Applications of systems science: Context, causality, and communities

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Roundtable on Obesity Solutions
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Brown School
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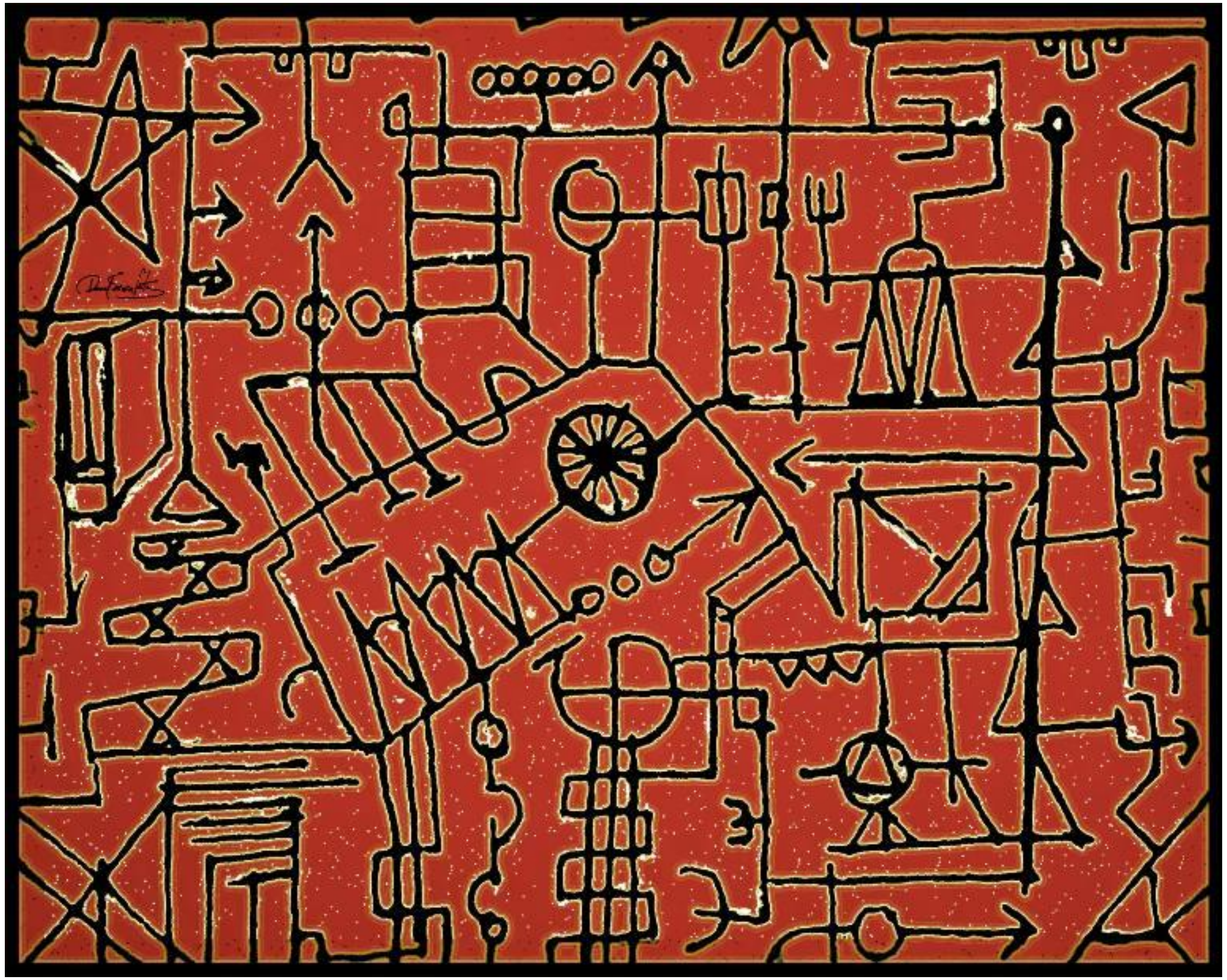
Goals

- Introduce examples of systems science research that illustrate 3 points
  - Ability to explore the role of *context* in chronic disease prevention and implementation
  - Ability to explore underlying *causal mechanisms*
  - Demonstrate utility of systems science dissemination tools and products for *community* stakeholders



Complex Systems – Daniel Ferreira-Leites Ciccarino

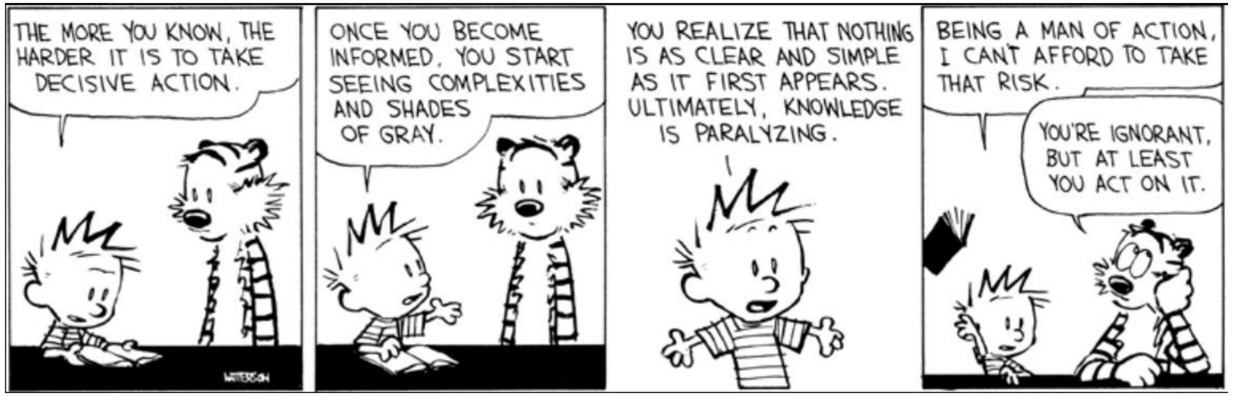
Rationale

Why are systems science approaches important for chronic disease prevention and policy implementation?

‘Wicked problems’ and systems science

- Complex problems that resist resolution
- Examples
  - Poverty
  - Gun-violence
  - Climate change
  - Obesity
  - Tobacco control
  - Healthcare access
  - Implementing evidence-based practices in health settings

- Characteristics of wicked problems
  - Many sectors/actors
  - Problem embedded across multiple biological, social, organizational levels
  - Incomplete knowledge
  - High economic/political stakes
  - Interconnectivity with other problems
  - Solution unclear or undefined



Tobacco control as a complex system

- Complex systems are:
  - Made up of heterogeneous members
  - Which interact with each other
- System behavior:
  - Emerges over time
  - Is not described wholly by the behaviors of the individual elements of the system

