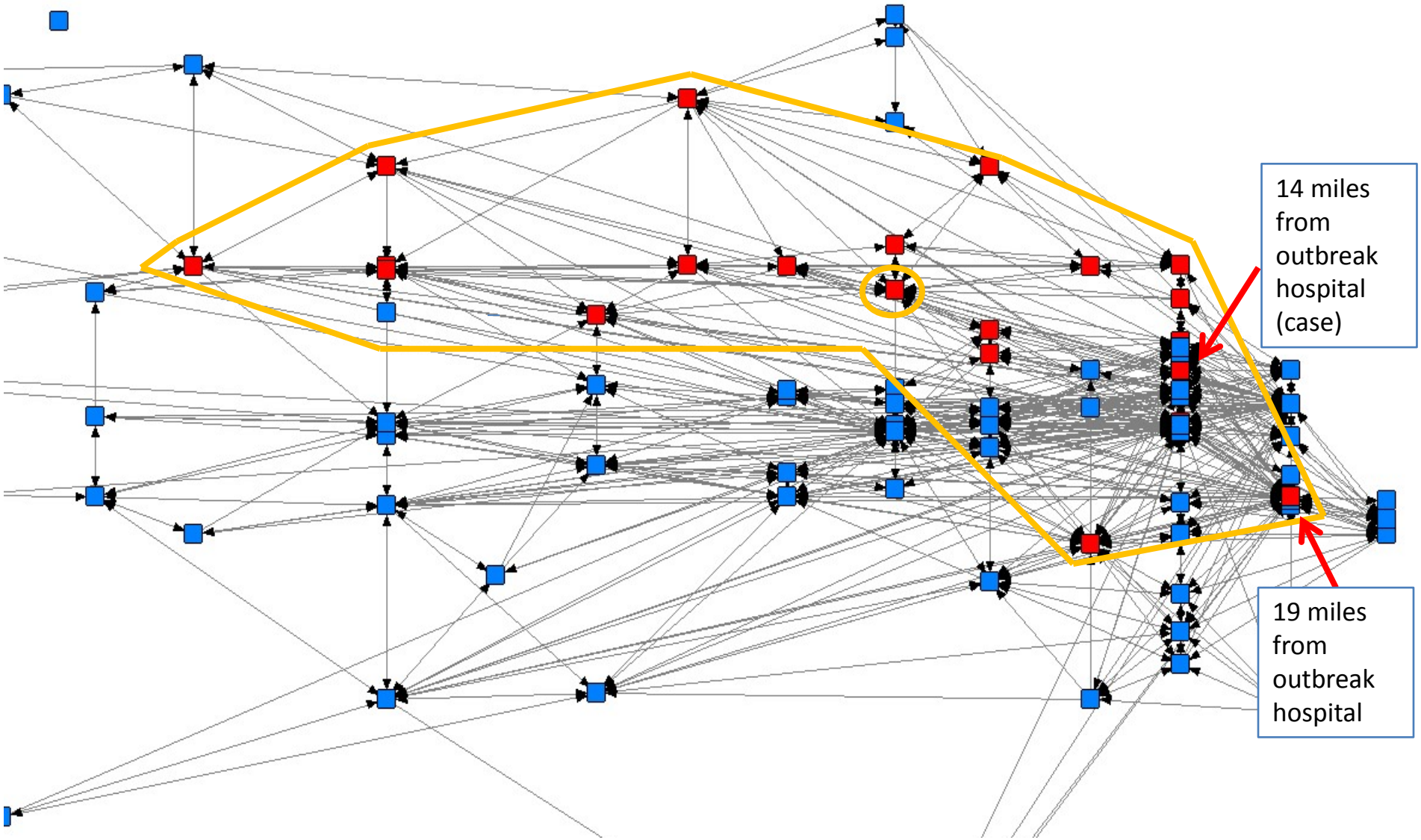

Does the ego network tell us something different from geography? There are 66 facilities within 20 miles of the outbreak hospital and 51 within 14 miles (furthest away case was 14 miles)!

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What we have learned:

- Our ego network predicted 9 out of 13 hospitals visited by outbreak patients and 5 of those 9 reported subsequent NDM cases
  - Only one facility visited by an outbreak patient and not in the ego network reported a case
- The highest ranked facility in terms of shared patients had the most cases (4) and the third ranked facility had the second most (2)

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Had we known this then…

- We could have alerted the facility that shares the most patients with the outbreak facility preventing at least 4 additional cases
- We could have prioritized facilities within the ego network preventing more cases

