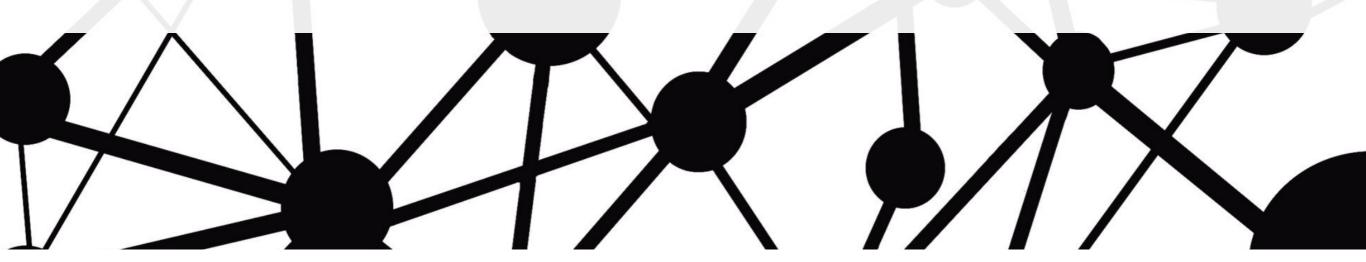


Modeling Epidemics on Multi-Layer Networks



Network Modeling for Epidemics 2025

Definition and Motivation

- Multi-layer networks are used to represent different types of edges in the same underlying model population
- Same node set, different edge set
- Flexibility in handling different types of relations that may vary in both formation and dissolution model
- General example for social contacts:
 - Family network in a household
 - High mean degree, complex age mixing, long persistence
 - Community network
 - Low mean degree, less complex mixing, short persistence

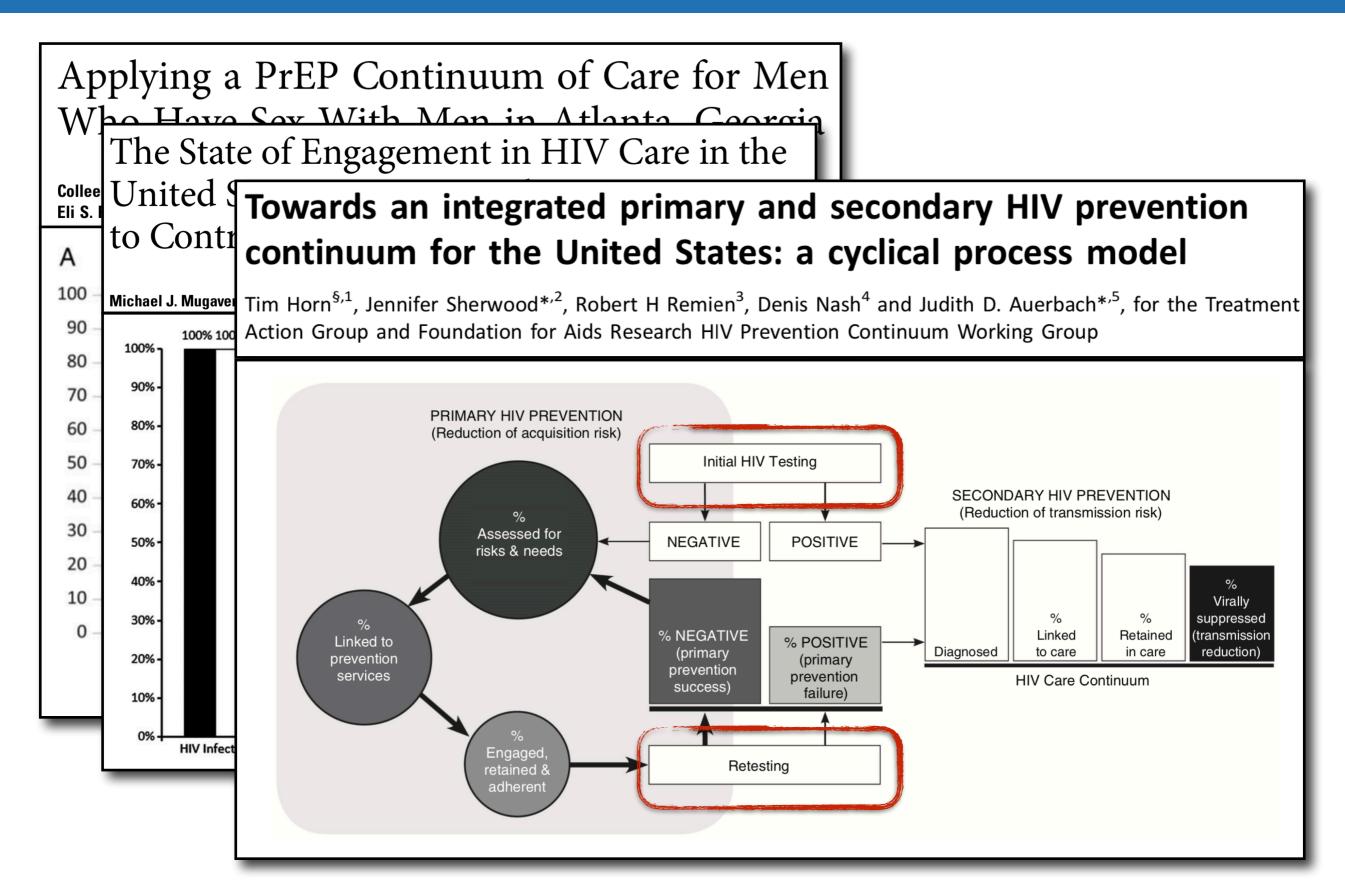
How Do Network Layers Interact?

- Network layers may be modeled independently...
- Or there may be interactions across layers:
 - Number of school contacts negatively correlated with number of work contacts
 - Number of main partners negatively correlated with number of casual partners
- Interactions can be modeled with degree in one layer as a model term in another layer
 - These cross-layer degrees can change over time and thus the network resimulations can (and should) adapt

HIV Model Example

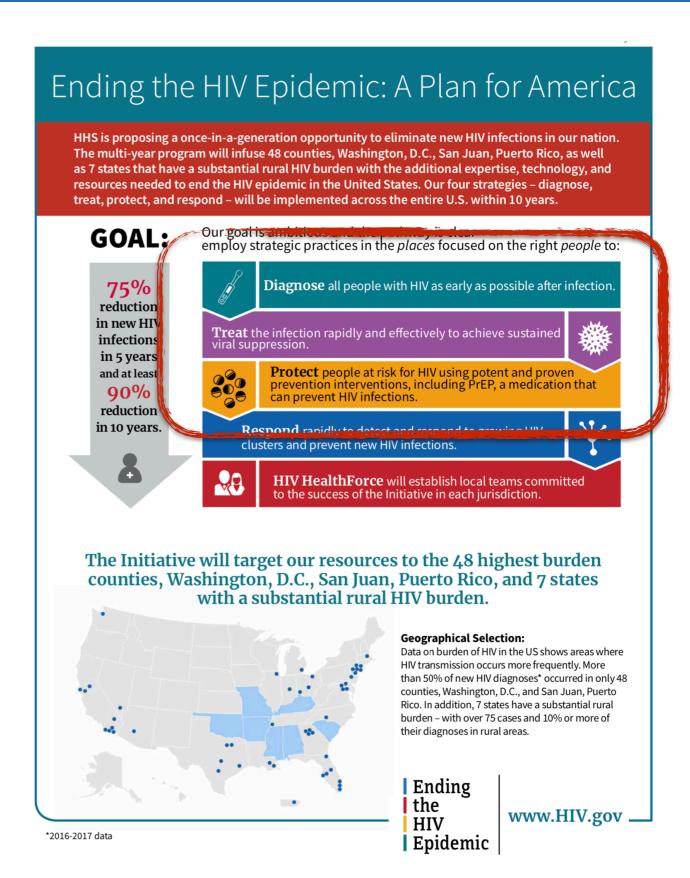
- Jenness SM, Johnson JA, Hoover KW, Smith DK, Delaney K. Modeling an Integrated HIV Prevention and Care Continuum to Achieve the Ending the HIV Epidemic Goals. *AIDS*. 2020; 34(14): 2103–2113.
 - PDF of paper: http://samueljenness.org/pdf/Jenness-2020-AIDS.pdf
 - EpiModelHIV Code: https://github.com/statnet/EpiModelHIV
 - Model scripts for paper: https://github.com/epimodel/combprev