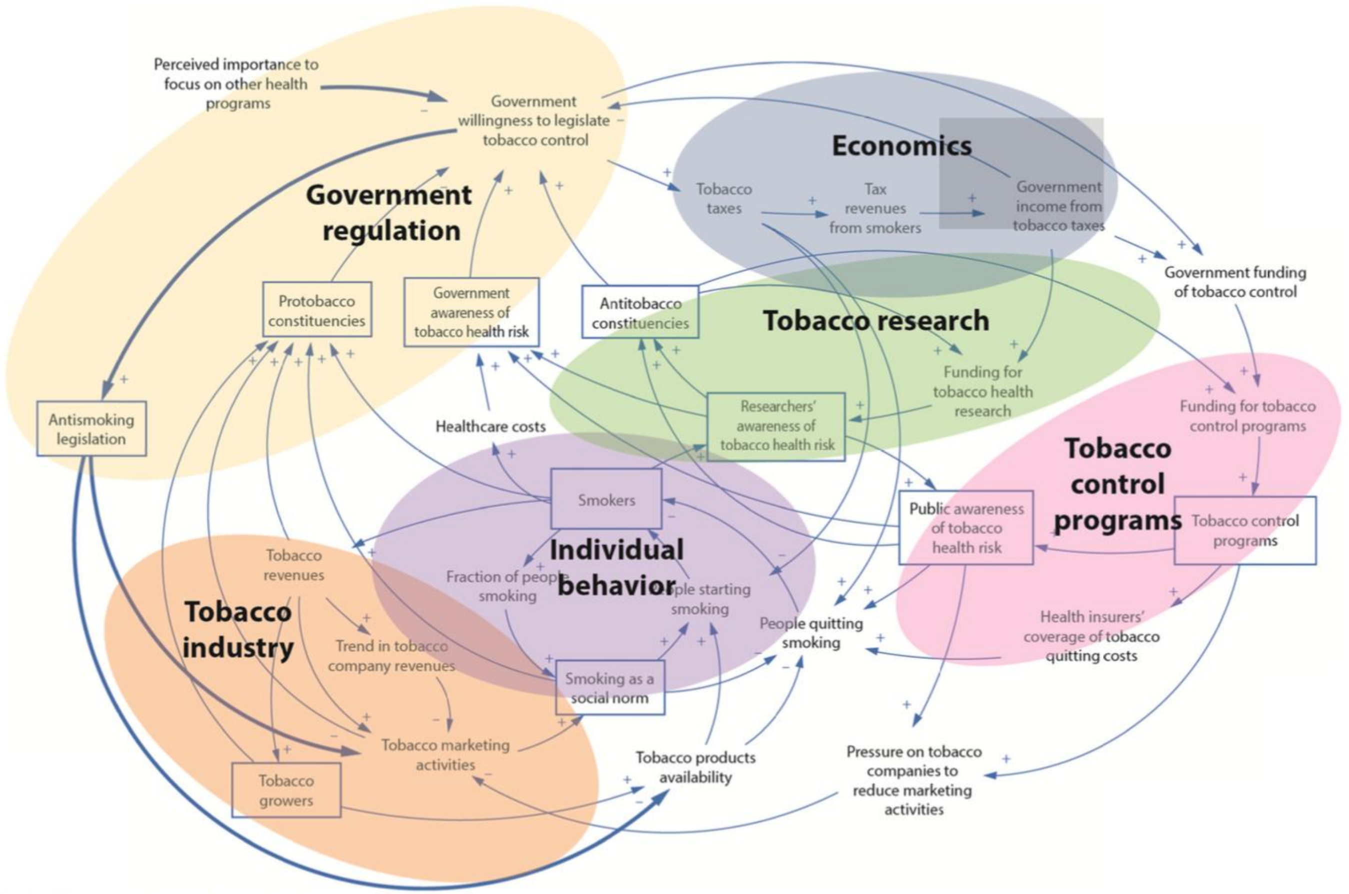


FIGURE 2-2 Complex tobacco landscape.
NOTE: This figure is not drawn to scale, nor is any meaning implied by the relative sizes of elements within the figure. See Kirkwood (1998) for more information about causal loop diagram construction.
SOURCE: NCI, 2007 adapted by Luke, 2013.

Systems science methods can handle wider variety of study design challenges and assumptions

Table 1 Comparison of traditional and complex system analytic assumptions

Domain	Traditional analytic techniques assumptions	Complex systems assumptions
Functional form	Linearity	Nonlinearity
Common distributions	Normality	Nonnormality
Characteristics of actors	Homogeneity	Heterogeneity
Level of analysis	Single level	Multiple levels
Temporality	Static or discretely longitudinal	Dynamic, with feedback
Fundamental relationships	Among variables	Interaction of actors
Perspective	Reductionist	Holistic

From Luke & Stamatakis, 2012, *ARPH*

Capturing context

Chronic disease processes and interventions shaped by numerous contextual factors that are often ignored by traditional methods

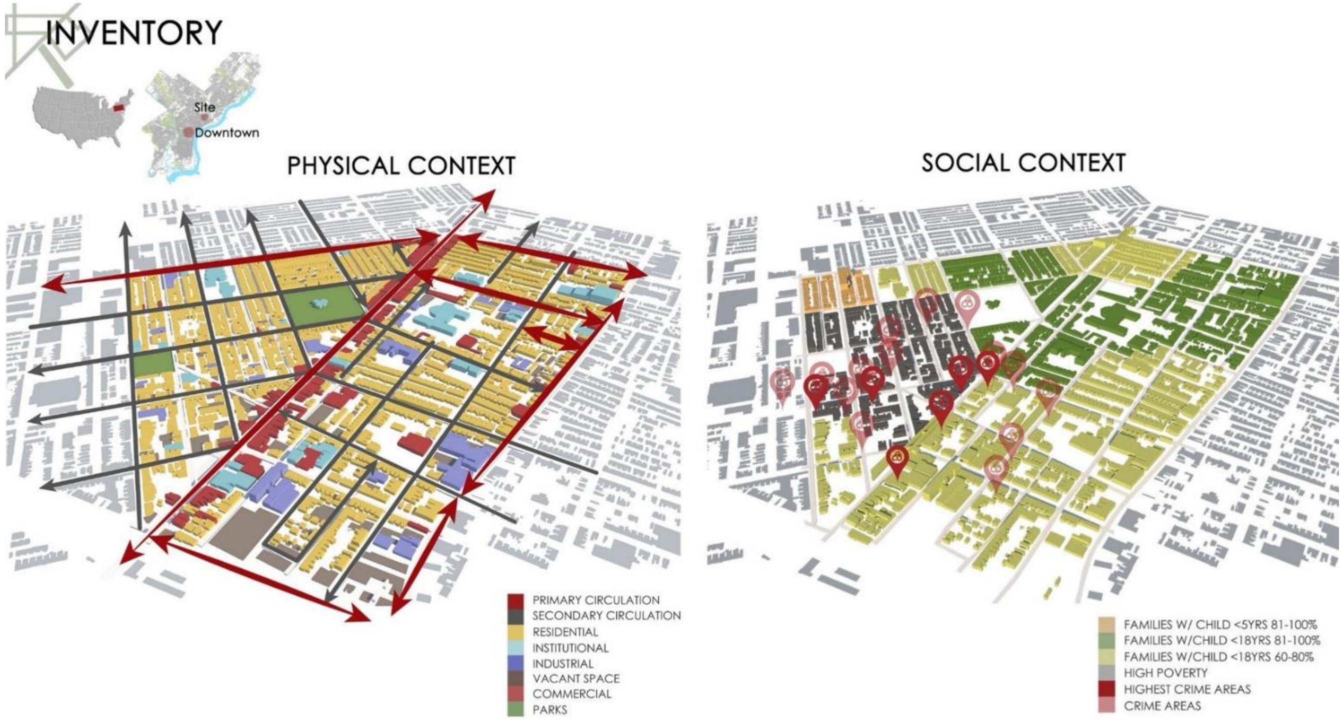
D&I science characteristics & implications for study design

Point #	Characteristic	Implication
Systems Perspective		
1	Context is critical	Research should focus on and describe context
2	Multilevel complexity	Most problems, and interventions are multilevel and complex
3	Focus on systems characteristics	More emphasis needed on interrelationships among system elements and systems rules
Robust, Practical Goals		
4	Representatives and reach	Focus on reaching broader segments of population and those most in need
5	Generalizability	Study generalization (or lack of such) across settings, subgroups, staff, and conditions
6	Pragmatic and practical	Producing answers to specific questions relevant to stakeholders
7	Scalability and sustainability	From outset, greater focus on scale-up potential and likelihood of sustainability
Research Methods to Enhance Relevance		
8	Rigorous	Identify and address plausible threats to validity in context of question. Greater focus on replication
9	Rapid	Approaches that produce faster answers
10	Adaptive	Best solutions usually evolve over time, as a result of informed hypotheses and mini-tests with feedback
11	Integration of methods; triangulation	For greater understanding, integrated Quantitative and Qualitative methods are often required
12	Relevance	Relevance to stakeholders should be top priority
Flexibility		
13	Multiplicity	Encourage and support diverse approaches with the above characteristics (all models are wrong)
14	Respect for diverse approaches; humility	Different perspectives, goals, methods and approaches are needed. Continuing the same existing approaches will produce the same unsatisfactory results