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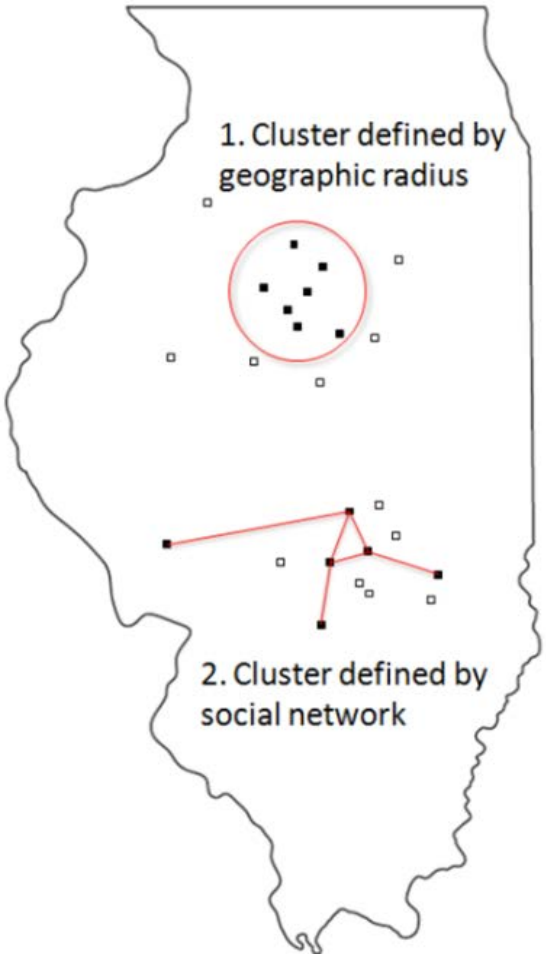
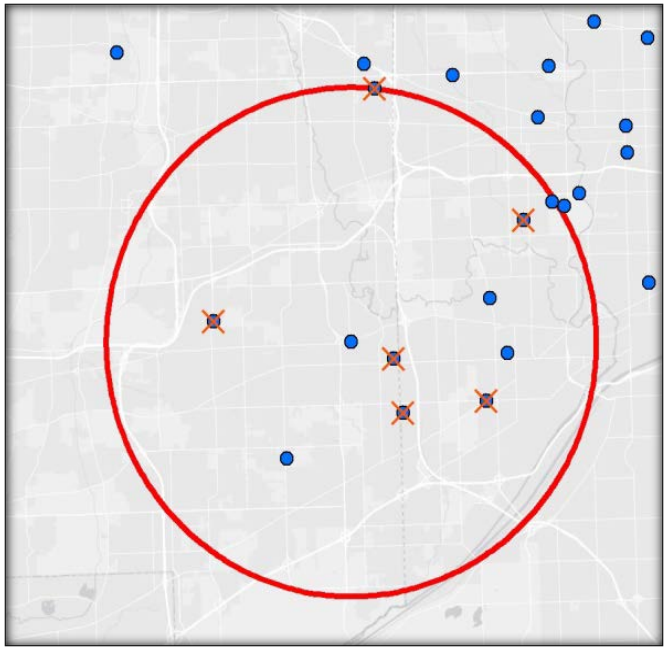
Cluster detection using SNA





Legend:

- Cluster region
- Participating facility
- CRE event during time period

CLUSTERS DETECTED (30-day maximum)

1.Location IDs included.: **[11 unique facilities]**
Coordinates / radius..: [center XY coordinates] / 10.13 km
Time frame.....: 2014/4/28 to 2014/5/11
Number of cases.....: 10
Expected cases.....: 1.57
Observed / expected...: 6.38
Test statistic.....: 10.150176
P-value.....: **0.019**

2.Location IDs included.: **[1 unique facility]**
Coordinates / radius..: [center XY coordinates] / 0 km
Time frame.....: 2014/10/6 to 2014/10/12
Number of cases.....: 5
Expected cases.....: 0.31
Observed / expected...: 16.09
Test statistic.....: 9.216841
P-value.....: **0.057**

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A More Simple Approach to Regional Coordination:
how a Program could to target activity to communities

- **Hospital specific prevention has come a long way**
  - i.e., CDI among hospitalized patients
    - Reported by all acute care facilities through NHSN
    - Hospital-onset CDI SIR publically reported on hospital compare
    - Data informs action – TAP reports tied to QIOs, State Programs
  - Similar for hospital-onset MRSA BSI, SSI, CAUTI, CLABSI
- **Non hospital-onset AR is suited for coordinated approach**
  - i.e., community-onset CDI (labID event facility-wide data) – in the cracks
    - Good proxy for nursing home onset CDI or transfer from other hospitals
    - About half of CO-CDI is from other facilities
  - Until LTC surveillance for CDI widely in place
    - CO-CDI reported to NHSN could help identify communities with a lot of CDI (or MRSA BSI) moving between facilities

Objectives

- **Explore the utility of maps for use by public health officials to identify areas (counties) with high community onset (CO) admission prevalence rates of CDI**
  - CO-CDI is the **"not my hospital"** CDI at admission
  - May represent higher incidence of CDI in the surrounding healthcare community (such as neighboring hospitals or nursing homes)
    - Indicate areas to investigate for targeted prevention of communities, opposed to hospitals

- **These maps should indicate areas of both high excess burden and high excess risk for CO-CDI Admissions.**

How can we identify regions (counties) of high CO-CDI? Predictive Model Development and Validation