An Integrated Prevention & Care Continuum



Ending the Epidemic Plan

- Ending the HIV Epidemic plan introduced in Feb 2019
 - 75% incidence reduction by 2025
 - 90% reduction by 2030
 - Resources directed at high-burden counties and states
- Will it be enough for HIV?
 - Lowest levels of HIV viral suppression in the Southern states where Medicaid not expanded through ACA



Study Aims

 Using modeling to understand an integrated HIV prevention and care continuum to achieve EHE goals

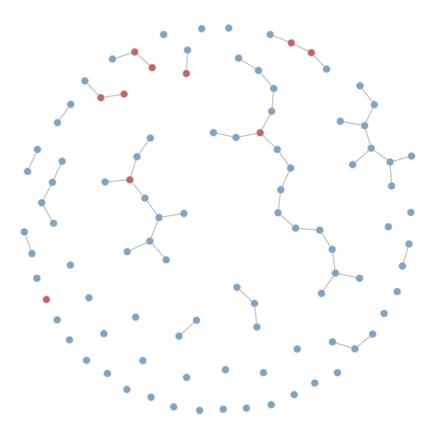
- Primary Study Question
 - What combinations of improvements to HIV screening (alone or as a gateway to PrEP initiation), HIV care linkage, and HIV care retention could meet the 2030 EHE goal of a 90% reduction in HIV incidence?

Methods Overview

- Stochastic network model for HIV transmission dynamics
- Target study population:
 - Men who have sex with men (MSM) in Atlanta metropolitan area
 - Aged 15 to 65, stratified by Black, Hispanic, White/Other race/ethnicity
- Model calibrated to recent estimates of HIV care continuum steps and PrEP utilization in population
- Intervention scenarios for improvements to:
 - HIV screening
 - · With and without PrEP initiation linked to HIV screening events
 - HIV care linkage
 - HIV retention in care

Network Modeling Methods

- Temporal exponential random graph models (TERGMs) define partnership formation and dissolution
 - Sexual network types: main, casual, one-off
 - Men form partnerships according to model terms based on numbers of each partner type, differential activity and mixing on race and age, sexual role segregation



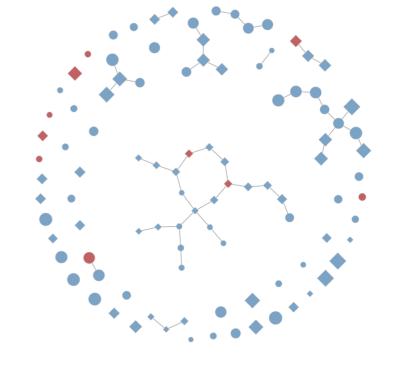
HIV epidemiology

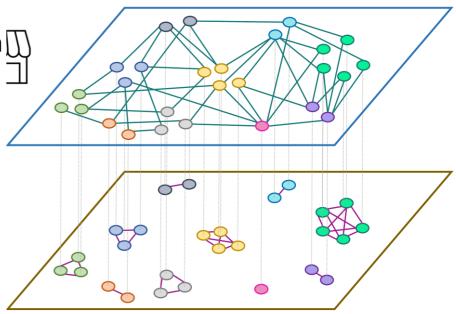
- Natural history (disease stages, continuous VL, HIV-related mortality)
- ART initiation and adherence
- HIV transmission dynamics within serodiscordant partnerships

Demographic processes

Multi-Layer Networks for MSM Sexual Partnerships

- Three partnership networks: main, casual, one-time
 - Same node set, different edge set
- Distinguished in both their formation and dissolution model components
 - Formation formula for main network differs from other two
 - Dissolution model varies (substantially) by average duration of partnerships
- Formation model for partnerships
 - ► Heterogeneity and assortative mixing by demographics, degree in other networks, sexual positioning; non-parametric degree distribution terms
- Dissolution model for partnerships
 - Mean duration of partnerships by type and age-group-specific durations (young-young partnerships shorter than old-old partnerships)

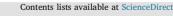




Empirical Data ---- Network Model Parameters

- Recently completed **ARTnet Study** of MSM in the US (R21 MH112449)
 - 4904 MSM reporting on 16198 sexual partnerships
- **Primary innovation:** data-driven statistical models embedded within ID transmission models where primary data available
 - TERGMs for network structure ---- simulate
 - Poisson models for coital frequency predict
 - Logit models for condom use ---- predict
- Allows for confounding adjustment and addressing parameter covariance, statistical interactions when necessary
- Secondary data for (more) universal parameters
 - PrEP/ART effectiveness, probability of HIV transmission per act, ...

Epidemics 30 (2020) 100386



Epidemics

journal homepage: www.elsevier.com/locate/epidemics



Egocentric sexual networks of men who have sex with men in the United States: Results from the ARTnet study



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 Departments of Statistics and Sociology, University of Washington, Seattle, Washington, United States

ARTICLE INFO

Men who have sex with men Sexual networks Mathematical modeling Network modeling

In this paper, we present an overview and descriptive results from one of the first egocentric network studies of men who have sex with men (MSM) from across the United States: the ARTnet study. ARTnet was designed to support prevention research for human immunodeficiency virus (HIV) and other sexually transmitted infections (STIs) that are transmitted across partnership networks. ARTnet implemented a population-based egocentric network study design that sampled egos from the target population and asked them to report on the number, attributes, and timing of their sexual partnerships. Such data provide the foundation needed for parameterizing stochastic network models that are used for disease projection and intervention planning. ARTnet collected data online from 2017 to 2019, with a final sample of 4904 participants who reported on 16198 sexual partnerships. The aims of this paper were to characterize the joint distribution of three network parameters needed for modeling: degree distributions, assortative mixing, and partnership age, with heterogeneity by partnership type (main, casual and one-time), demography, and geography. Participants had an average of 1.19 currently active partnerships ("mean degree"), which was higher for casual partnerships (0.74) than main partnerships (0.45). The mean rate of one-time partnership acquisition was 0.16 per week (8.5 partners per year). Main partnerships lasted 272.5 weeks on average, while casual partnerships lasted 133.0 weeks. There was strong but heterogenous assortative mixing by race/ethnicity for all groups. The mean absolute age difference for all partnership types was 9.5 years, with main partners differing by 6.3 years compared to 10.8 years for casual partners. Our analysis suggests that MSM may be at sustained risk for HIV/STI acquisition and transmission through high network degree of sexual partnerships. The ARTnet network study provides a robust and reproducible foundation for understanding the dynamics of HIV/STI epidemiology among U.S. MSM and supporting the implementation science that seeks to address persistent challenges in HIV/STI prevention

1. Introduction

Human immunodeficiency virus (HIV) and other sexually transmitted infections (STIs) continue to present significant public health challenges. In the United States, HIV and STI incidence disparities are linked to demographics (Singh et al., 2014), risk behavior (Goldstein et al., 2017), clinical care access (Beer et al., 2017), and geography (Oster et al., 2015). Of the estimated 40,000 new HIV infections occurring in 2017, two-thirds were among men who have sex with men (MSM) (Centers for Disease Control and Prevention, 2019b), The large disparities in HIV/STI cases by race and age have worsened, with incidence increasing among younger non-white MSM while decreasing in

other MSM groups (Rosenberg et al., 2018). Syphilis has also concentrated among MSM (de Voux et al., 2015), following similar demographic and geographic patterns as HIV (Grey et al., 2017; Sullivan et al., 2018). Understanding the persistent and emerging drivers of HIV/STI transmission dynamics among MSM is critical to prevention.