Glasgow, R. E. & Chambers, D. *Clin Transl Sci 2012:5,* 48-55

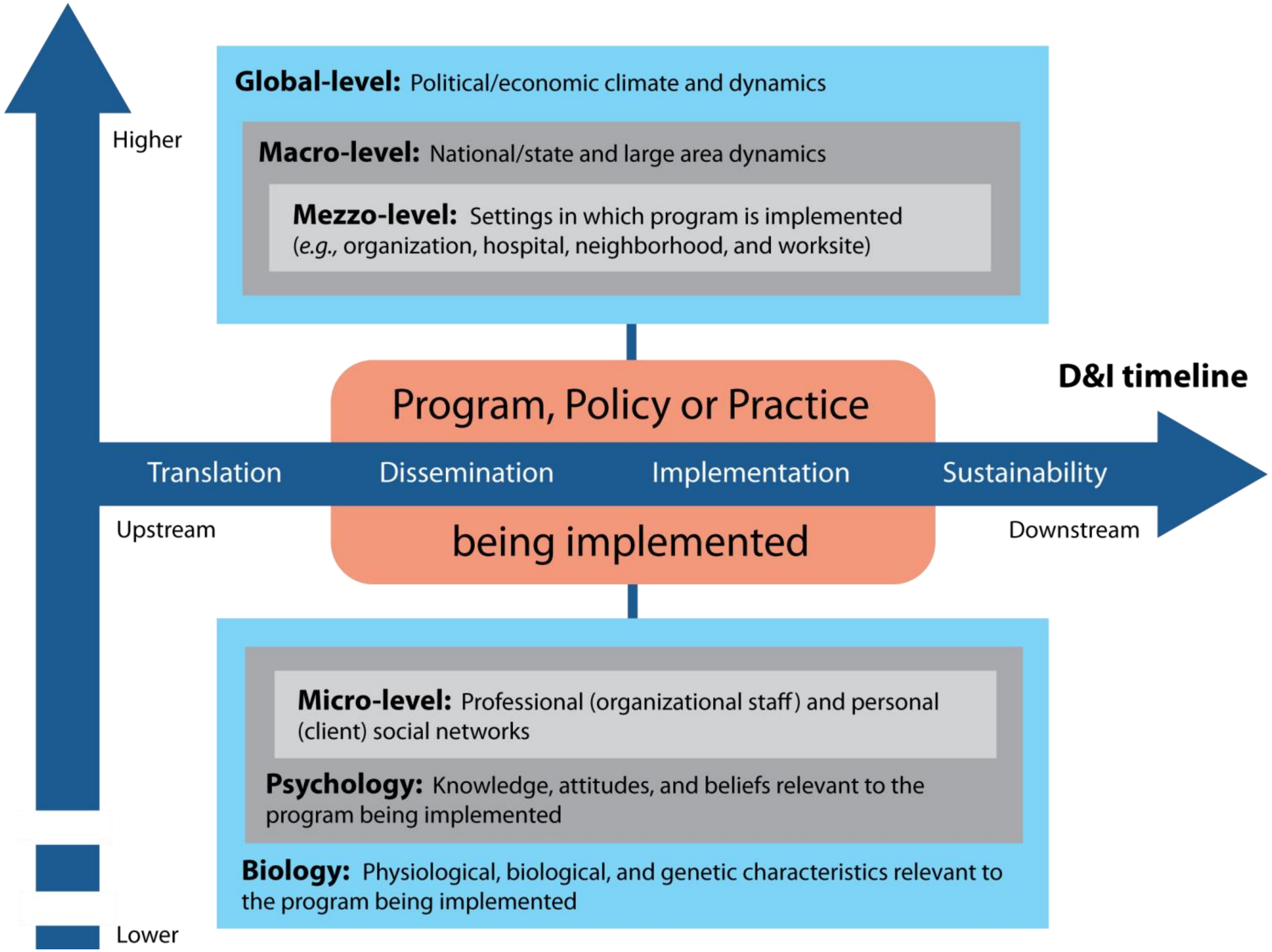
Important types of context

- Social – individual
- Social – organizational
- Economic
- Physical
- Temporal
- Political/historical



https://www.philadelphiacfa.org/2019-re-imagining-heart-kensington

A social-ecological framework for D&I research



Inspired by Glass & McAtee, 2006, *SSM*

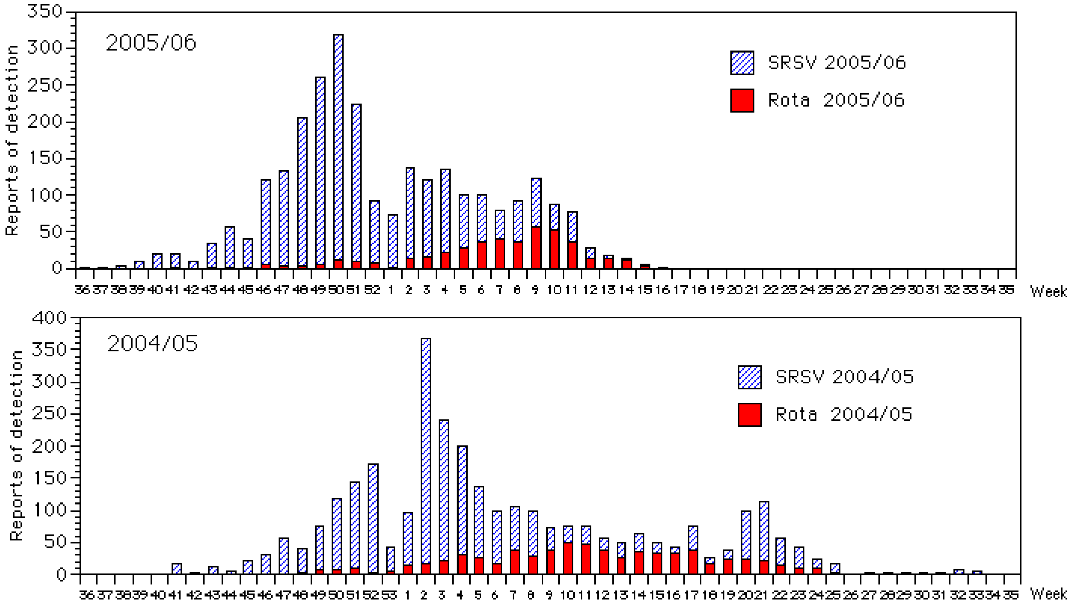
Traditional S-I-R models ignore social structure

Symbol	Name	Definition
S	Susceptible	not infected but can be infected
E	Exposed	Infected but cannot infect others (Latent)
I	Infectious	Infectious TB, can infect others (Active)
T	Treated	Treated either from latent or Active TB
V	Vaccination	vaccinated, no longer susceptible to TB

Symbol	Explanation
Λ	recruitment rate
β	transmission rate (meaning varies)
c	average number of contacts per person per unit time
k	per-capita regular progression rate
μ	per-capita natural mortality rate
d	per-capita excess death rate due to TB
r_0	per-capita treatment rate for recently latently-infected
r_1	per-capita treatment rate for latently-infected
r_2	per-capita treatment rate for actively-infected
ω	per-capita progress rate for early latent-TB progression

Weekly reports of SRSV(norovirus,sapovirus) & rotavirus detection, 2005/06

(Infectious Agents Surveillance Report: Data based on the reports received before April 21, 2006 from public health institutes)



(http://dimacs.rutgers.edu/Workshops/EpidTutorial)

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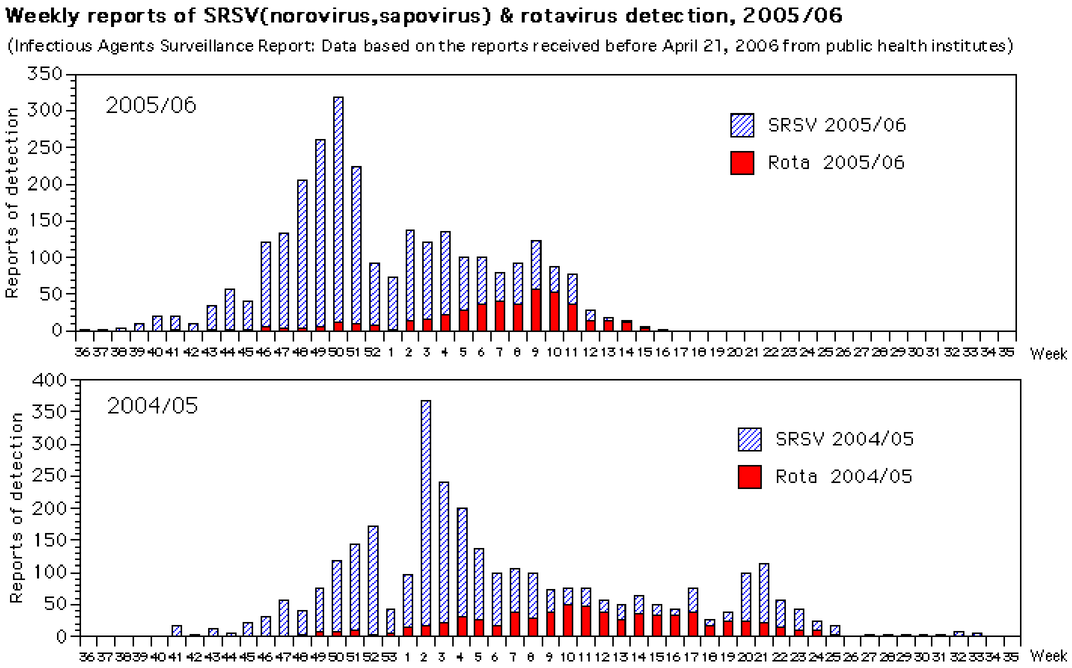
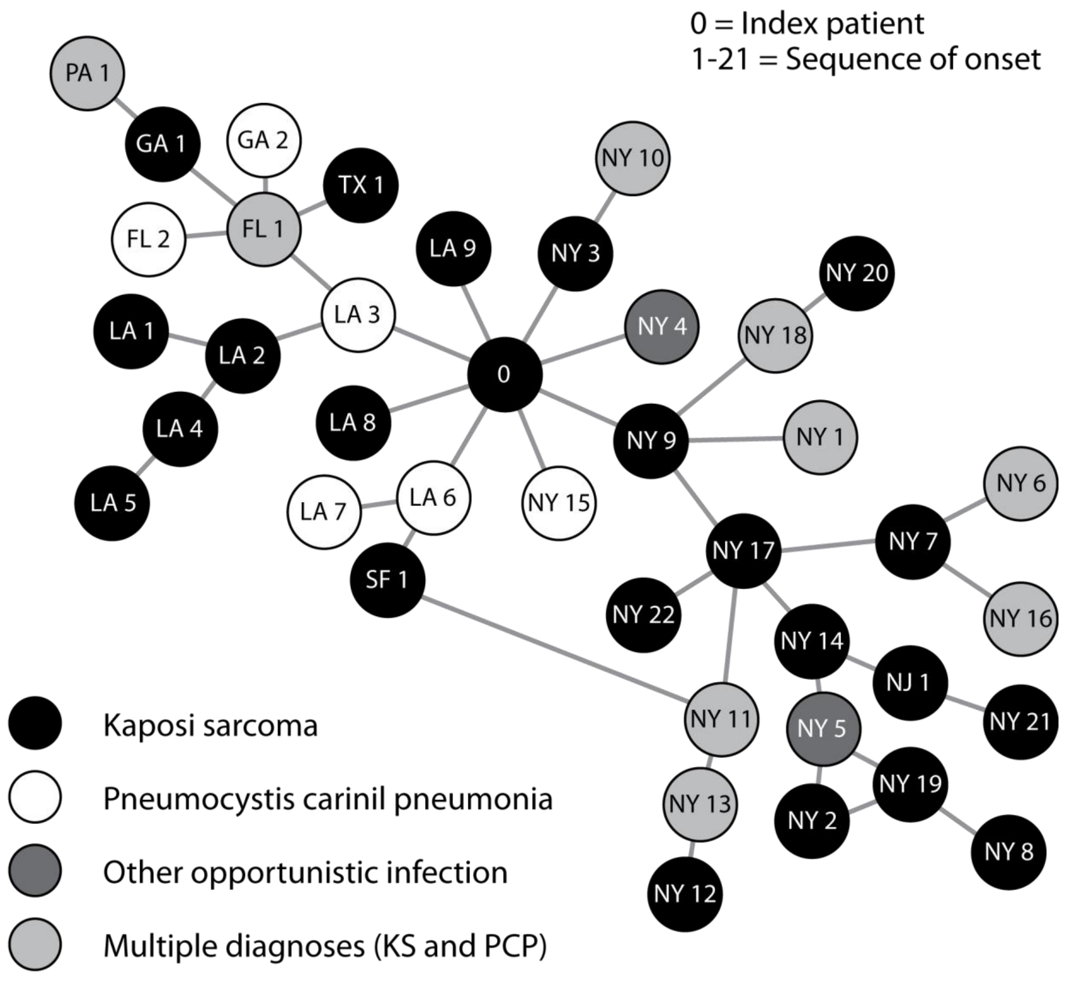