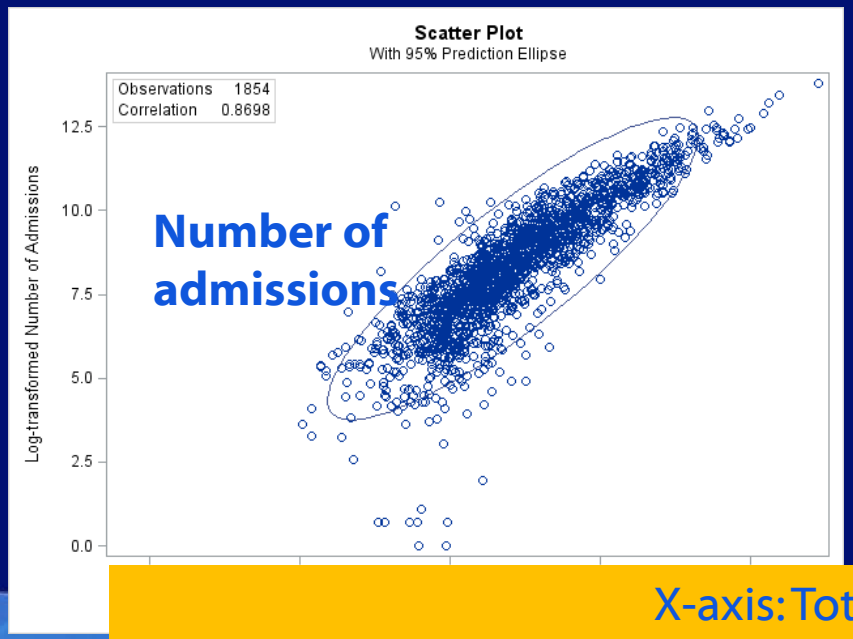
- **Developed and validated a regression model to estimate CDI CO Admission Prevalence Rates in this baseline time period**
  - Data Source: NHSN FACWIDE reporting for LabID CDI
  - Time Period: January 2013 – June 2014 (18 months of data)
  - Negative binomial model with an offset of log-number of admissions
  - Adjusts for testing type (NAAT, EIA, Other) and Facility-level clustering
    - We did not adjust for additional patient, facility, or region-specific factors (e.g., facility teaching status, bed size, urban/rural designation because the goal of our project is to only identify areas with high CO-CDI, not compare or rank facilities performance

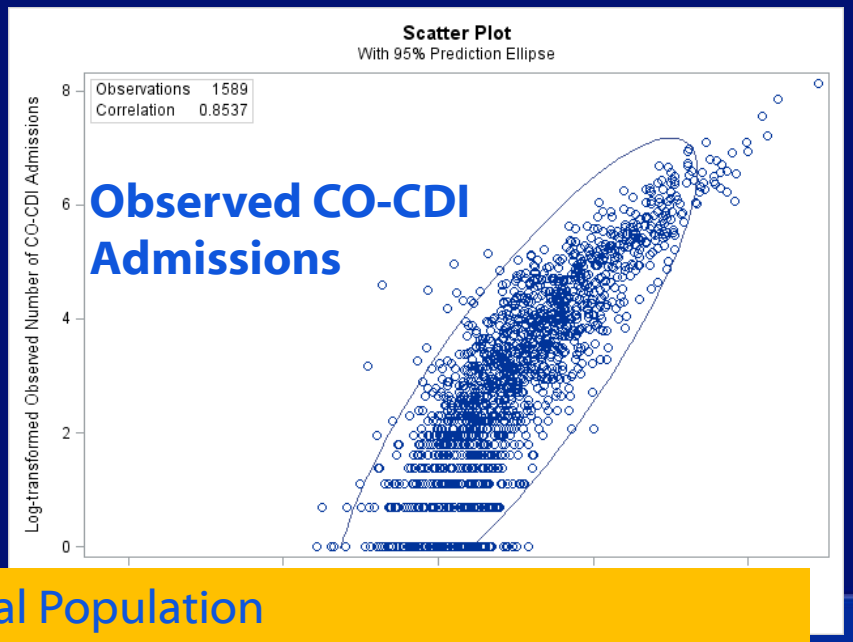
How can we identify regions (counties) of high CO-CDI? Predictive Model Application

- **Used estimated baseline rates to calculate a predicted number of CO-CDI admissions in more recent data**
  - Time Period: July 2014 – June 2015 (12 months)
- **Summed observed and predicted CO-CDI for all facilities in a given county for the one-year time period**
- **Created two metrics to measure high CDI**
  - **Risk Ratios:** *observed/ predicted*
  - **Risk Differences:** *observed – predicted*

Checking Utility of Risk Ratio and Difference Measures

- **We wanted to check if we had created useful measures of risk and burden with our total population**
  - As expected, county population is correlated with the number of admissions in that county (denominator in admission prevalence rate)
  - As expected, county population is correlated with the observed frequency of CO-CDI admissions (numerator in admission prevalence rate)