Sexual partnership networks are the mechanism through which all STI and most HIV transmissions circulate. The pathogens are transmitted by sexual acts embedded within partnerships, and circulation through the population depends on how those partnerships form and dissolve — a highly structured and population-specific dynamic process (Morris et al., 2009; Goodreau et al., 2012; Jenness et al., 2016a), While sexual network structure can be measured and analyzed either cross-

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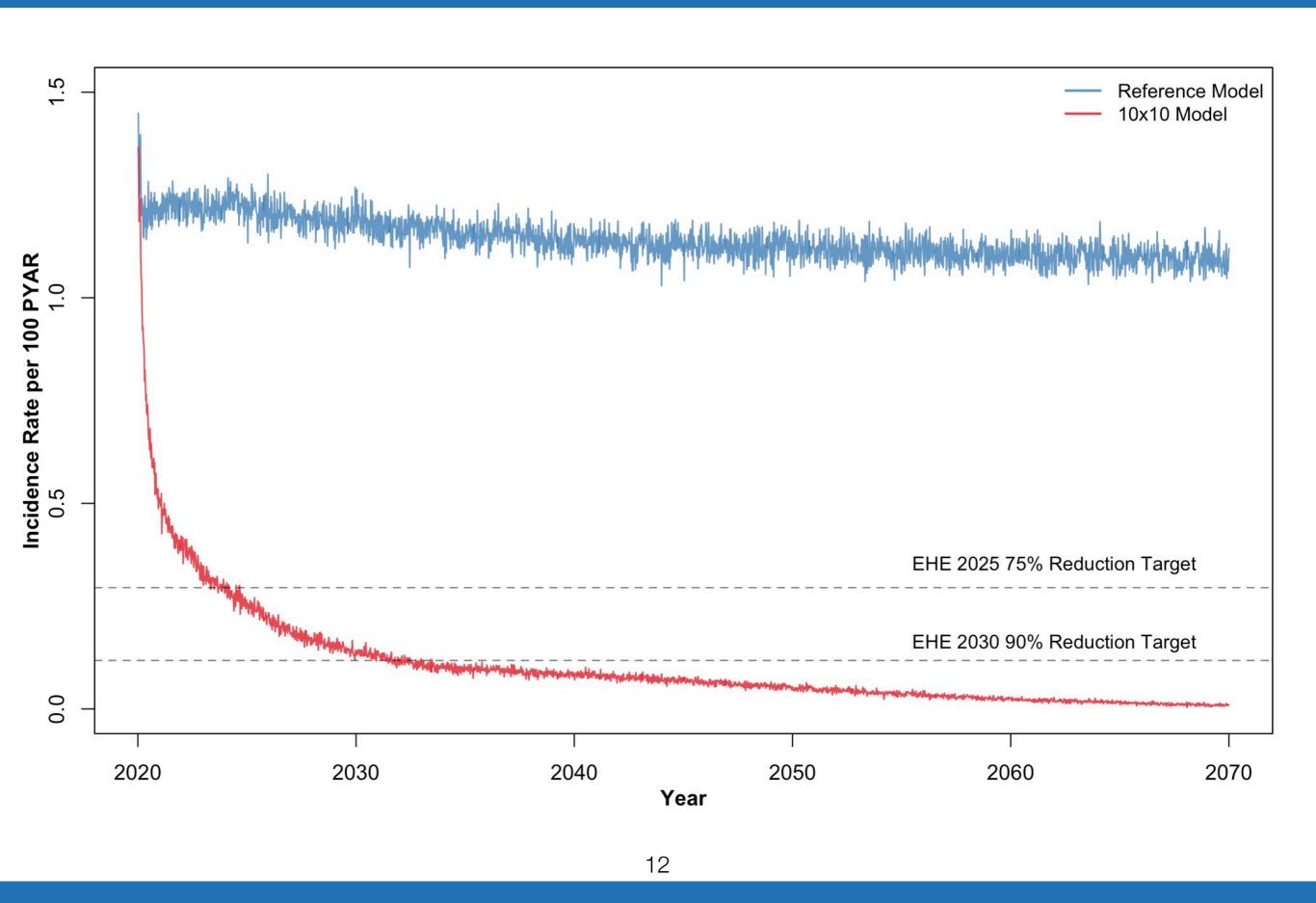
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https://pubmed.ncbi.nlm.nih.gov/32004795/

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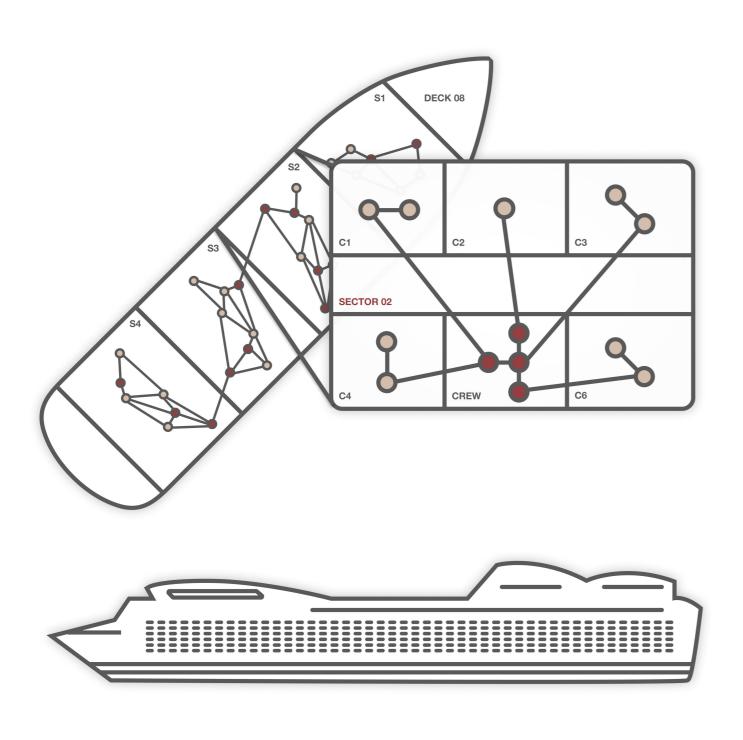
How Long Will it Take to Achieve the EHE Goals?

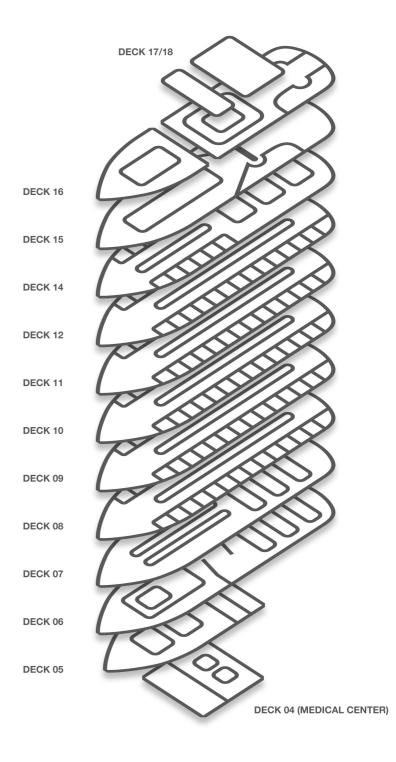


COVID Model Example

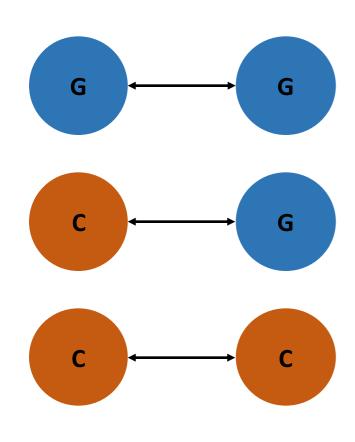
- Jenness SM, Willebrand KS, Malik AA, Lopman BA, Omer SB. Modeling Dynamic Network Strategies for SARS-CoV-2 Control on a Cruise Ship.
 - Paper: https://epimodel.github.io/sismid/0_nme_prep/pdf/Jenness-Epidemics-COVIDCruise.pdf
 - EpiModelCOVID Code: https://github.com/epimodel/epimodelcovid
 - Model scripts for paper: https://github.com/EpiModel/COVID-CruiseShip