Assumes random mixing

(http://dimacs.rutgers.edu/Workshops/EpidTutorial)

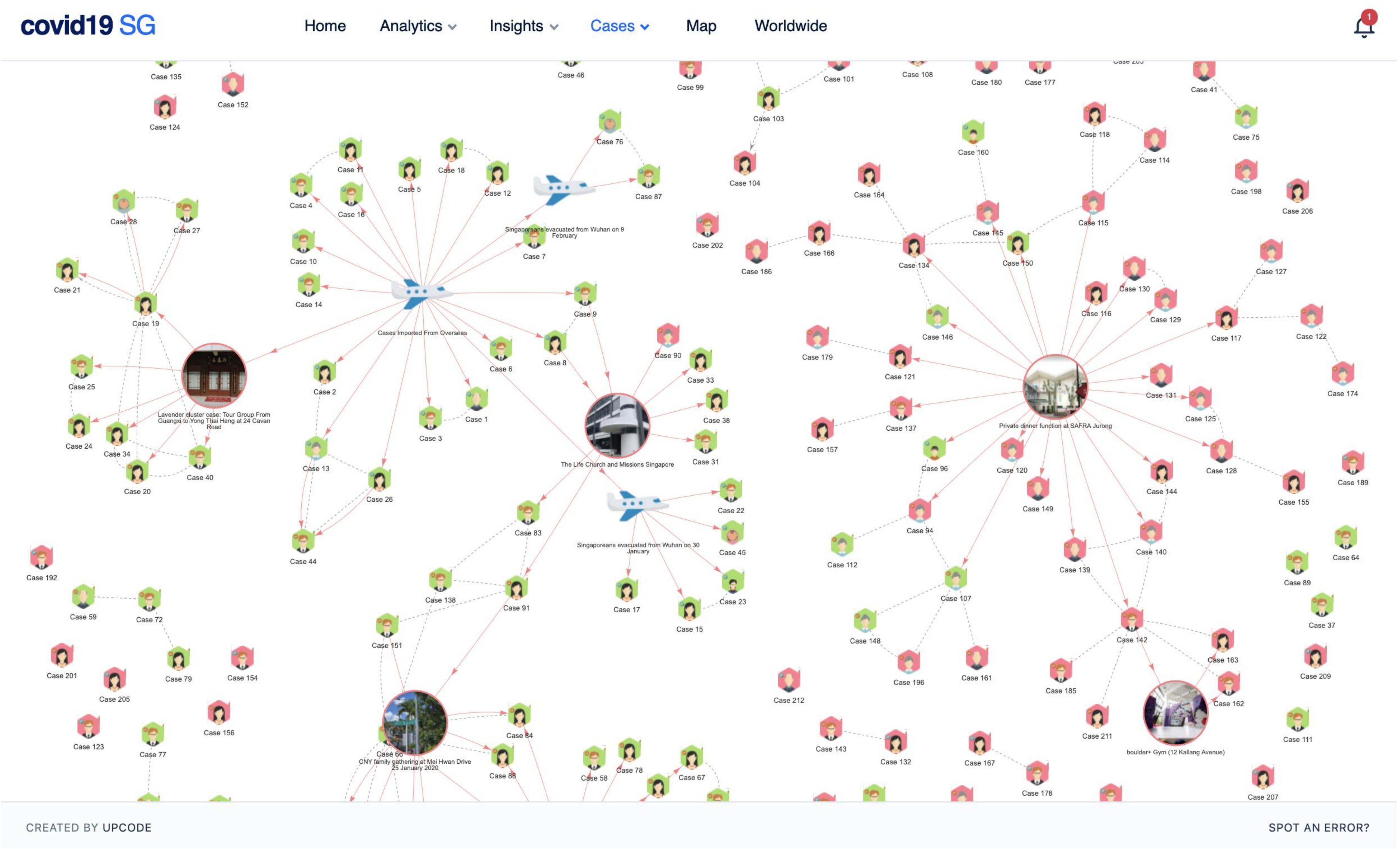
First HIV/AIDS network graphic



City LA-Los Angeles, NY-New York City, SF-San Francisco

State FL-Florida, GA-Georgia, NJ-New Jersey, PA-Pennsylvania, TX-Texas

(Auerbach et al, 1984; Luke & Stamatakis, 2012)