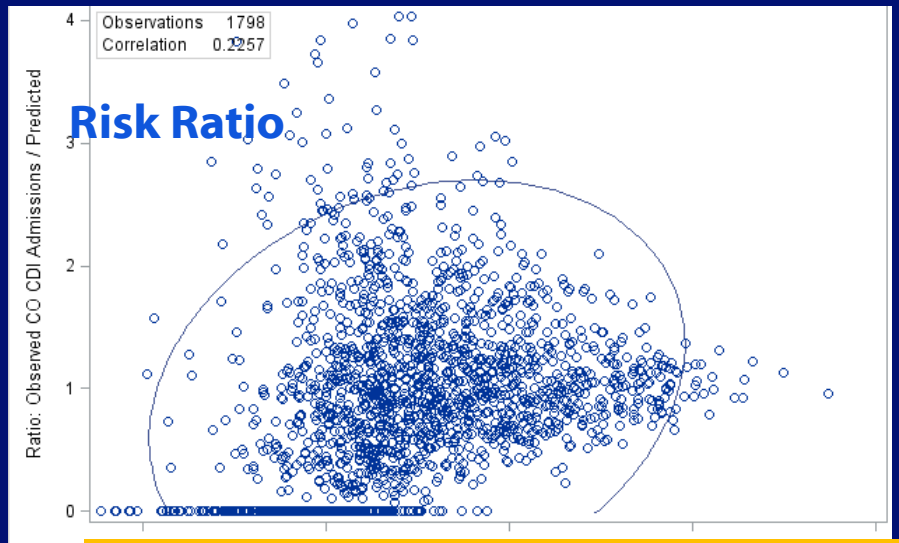


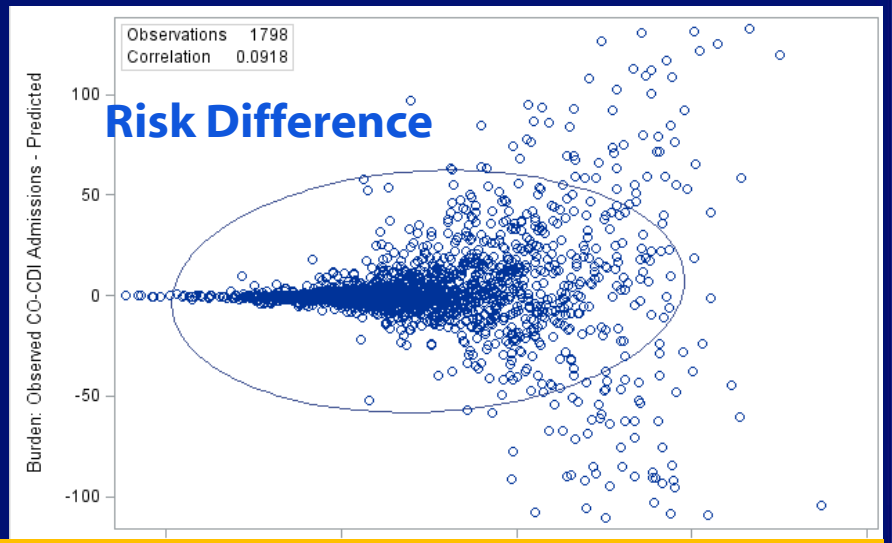


X-axis: Total Population

Do our newly calculated metrics identify areas of only high or low population density?

- **No!** County-level risk ratios and excess burden do not appear correlated with county-level population



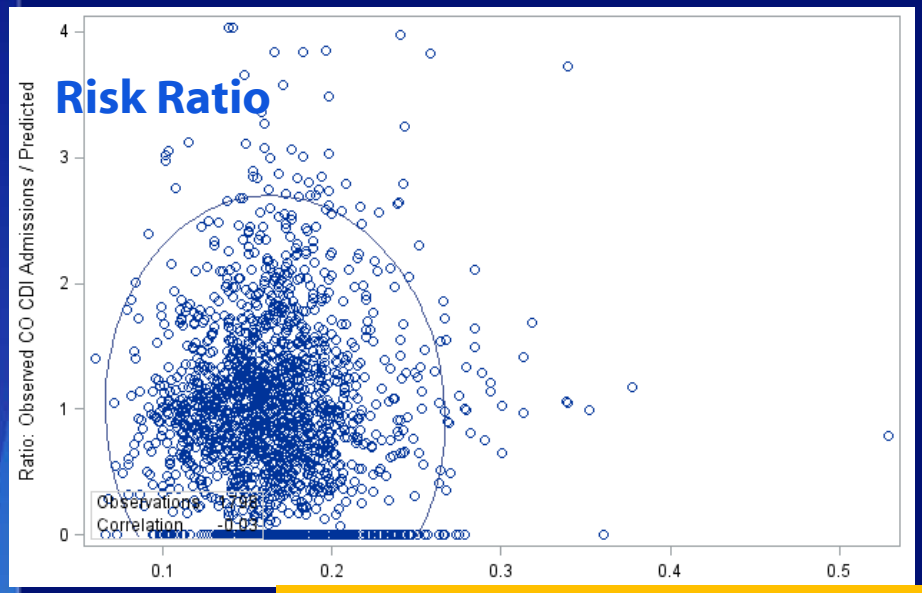


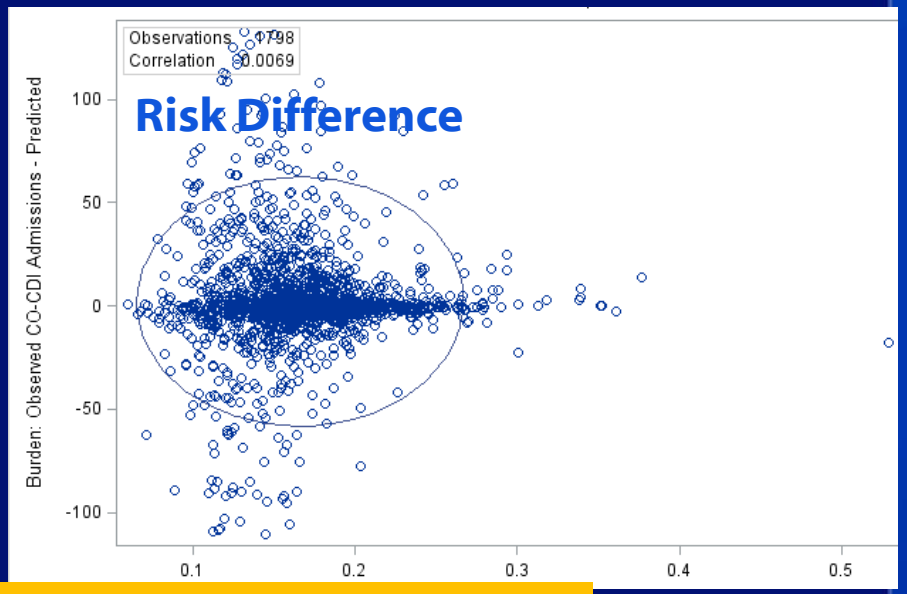
X-axis: Total Population

- Population alone does not identify high risk or high burden counties

Do our newly calculated metrics identify only areas with more residents 65 and older?