Cruise Ship Network Model Schematic



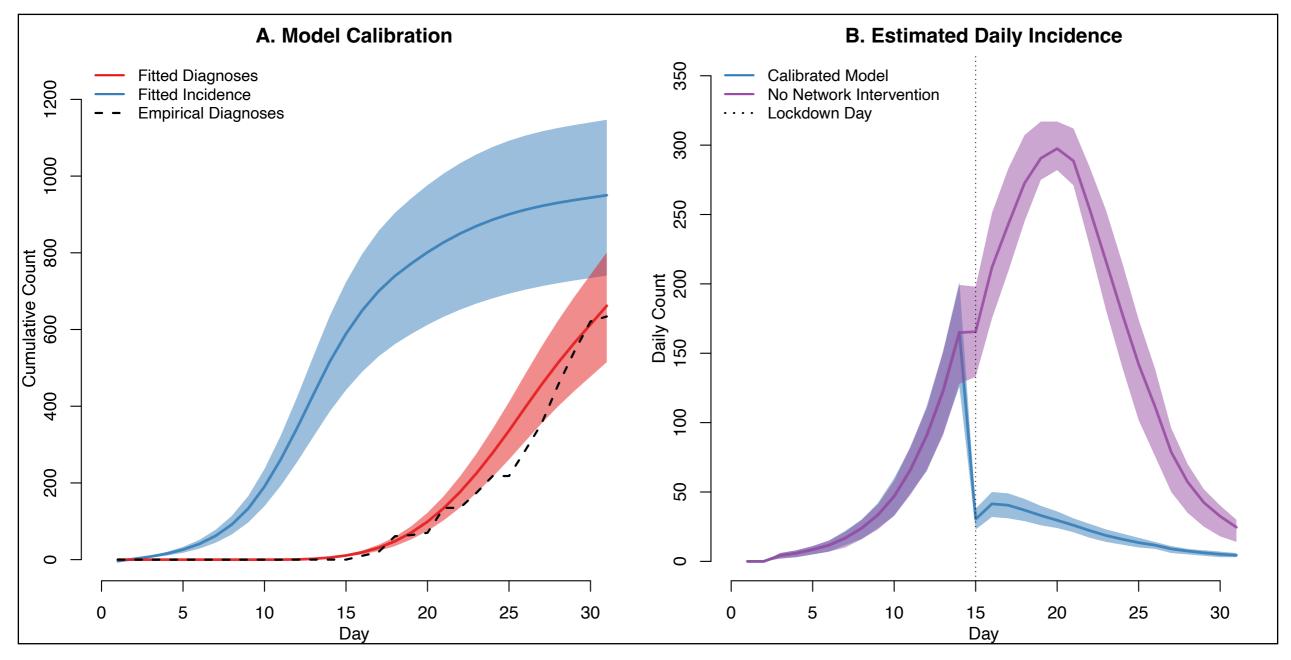


Multi-Layer Dynamic Contact Networks



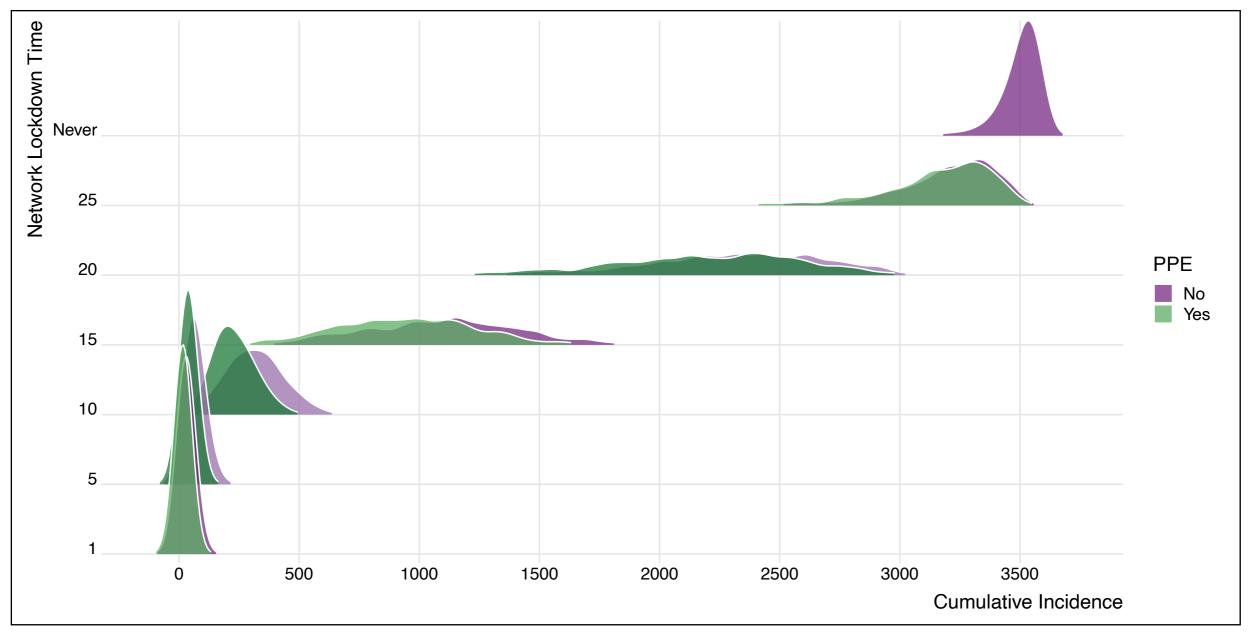
- Three overlapping ERGMs to represent guest/guest, crew/guest, and crew/crew contacts
- Multi-level structure: guests within cabins, cabins within ship sectors, crew assigned to cabins within sectors
 - x2 ERGMs, for pre-lockdown and post-lockdown network structures
- ERGMs with ship structure allow for repeated contacts with deterministic dissolution
- Scenarios focused on timing of lockdown, design of sectorization, and degree and within-cabin and withinsector mixing constraints given lockdown
 - Control-based strategies: after outbreak has started
 - Prevention-based strategies: informing future ship design

Model Results 1: Calibration



- Fit the model transmission parameters to daily screening rates and diagnoses on ship
 - True incidence > diagnosed incidence
- Empirical lockdown occurred Day 15 of the cruise

Model Results 2: Timing of Network Lockdown



- Distribution of cumulative incidence across 1000 simulations in each scenario
- Earlier (counterfactual) lockdown associated with major reduction in cumulative incidence compared to empirical (actual) lockdown on Day
 - Little impact of PPE in these settings: high-intensity contact and directionality of transmission...

Model Results 3: Directionality of Transmission

	Total	Passenger to Passenge	Passenger to Crew	Crew to Passenger	Crew to Crew
Scenario	Cuml. Incid.	Cuml. Incid.	Cuml. Incid.	Cuml. Incid.	Cuml. Incid. Median (95% SI)
	Median (95% SI)	Median (95% SI)	Median (95% SI)	Median (95% SI)	
With Contact Intensity Re	eductions, Network Lock	down, and PPE at Day 15			
Base Scenario					
No Intensity Reduction	933.5 (366.0, 1556.2)	551.0 (213.9, 941.0)	163.0 (66.0, 265.0)	124.0 (46.0, 211.0)	93.0 (33.0, 175.0)
Varying Passenger-Passen	ger Contact Intensity				
50% Reduction	862.5 (353.9, 1454.0)	488.0 (203.9, 843.0)	155.0 (67.0, 257.0)	124.5 (47.0, 216.0)	93.5 (29.0, 174.0)
90% Reduction	765.5 (316.9, 1348.0)	401.0 (164.9, 727.0)	145.5 (63.0, 248.0)	122.0 (44.0, 214.0)	90.0 (31.0, 173.0)
100% Reduction	749.0 (297.9, 1255.1)	381.0 (155.9, 677.0)	147.5 (61.0, 241.0)	126.0 (44.0, 208.0)	93.0 (32.0, 168.0)
Varying Passenger-Crew C	ontact Intensity				
50% Reduction	849.0 (352.9, 1379.1)	545.0 (230.0, 868.0)	125.5 (54.0, 203.0)	87.0 (31.0, 158.1)	90.0 (31.0, 168.0)
90% Reduction	787.0 (332.9, 1346.1)	535.5 (227.0, 899.0)	96.0 (41.0, 173.0)	62.0 (17.0, 130.0)	87.0 (30.0, 170.0)
100% Reduction	744.0 (325.0, 1274.1)	519.5 (225.9, 865.0)	86.0 (37.0, 152.0)	55.0 (17.0, 117.0)	84.0 (29.0, 167.0)
Varying Crew-Crew Contac	t Intensity	<u>'</u>			
50% Reduction	897.0 (379.9, 1471.2)	542.0 (220.8, 904.0)	161.0 (70.0, 254.0)	120.0 (48.0, 203.1)	74.0 (23.0, 142.0)
90% Reduction	899.0 (404.0, 1529.2)	558.0 (255.0, 943.2)	165.0 (78.0, 274.0)	118.0 (47.0, 206.0)	61.0 (17.0, 132.0)
100% Reduction	895.5 (362.9, 1459.1)	558.0 (218.0, 909.1)	162.0 (68.0, 263.0)	115.0 (44.0, 200.0)	55.0 (15.0, 119.0)