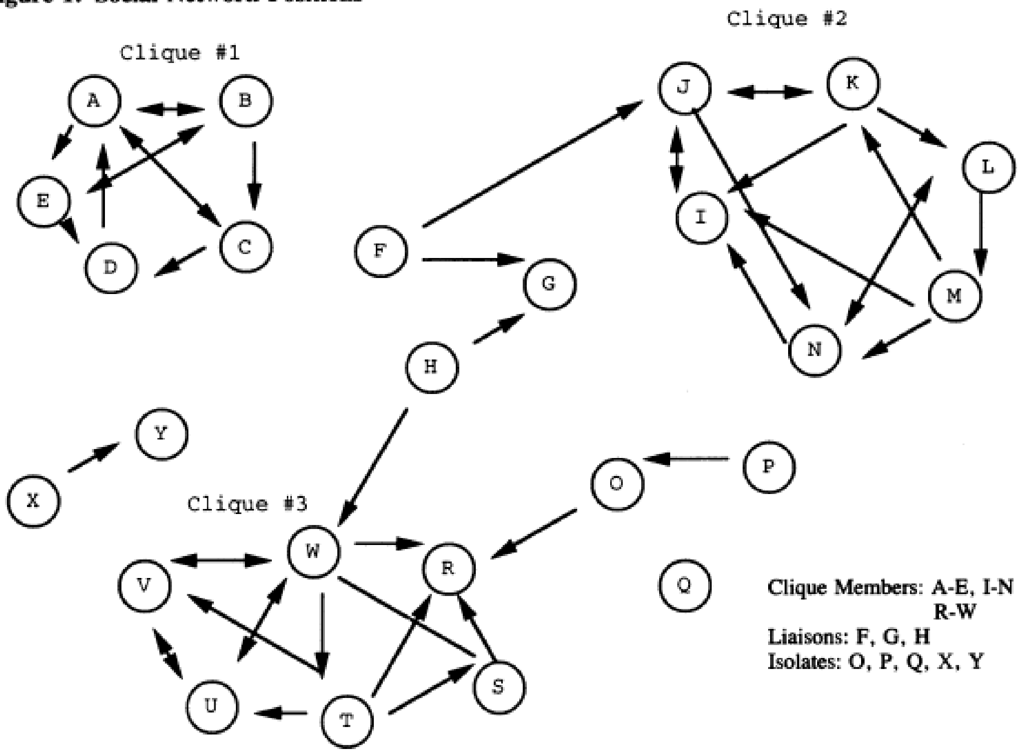


https://www.againstcovid19.com/singapore/cases

Network analysis in chronic disease

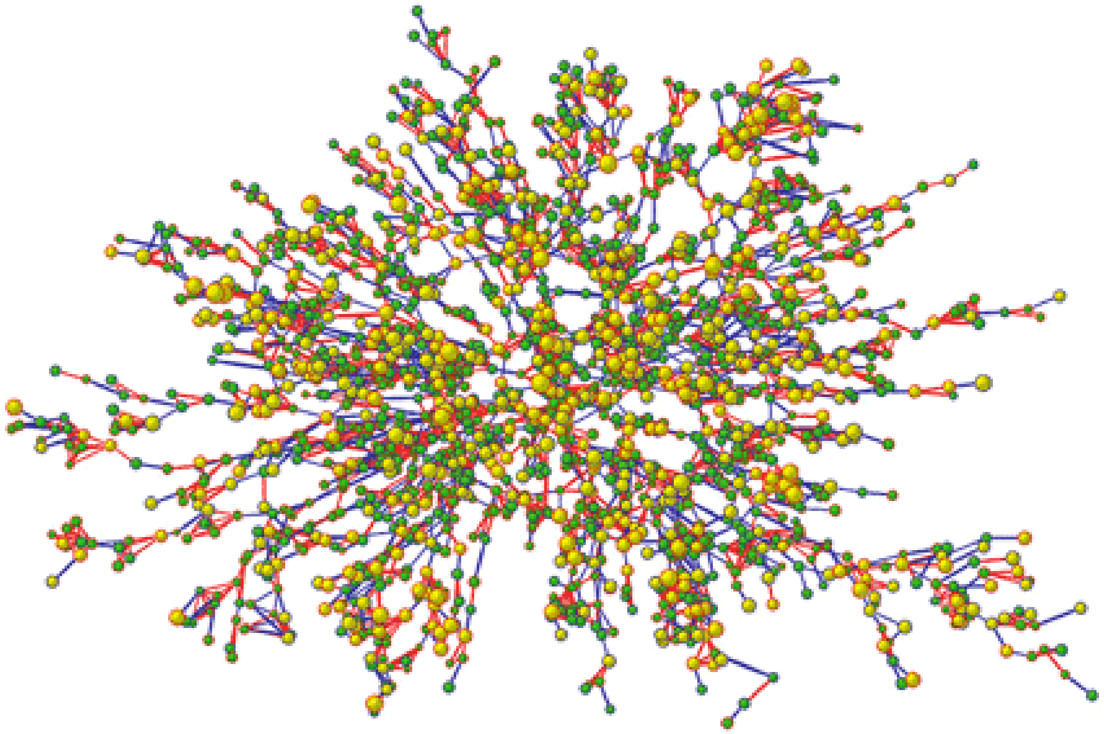
Peer group structure and smoking

Figure 1. Social Network Positions



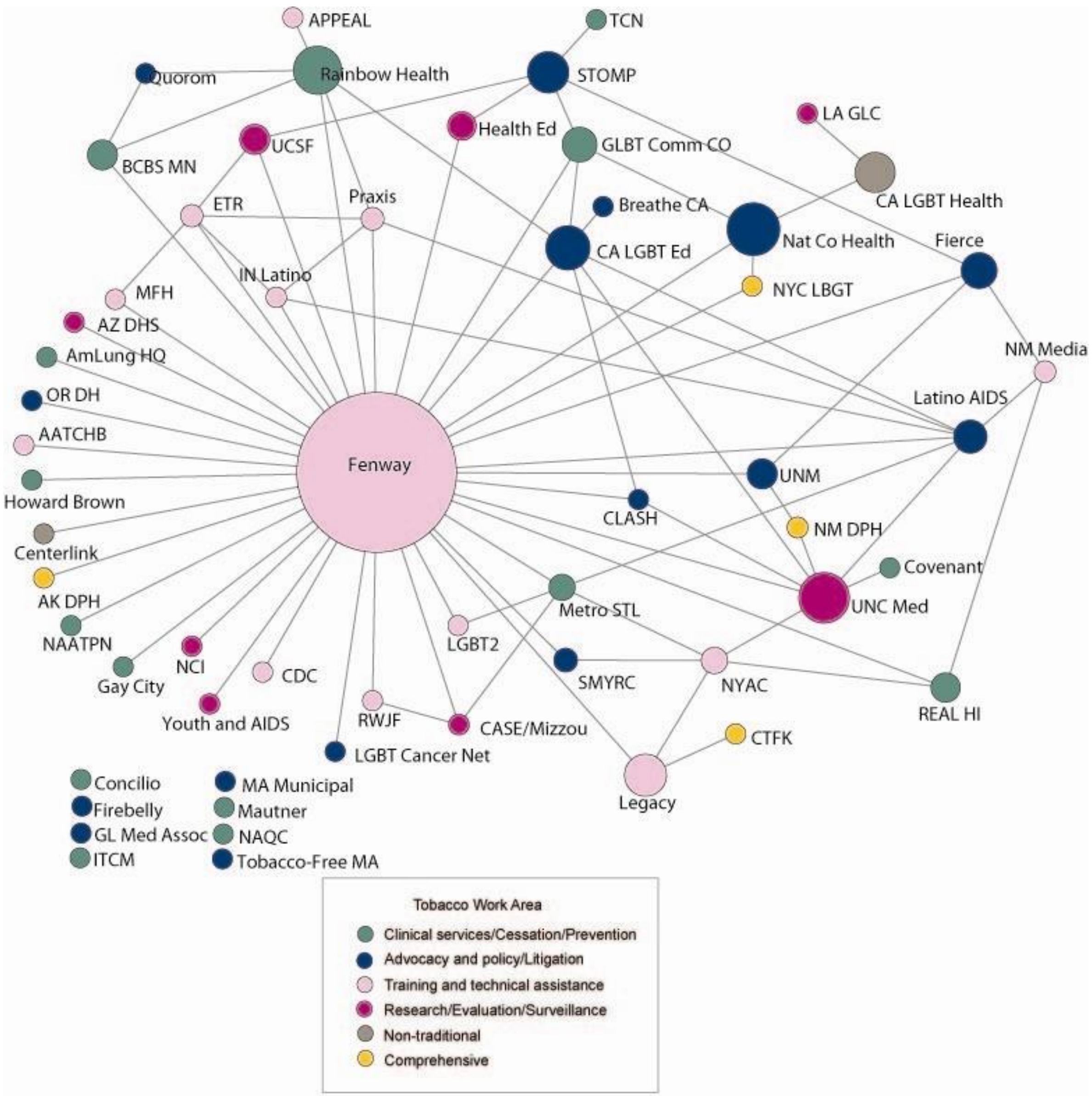
Ennett & Bauman, 1993, *JHSB*

Clustering of obesity in personal networks

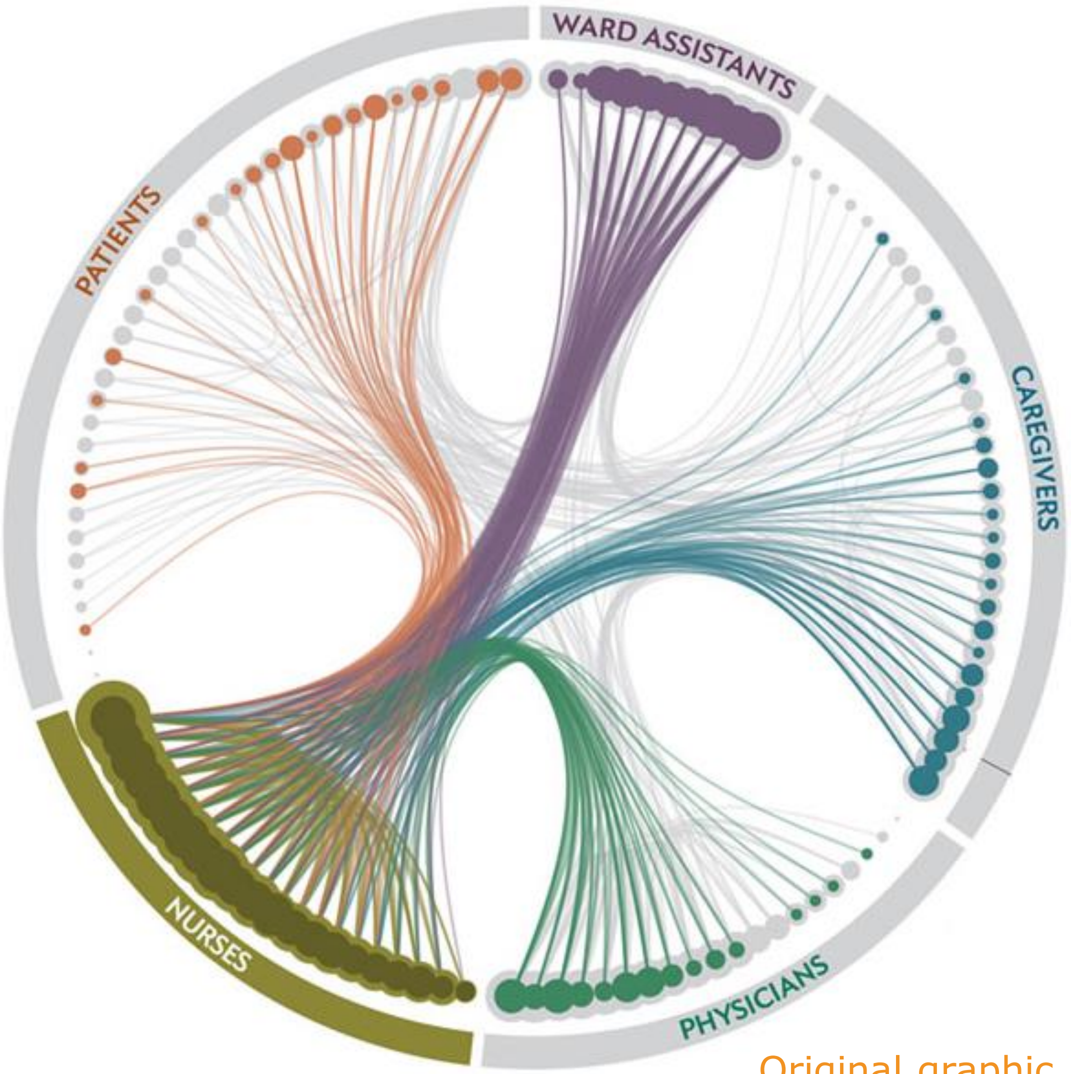


Christakis & Fowler, 2007, *NEJM*

Mapping of organizational systems



Who are the critical players in a pediatric hospital ward?



Original graphic by Jan Willem Tulp.
Based on Isella, 2011, *PLOS One*.

Exploring underlying causal mechanisms

Computational systems models are very useful tools for exploring *how* something works, not just *whether* it works

1 + 16 reasons to do complex systems modeling

- Prediction
- Other reasons
  - Explain
  - Guide data collection
  - Illuminate core dynamics
  - Suggest dynamical analogies
  - Discover new questions
  - Promote scientific habit of mind