- **No!** County-level risk ratios and excess burden do not appear correlated with the proportion of county residents 65 and over





X-axis: Proportion of County Population 65 and older

- **Population alone does not identify high risk or high burden counties**

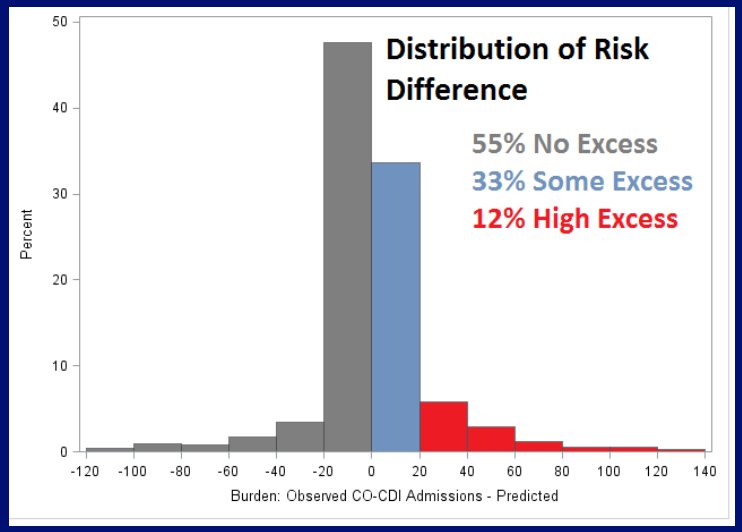
What does this mean?

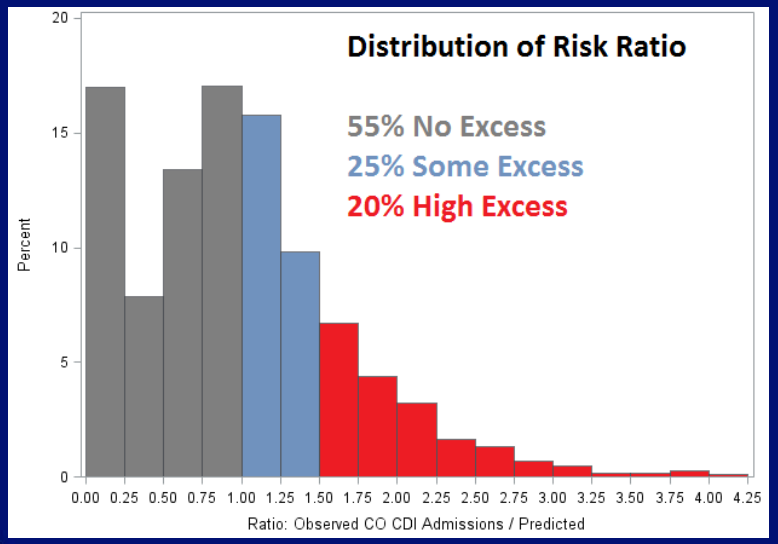
- **We do not find strong associations with the CO-CDI excess risk or burden with population density or the proportion of the population 65 and over**
  - We believe these measures are able to identify counties with high excess CO-CDI better than simply targeting using population density.
  - We believe these measures are able to better identify counties than simply targeting counties with high proportion of older adults.
- **Now, we want to use this information to find areas with "High" excess risk and excess burden to target**