- In base model, most transmissions were passenger to passenger
 - No/limited PPE was used within cabins
- Reducing the contact intensity could avert hundreds of infections

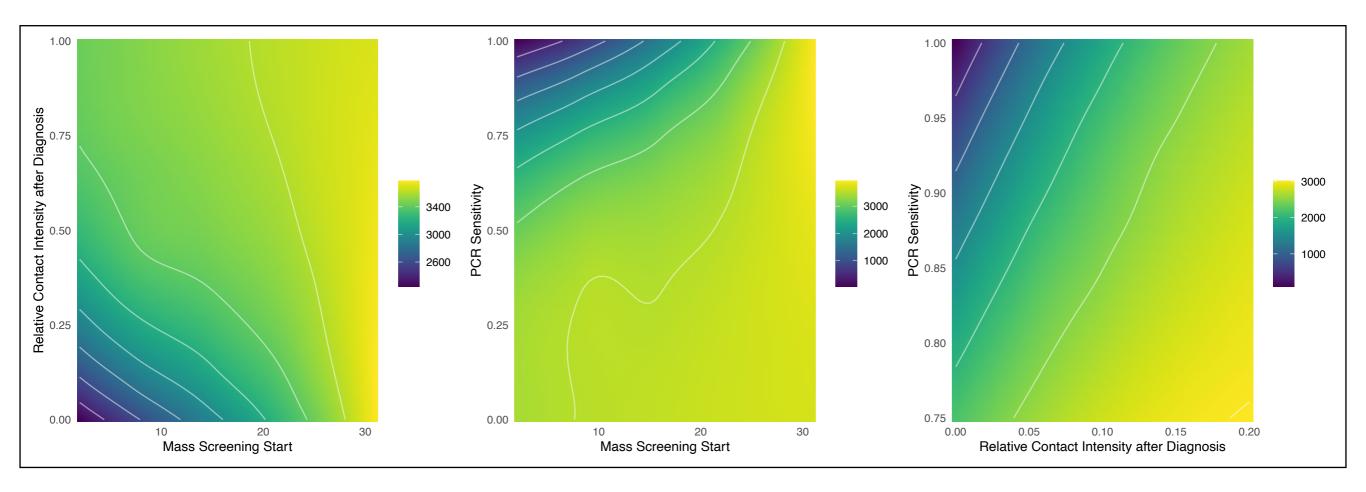
Model Results 4: Prevention with Mass Screening

Table 4. Impact of Timing of Mass Asymptomatic Screening and Diagnosis-Based Case Isolation, with No Network Lockdown and Stratified by PPE Use, on COVID Incidence and Mortality at 1 Month

Scenario	Cumulative Incidence			Cumulative Mortality		
	Total	NIA ¹	PIA ²	Total	NDA ³	PDA ⁴
	Median (95% SI)	Median (95% SI)	Median (95% SI)	Median (95% SI)	Median (95% SI)	Median (95% SI)
/arying Timing of Mas	ss Screening (Never PPE)					
Day 1	2286.0 (0.0, 3421.0)	1403.5 (1396.0, 1409.0)	38.0 (37.9, 38.1)	7.0 (0.0, 24.0)	29.0 (28.0, 29.0)	81.2 (80.6, 81.8)
Day 5	2621.5 (16.0, 3353.1)	1070.5 (1067.0, 1074.0)	29.0 (28.9, 29.1)	9.0 (0.0, 23.0)	27.0 (27.0, 27.0)	75.6 (75.0, 76.0)
Day 10	2917.0 (1787.8, 3310.1)	775.0 (772.5, 777.5)	21.0 (20.9, 21.1)	13.0 (4.0, 25.0)	23.0 (22.0, 23.0)	63.6 (62.9, 64.1)
Day 15	2944.5 (2256.8, 3176.1)	746.0 (744.0, 748.0)	20.2 (20.2, 20.3)	18.0 (8.0, 32.0)	18.0 (17.0, 18.0)	50.0 (48.6, 50.0)
Day 20	3102.5 (2588.8, 3360.1)	590.0 (588.0, 591.5)	16.0 (15.9, 16.0)	30.0 (16.0, 45.0)	6.0 (6.0, 7.0)	17.1 (16.1, 18.4)
Day 25	3607.0 (3360.9, 3668.0)	85.0 (84.0, 86.0)	2.3 (2.3, 2.3)	36.0 (24.0, 50.0)	0.0 (-1.0, 0.0)	0.0 (-2.5, 0.0)
Never (Reference)	3692.0 (3679.0, 3699.0)	0.0 (0.0, 0.0)	0.0 (0.0, 0.0)	36.0 (25.0, 49.0)	0.0 (0.0, 0.0)	0.0 (0.0, 0.0)
arying Timing of Mas	ss Screening (Always PPE)				
Day 1	1629.5 (0.0, 3013.0)	2012.0 (1998.0, 2023.0)	55.3 (55.0, 55.4)	5.0 (0.0, 20.0)	27.0 (27.0, 28.0)	85.2 (84.5, 85.7)
Day 5	1856.5 (12.0, 2837.4)	1776.0 (1766.0, 1784.5)	48.8 (48.6, 49.0)	6.0 (0.0, 19.0)	26.0 (26.0, 27.0)	81.0 (80.5, 81.5)
Day 10	2240.5 (1058.0, 2815.1)	1395.0 (1387.0, 1402.0)	38.3 (38.2, 38.5)	10.0 (2.0, 20.0)	23.0 (23.0, 23.0)	70.6 (70.0, 71.1)
Day 15	2372.0 (1585.6, 2755.0)	1267.5 (1262.0, 1273.0)	34.8 (34.7, 34.9)	15.0 (5.0, 27.0)	18.0 (17.0, 18.0)	54.3 (53.5, 55.0)
Day 20	2656.0 (1980.9, 3033.0)	983.5 (977.5, 988.5)	27.0 (26.9, 27.2)	26.0 (12.0, 40.0)	7.0 (7.0, 8.0)	22.2 (20.9, 23.3)
Day 25	3354.0 (2831.8, 3537.1)	285.5 (282.0, 290.0)	7.8 (7.8, 7.9)	33.0 (20.0, 47.0)	0.0 (0.0, 1.0)	0.0 (0.0, 2.5)
Never (Reference)	3643.0 (3563.0, 3669.0)	0.0 (-1.0, 1.0)	0.0 (-0.0, 0.0)	33.0 (20.0, 45.0)	0.0 (0.0, 0.0)	0.0 (0.0, 0.0)

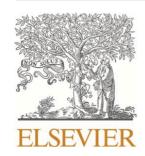
- In absence of behavioral change, screening and diagnosis-based case isolation could avert a substantial number of infections but not 100%
 - Here, PPE has an impact!
 - Why does Day 1 screening not prevent an outbreak?