  - Bound outcomes to plausible ranges
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  - Demonstrate tradeoffs
  - Challenge robustness of prevailing theory
  - Expose prevailing wisdom as incompatible with available data
  - Train practitioners
  - Discipline the policy dialogue
  - Educate the public
  - Reveal the simple to be complex, and vice versa

From Epstein, 2008; *Why Model?*
http://www.santafe.edu/media/workingpapers/08-09-040.pdf

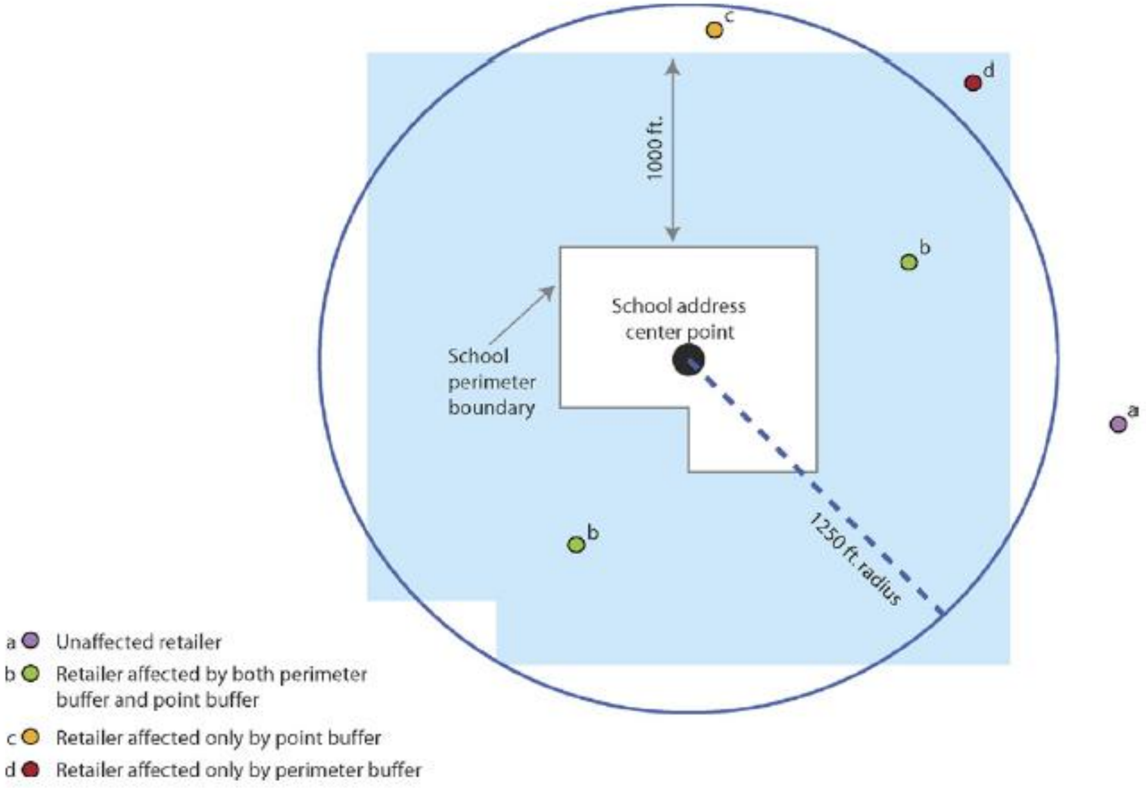
Tobacco Town

Using agent-based modeling as a policy laboratory in tobacco control

R21 CA172938 – NCI
U01 CA154281 - NCI
(With Ross Hammond, WU/Brookings Institution;
Kurt Ribisl, UNC; Lisa Henriksen, Stanford)

Rationale for studying implementation of density reduction policies

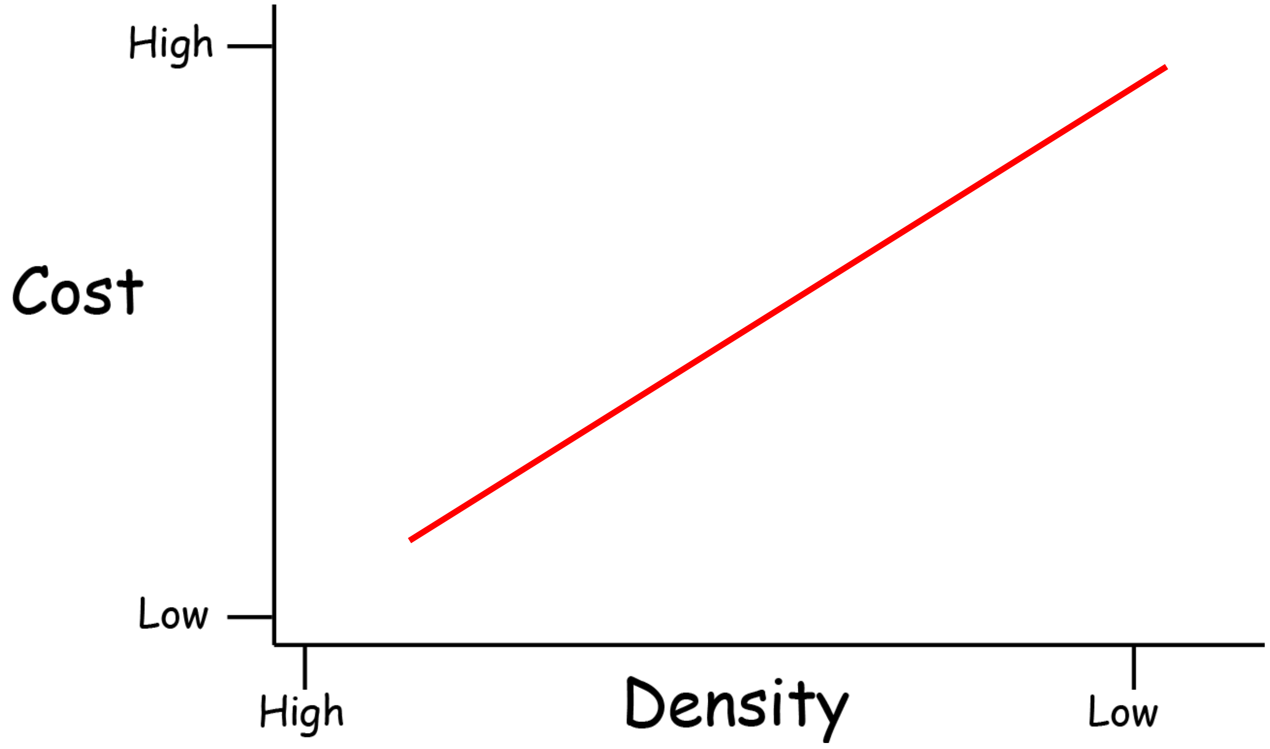
- Decrease availability
- Increase search cost of obtaining
- Decreases visibility of environmental cues to smoke
- Changes social norms, reduces “insidious ordinariness” of tobacco
- Reduces “Tobacco Swamps”