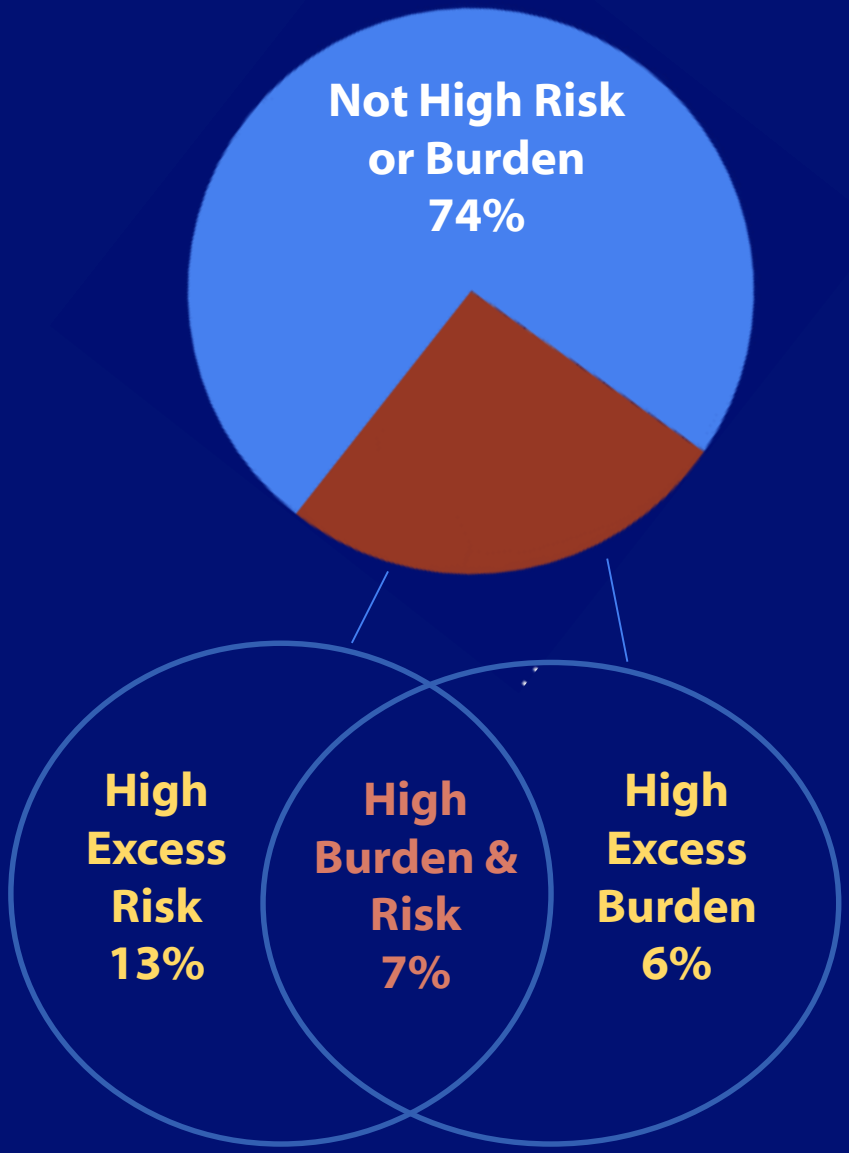
Measuring High Levels of CDI

- **Created two metrics to measure high CDI**
- **Risk Ratios: *observed/ predicted* *(Excess Risk)***
  - *0 – 1: **No** excess risk (rate is equivalent or lower than predicted)*
  - *1 – 1.5: **Some** excess risk (rate is up to 150% of predicted)*
  - *> 1.5: **High excess risk** (rate is greater than 150% of predicted)*
- ***Risk Differences: observed – predicted (Excess Burden)***
  - *≤ 0: **No** excess burden (observed count is equal to or less than predicted)*
  - *0 - 20: **Some** excess burden (observed count is 1 - 20 greater than predicted)*
  - *≥ 20: **High excess burden** (observed count is greater than 20 admissions over predicted)*