Model Results 5: Sensitivity Analysis for Screening Interventions



- Base model assumed 100% reduction in contacts after case isolation, 80% PCR test sensitivity, and a Day 1 screening strategy
- Only when PCR sensitivity reaches 100% is an outbreak averted in the absence of behavioral change

Modeling SARS-CoV-2 in Carceral Settings



Contents lists available at ScienceDirect

Epidemics

journal homepage: www.elsevier.com/locate/epidemics





Dynamic contact networks of residents of an urban jail in the era of SARS-CoV-2

Samuel M. Jenness ^{a, *}, Karina Wallrafen-Sam ^a, Isaac Schneider ^a, Shanika Kennedy ^a, Matthew J. Akiyama ^b, Anne C. Spaulding ^a



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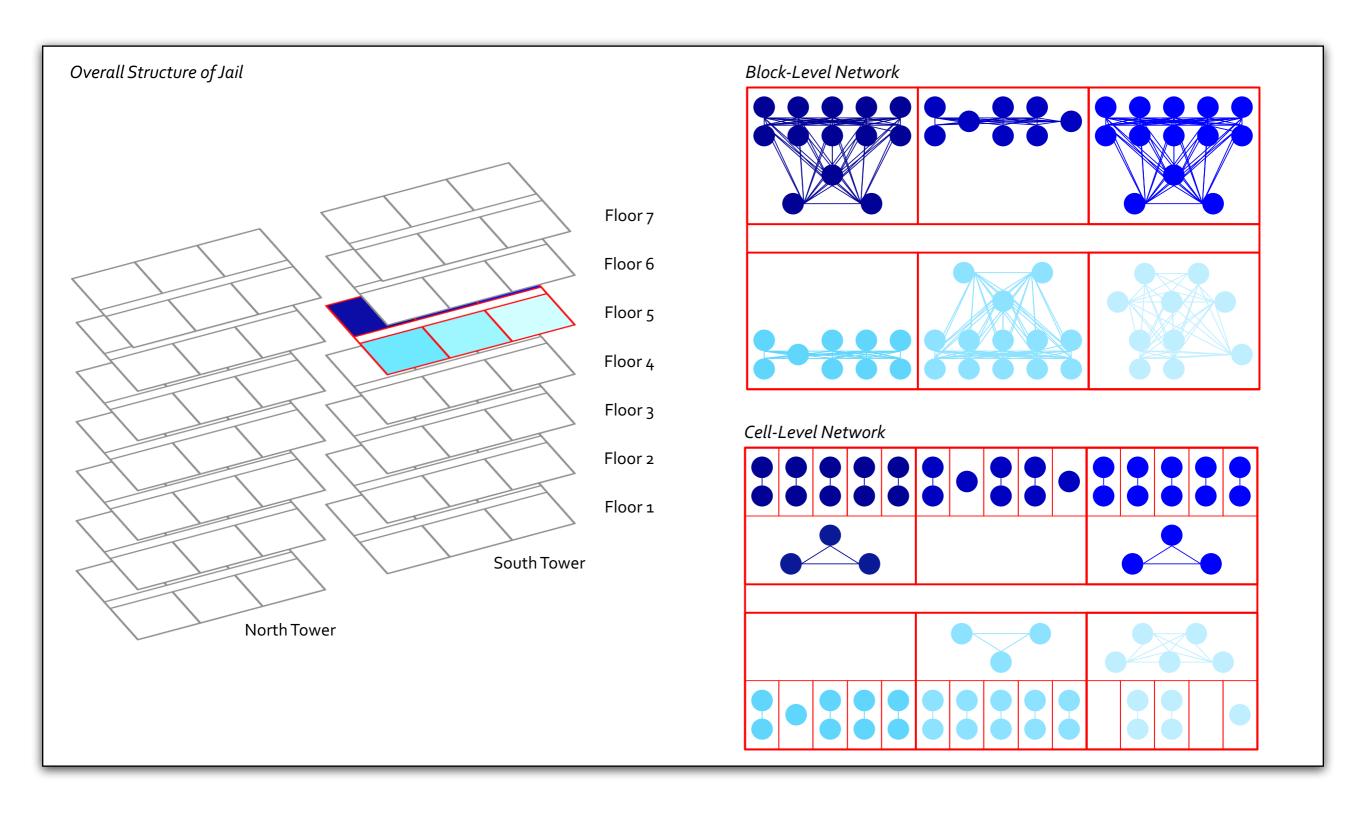
Interventions for SARS-CoV-2 prevention among Jailed adults: A network-based modeling analysis



Isaac Schneider ^{a, *}, Karina Wallrafen-Sam ^a, Shanika Kennedy ^a, Matthew J. Akiyama ^b, Anne C. Spaulding ^a, Samuel M. Jenness ^a

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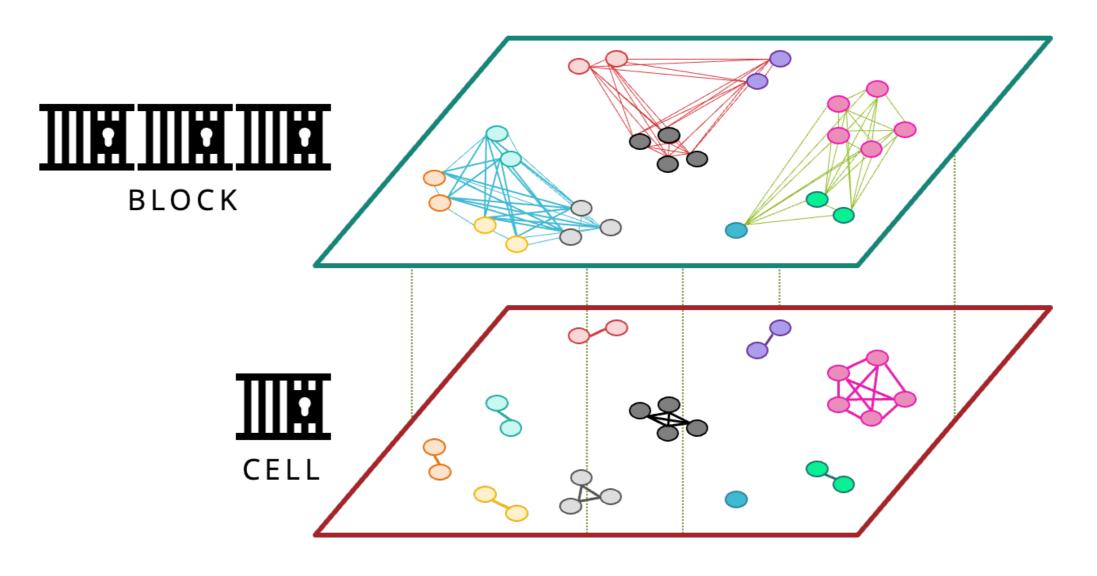
Modeling SARS-CoV-2 in Carceral Settings



Fulton County Jail Roster Data

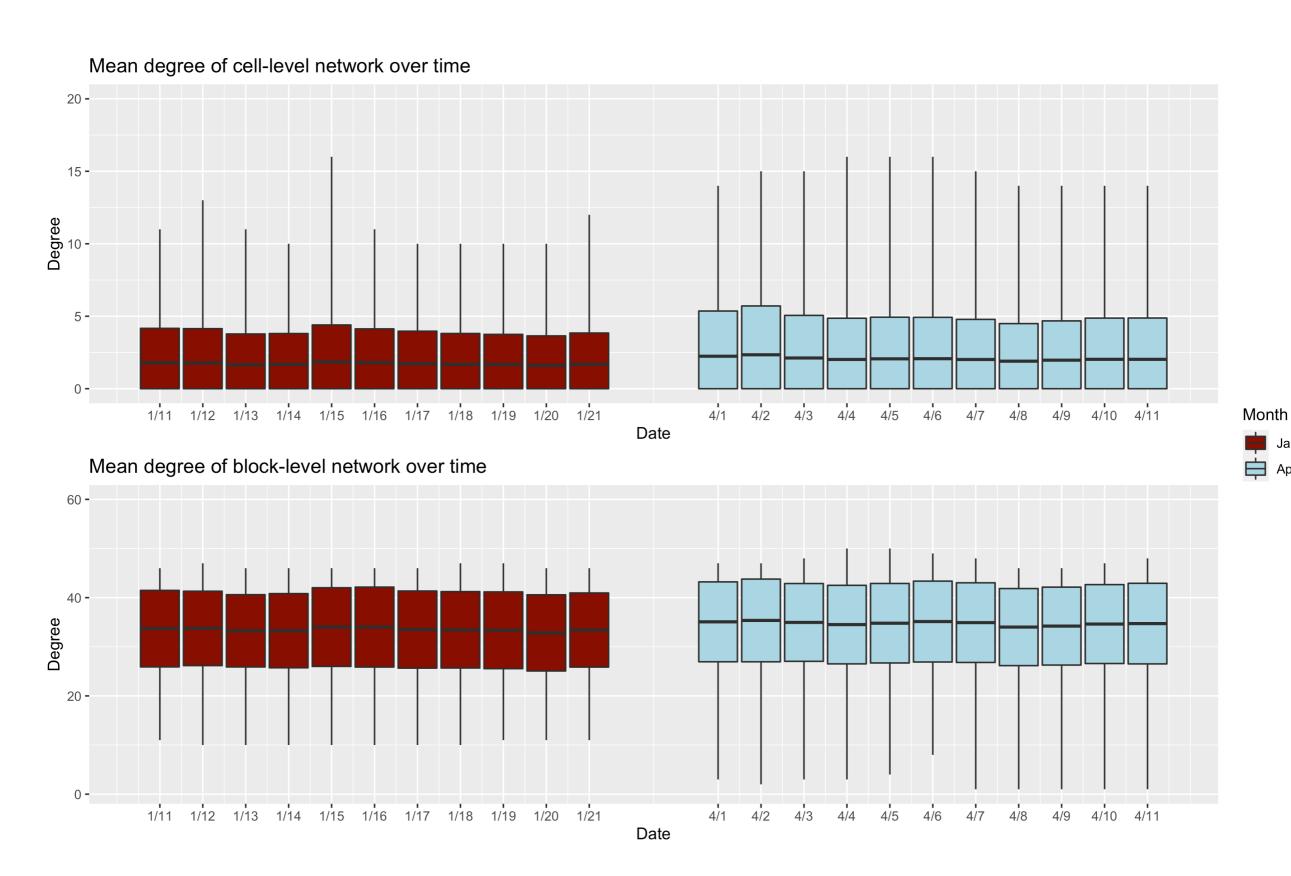
- Location of jail residents coded in the format: 1N103
 - ► 1 = floor (1 7)
 - N = tower (N and S)
 - ► 1XX = block
 - X00 = cell within block
- Focusing on FCJ main building only
 - Excluding annex buildings
 - Excluding women in FCJ due to small size in building
- Some challenges in coding for non-standard locations
 - Intake, holding, transportation, medical areas