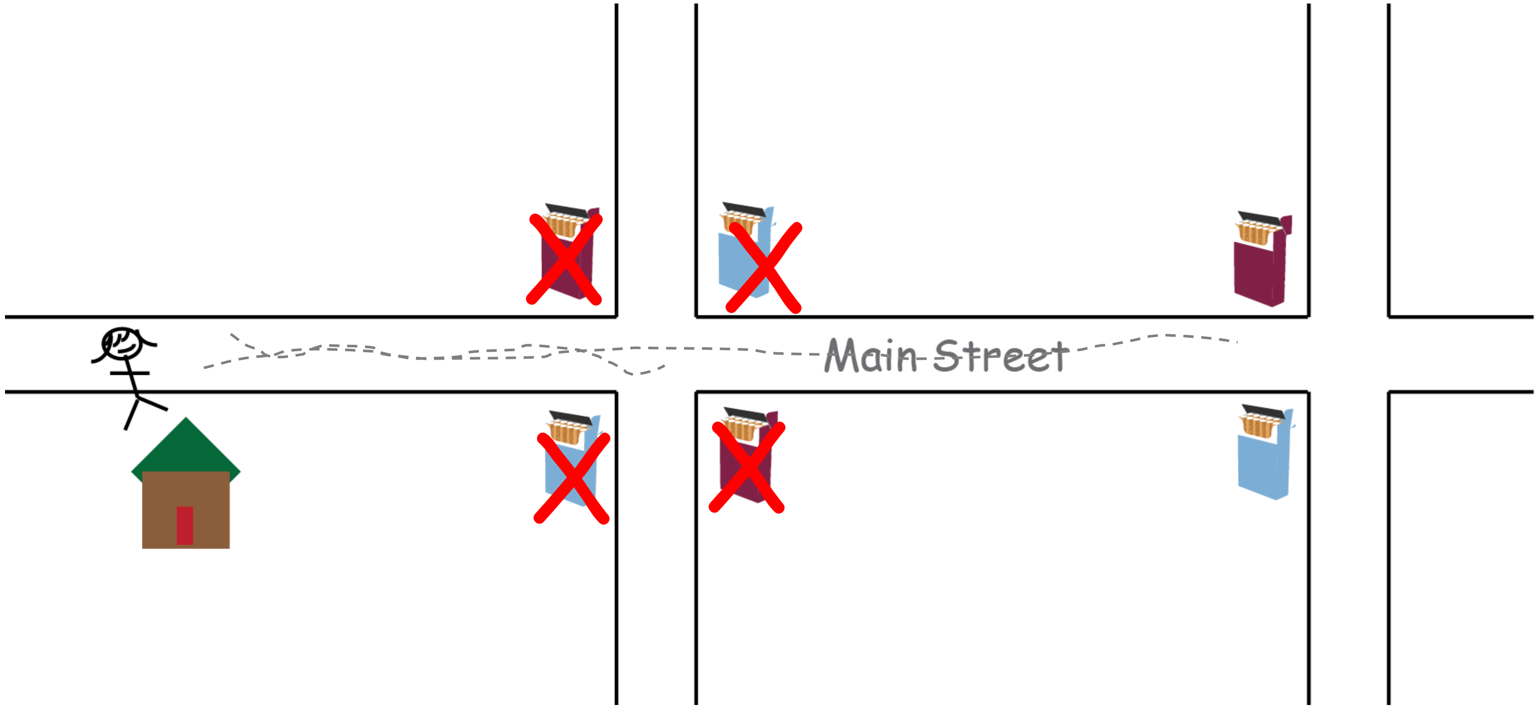
From Luke, et al, 2011, *Am J Prev Med*

Thinking about retailer density and cost…

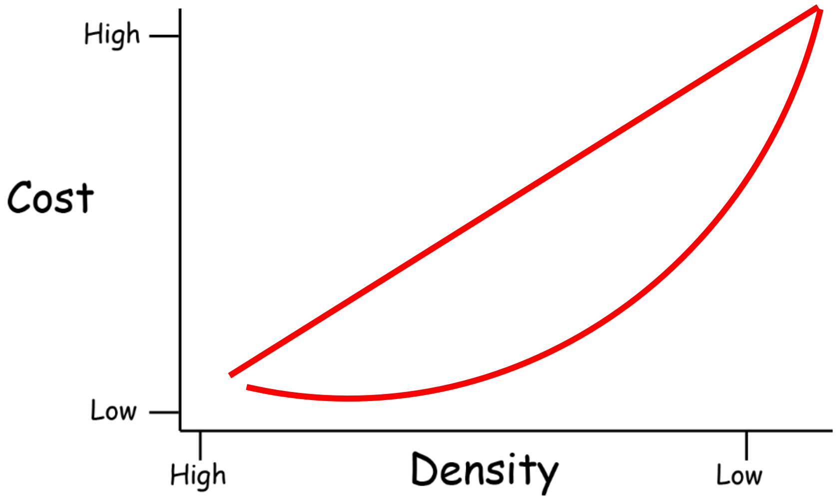
- We might assume…



How does reduced density actually affect behavior?



So, in reality…



Tobacco Town Goals

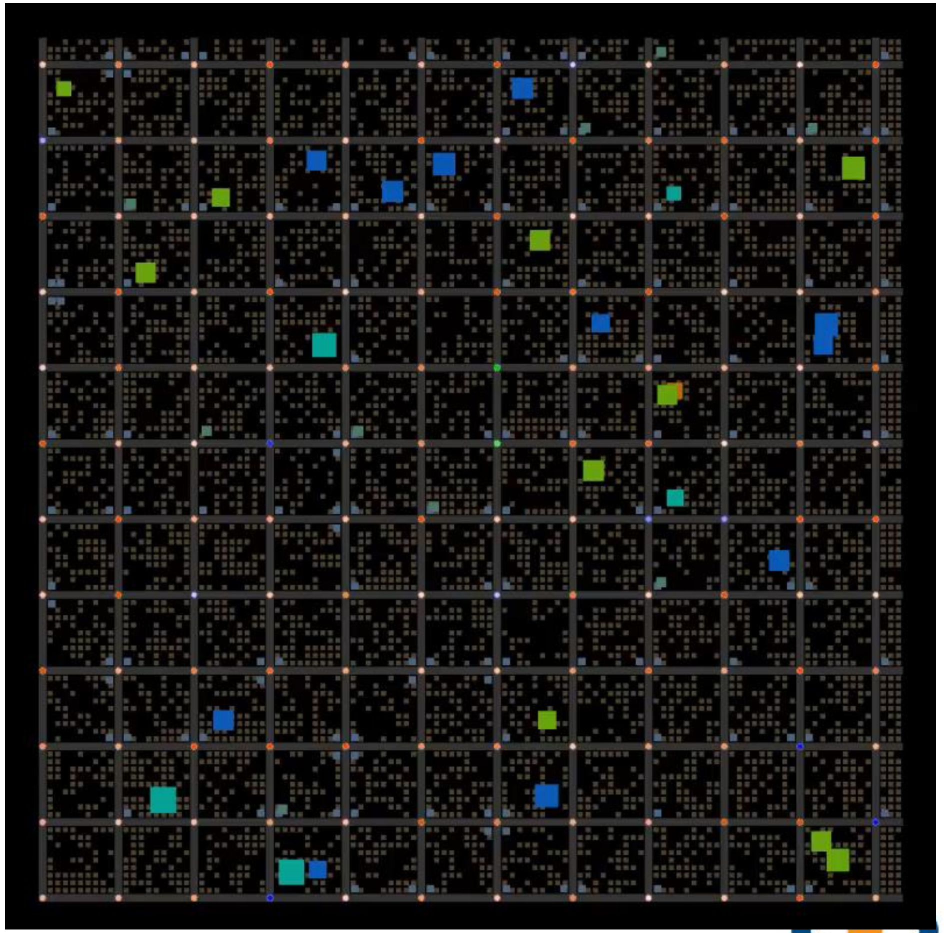
- Build a series of ***simulation models*** to identify interactions between the retail environment for tobacco and purchase and use behaviors

- Use the models as ***policy laboratories*** to explore potential impact of various retail policies across contexts and populations