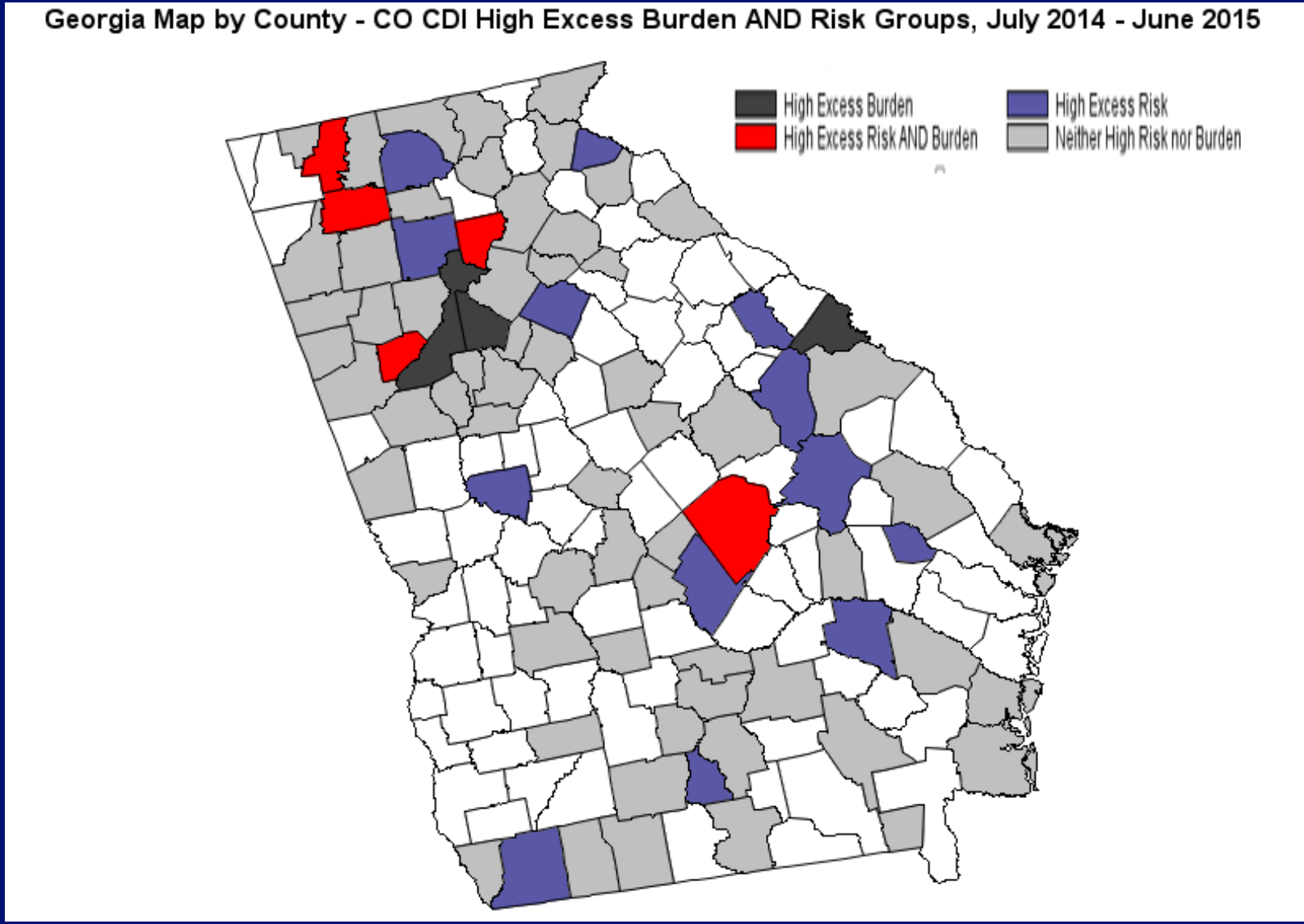
Results


Distribution of Risk Difference
55% No Excess
33% Some Excess
12% High Excess
Percent
50
40
30
20
10
0
-120 -100 -80 -60 -40 -20 0 20 40 60 80 100 120 140
Burden: Observed CO-CDI Admissions - Predicted


Distribution of Risk Ratio
55% No Excess
25% Some Excess
20% High Excess
Percent
20
15
10
5
0
0.00 0.25 0.50 0.75 1.00 1.25 1.50 1.75 2.00 2.25 2.50 2.75 3.00 3.25 3.50 3.75 4.00 4.25
Ratio: Observed CO CDI Admissions / Predicted


Not High Risk or Burden 74%
High Excess Risk 13%
High Burden & Risk 7%
High Excess Burden 6%

State Example



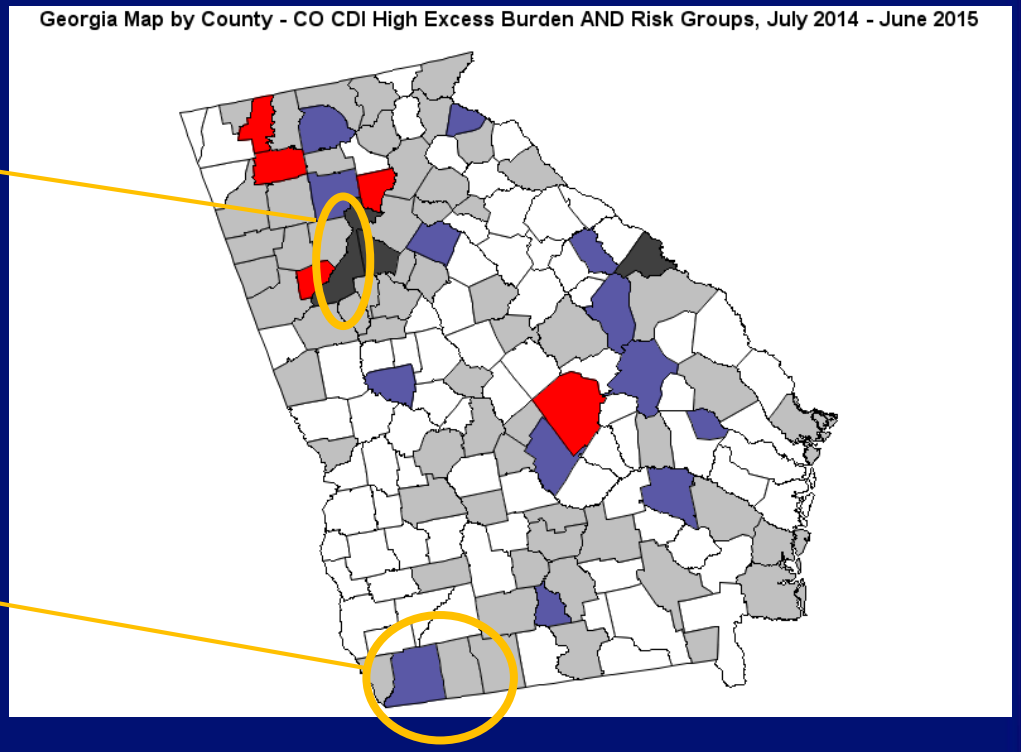
State Example – A closer look

Dark Gray County A

- Rate: 0.38 per 100 admissions
- Predicted: 527.5
- Observed: 604
- Risk Ratio: 1.14
- Excess Burden: 76.47

Blue County A

- Rate: 0.68 per 100 admissions
- Predicted: 4.0
- Observed: 9
- Risk Ratio: 2.24
- Excess Burden: 5.0