Network of Contacts within Carceral Setting

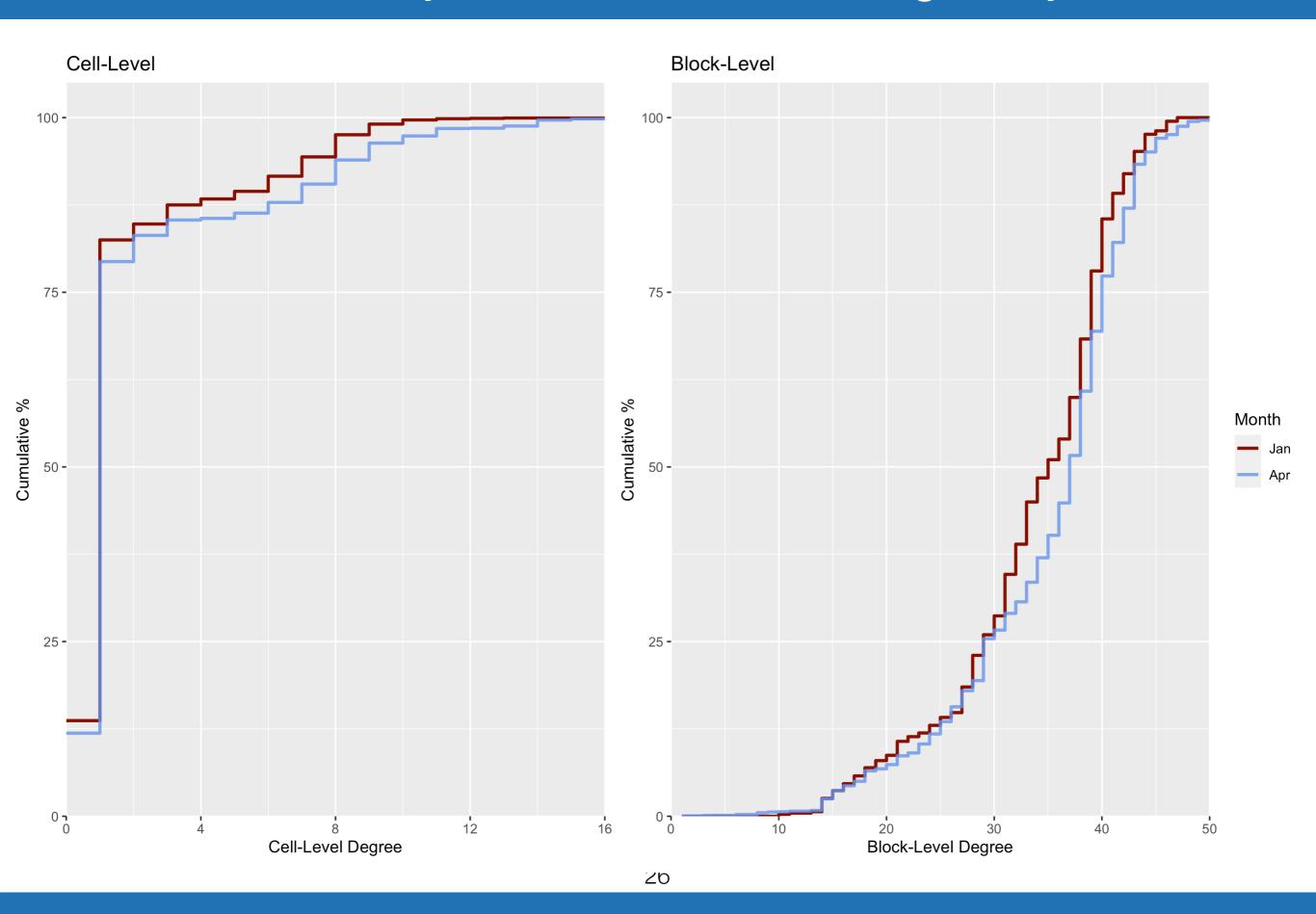


- Contact networks in cells were assumed to be saturated with strong exposures per time step
- Contact networks in blocks were assumed to be random with weaker exposures per time step

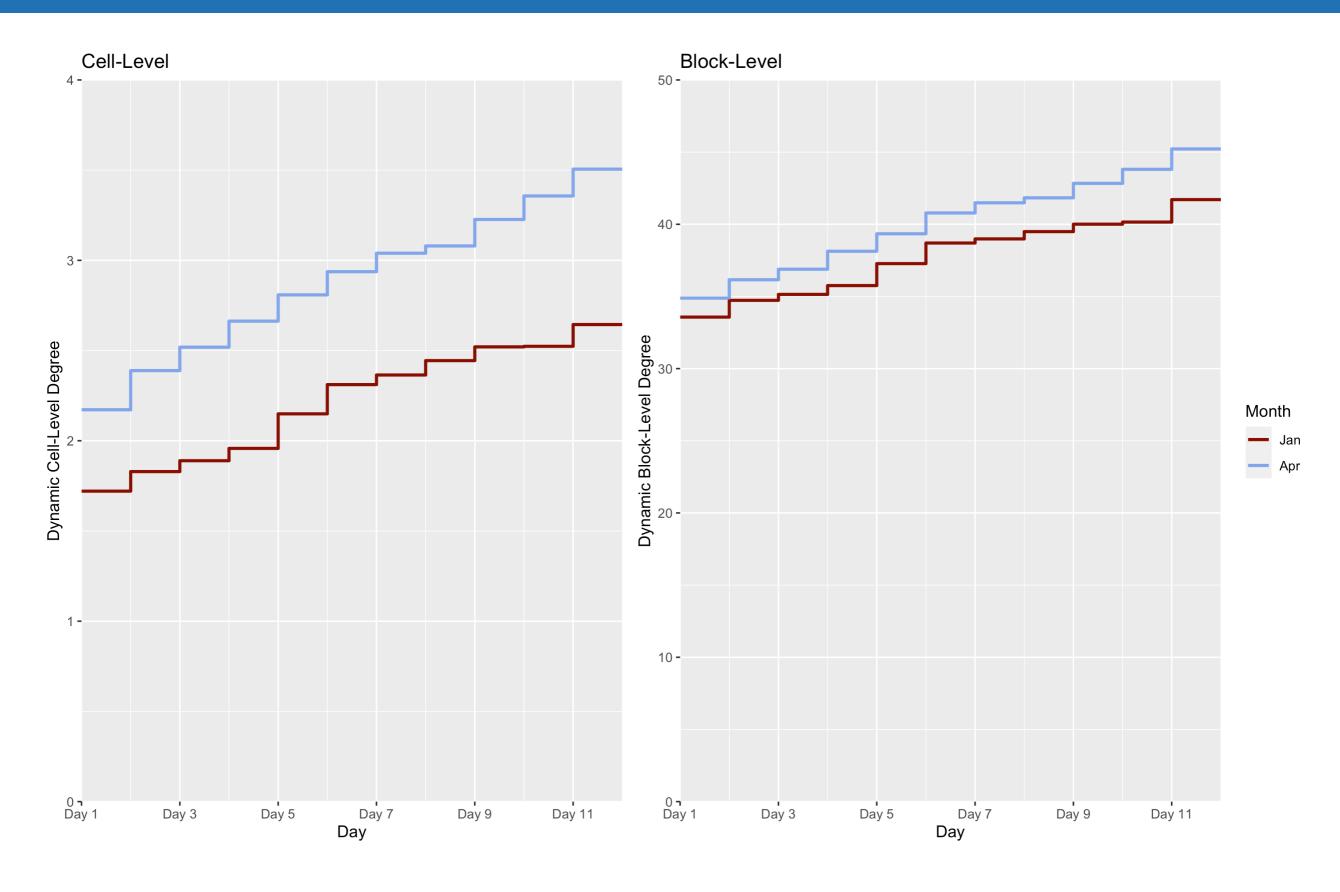
Mean Degree During Omicron Wave and Post-Wave