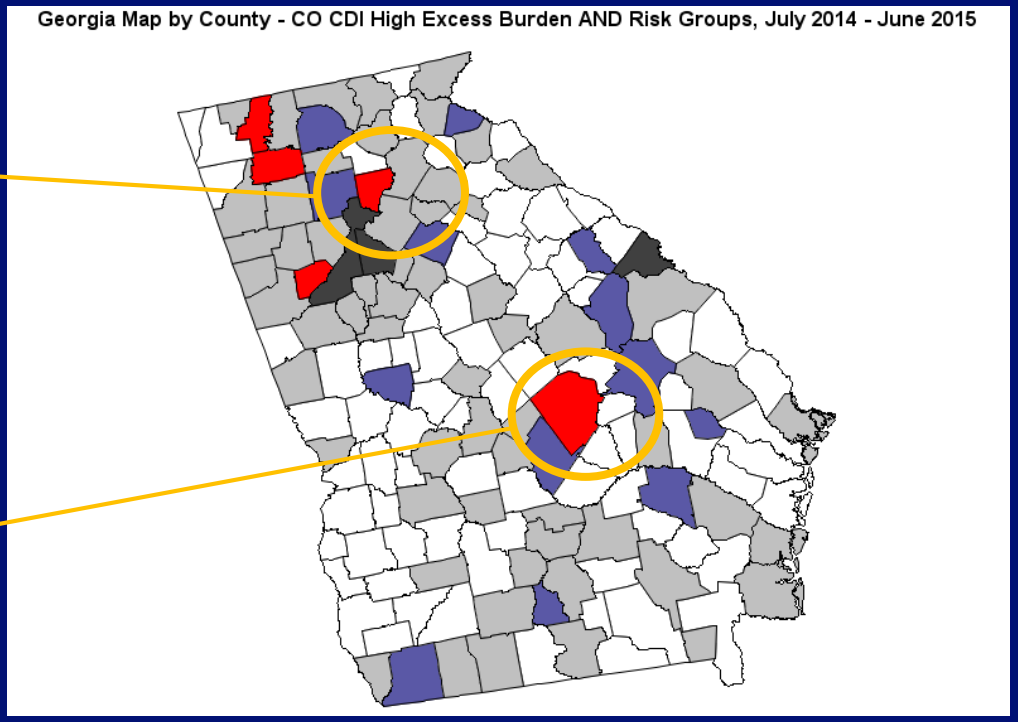
State Example – A closer look

Red County A

Rate: 0.97 per 100 admissions
Predicted: 34.4
Observed: 59
Risk Ratio: 1.71
Excess Burden: 24.6

Red County B

Rate: 0.73 per 100 admissions
Predicted: 19.0
Observed: 52
Risk Ratio: 2.74
Excess Burden: 33



Summary

- **Some states will have too many or too few counties light up in red**
  - Relax or Tighten cut off points – change "signal detection" to identify actionable results depending on resource availability
- **Maps may indicate counties where CDI is a problem in the surrounding community (i.e., "not my hospital" CDI)**
  - CO-CDI may be coming from other facilities that share patients (other hospitals, long term care facilities, etc.)
- **Further investigation of these CO-CDI cases may be warranted**
  - Identify other potential healthcare exposures of these patients

Still Exploratory
What Potential Action Could Be Based on Georgia County Level CO-CDI Metrics?

- **Explore role of bad testing practices at acute care hospitals in priority counties**
- **Enhance Surveillance for CDI in LTCF in priority counties**
  - Partner with QIO to enroll LTCF into NHSN LTCF HAI surveillance
  - Require acute care hospitals to "voluntarily" use LabID event custom fields to enter transferring facilities
- **Explore quick look at suspect transferring facilities**
  - Discussion with hospital-nursing staff about impressions
  - Use of Medicare data or hospital administrative data to identify high frequency transfers
- **On-site assessment of acute care and LTCF with infection control and stewardship assessment tools**

Spectrum of Coordinated Regional AR Prevention

A. Exploring use of Medicare Data (or State Inpatient database) to define connectedness
B. Identifying potential spread of new AR through Social Network Analysis (IL)
C. Proxy measures to help target communities (NHSN labID event)

- All are exploratory
- Practical approach will vary by state: different steps to get to different points on spectrum

Inventory of Facilities	Quantify Hot Spots of Cases	Quantify connectedness of facilities	Track Patients/Cases, Alerts

Quick Start Approach – How to get started

- **Inventory of Hospitals**
  - List, map, link descriptors, admissions, patient-days
  - Consider hospital discharge database, state surveys, NHSN survey (Stewardship example)
- **Inventory of LTCF**
  - Consider nursing home compare, Medicare cost reports
- **Access case reporting data**
  - Hospital based
    - NHSN AR report functionality (line list of AR HAIs for group)
  - Outside of acute care or between facilities
    - State-based systems (TN, CRE example)
    - NHSN LabID Event (CDI example)

Summary of considerations regarding Coordinating Regional Prevention of HAI AR

- **Situational awareness extends to understanding connectivity (transfers) data and can be quantified to help make decisions around intervention and surveillance**
- **Progress requires access to data; all sites should have a defined pathway forward to access NHSN data, and pathways to gain access to state inpatient datasets**
- **Simple approaches and complex approaches are in exploratory phase; early experience will be shared so all can move forward**
- **All sites can identify pathway forward now by exploring and securing**
  - Access to data
  - Access to expertise (Health Systems Integration Program (HSIP) Fellow, partnerships with academic centers)
  - Leverage existing partners (assessment teams, QIOs)

Panel Discussion/Questions

- How can DHQP help State HAI AR Programs now
- Examples of leveraging existing partnerships to tackle regional/community-wide HAI AR issues