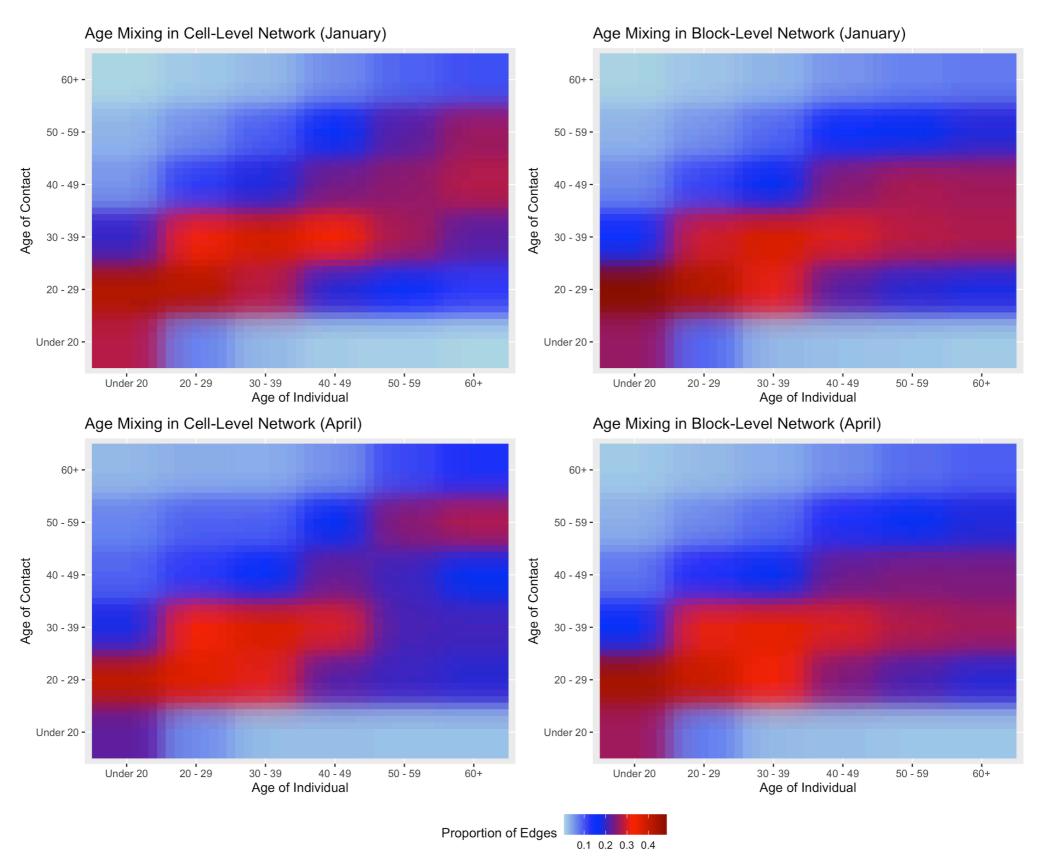
Cumulative Density Function for Mean Degree by Period



Forward Reachable Paths Over Time Periods



Age Mixing in Different Network Layers by Period



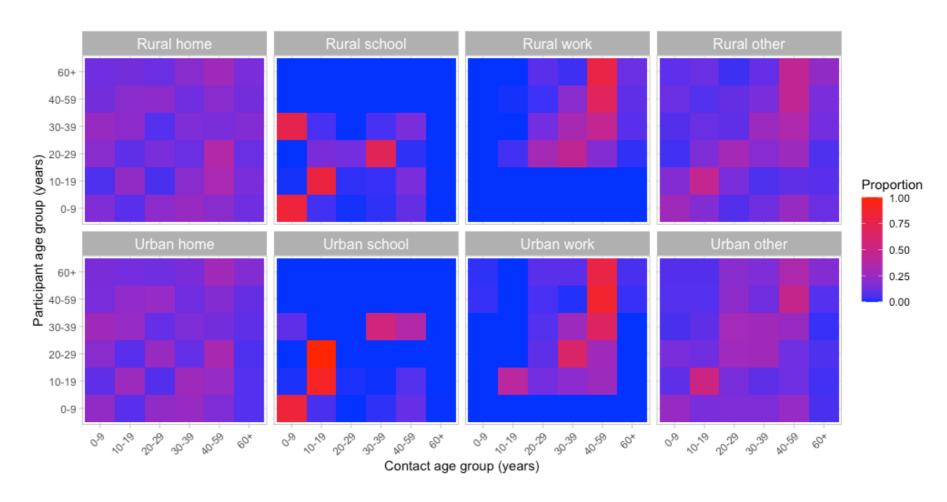
Global Mix Study

Comprehensive profiling of social mixing patterns in resource poor countries: A mixed methods research protocol

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Obianuju Genevieve Aguolu<sup>1</sup>*, Moses Chapa Kiti<sup>2</sup>, Kristin Nelson<sup>2</sup>, Carol Y. Liu<sup>2</sup>, Maria Sundaram<sup>3</sup>, Sergio Gramacho<sup>2</sup>, Samuel Jenness<sup>2</sup>, Alessia Melegaro<sup>4</sup>, Charfudin Sacoor<sup>5</sup>, Azucena Bardaji<sup>5,6,7</sup>, Ivalda Macicame<sup>8</sup>, Americo Jose<sup>8</sup>, Nilzio Cavele<sup>8</sup>, Felizarda Amosse<sup>5</sup>, Migdalia Uamba<sup>8</sup>, Edgar Jamisse<sup>5</sup>, Corssino Tchavana<sup>5</sup>, Herberth Giovanni Maldonado Briones<sup>9</sup>, Claudia Jarquín<sup>9</sup>, María Ajsivinac<sup>9</sup>, Lauren Pischel<sup>10</sup>, Noureen Ahmed<sup>11</sup>, Venkata Raghava Mohan<sup>12</sup>, Rajan Srinivasan<sup>12</sup>, Prasanna Samuel<sup>12</sup>, Gifta John<sup>12</sup>, Kye Ellington<sup>2</sup>, Orvalho Augusto Joaquim<sup>5</sup>, Alana Zelaya<sup>2</sup>, Sara Kim<sup>2</sup>, Holin Chen<sup>2</sup>, Momin Kazi<sup>13</sup>, Fauzia Malik<sup>11</sup>, Inci Yildirim<sup>10</sup>, Benjamin Lopman<sup>2‡</sup>, Saad B. Omer<sup>11‡</sup>
```

- Social contact diary study of contacts rural and urban study sites in India,
 Pakistan, Mozambique, and Guatemala
- Fills key gap in social contact data for ID modelingin low-and-middle income countries

Global Mix Survey Design



- Two-day social contact diary
- All contacts enumerated and categorized with respect to ego and alter
- Estimated duration of relation
- Location of relation
- Four key locations emerged in data analysis for distinct types of contacts: home, school, work, and all other (community) locations

Cross-Layer Design

- Separate layers for home, school, work, and community contacts
- Home network represented as separated and saturated network subcomponents (no ergm needed)
- Other layers represented with degree distribution and age mixing terms in formation model and distinct mean durations for dissolution model
 - Strong cross-layer effect for school and work layers