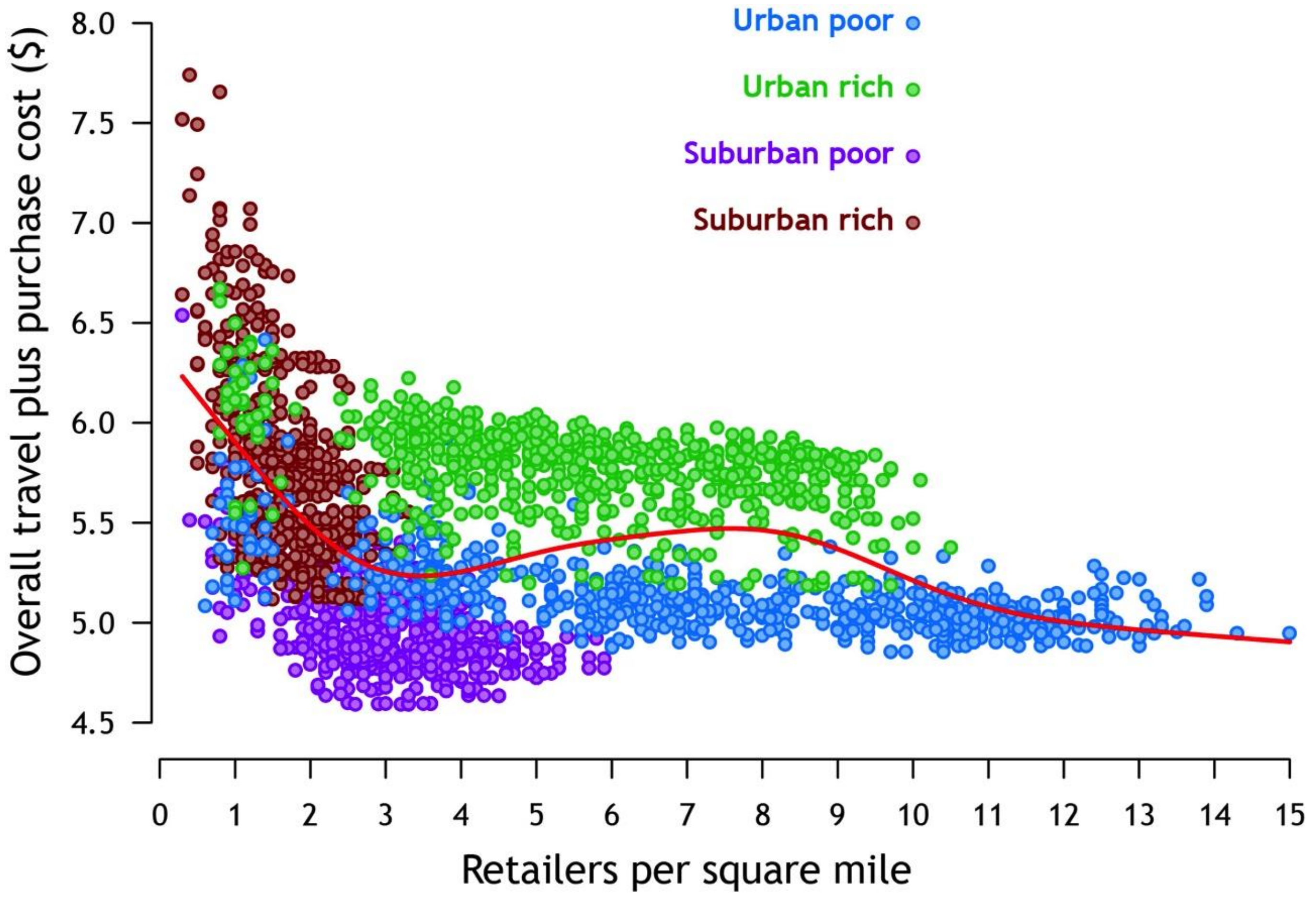
- Work with stakeholders to ***tailor models to communities***, test the likely impact of prioritized policies and disseminate results

Tobacco Town model visualization

- Agent color = transportation type
- Box color = retailer type
- Box size = cigarette price
- Box flashes when agent purchases cigarettes

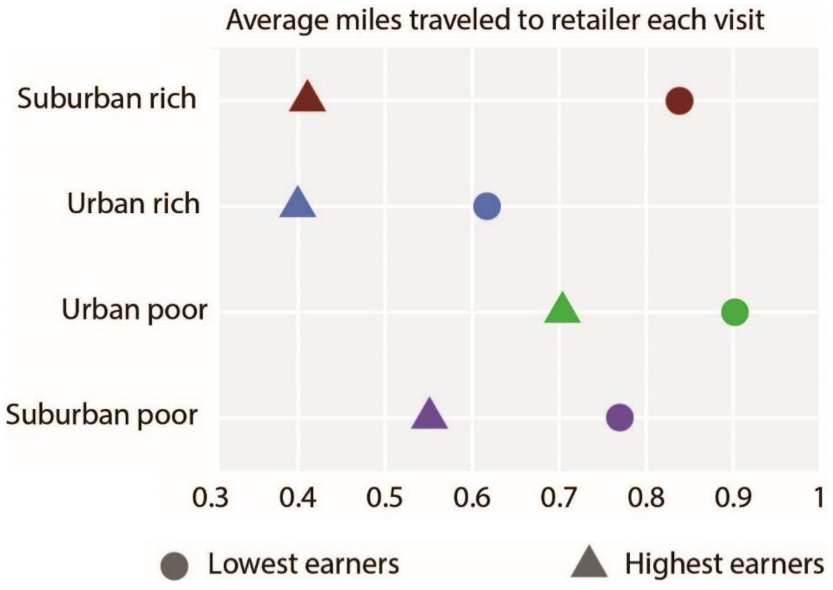


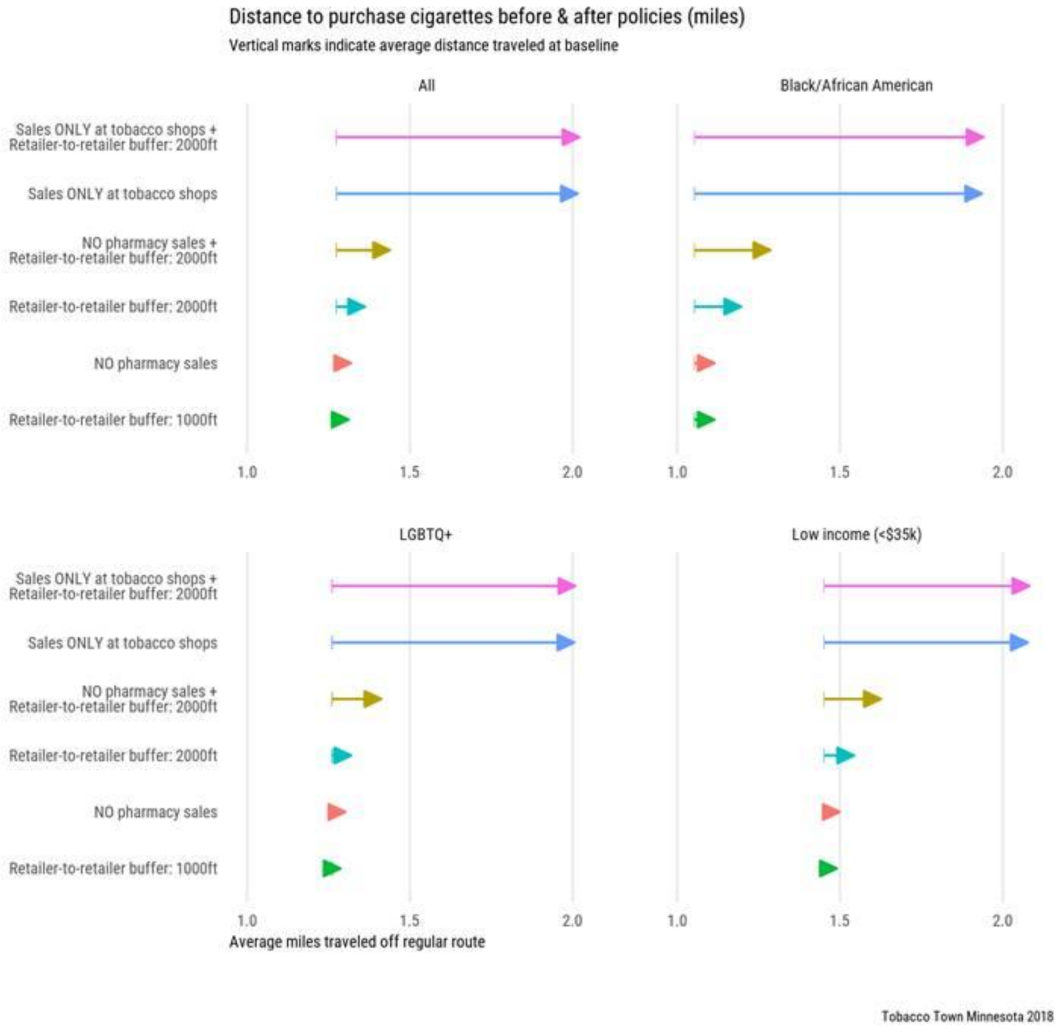
Density reduction may need to reach threshold before effects are seen



Policies have different potential for affecting disparities & behavior

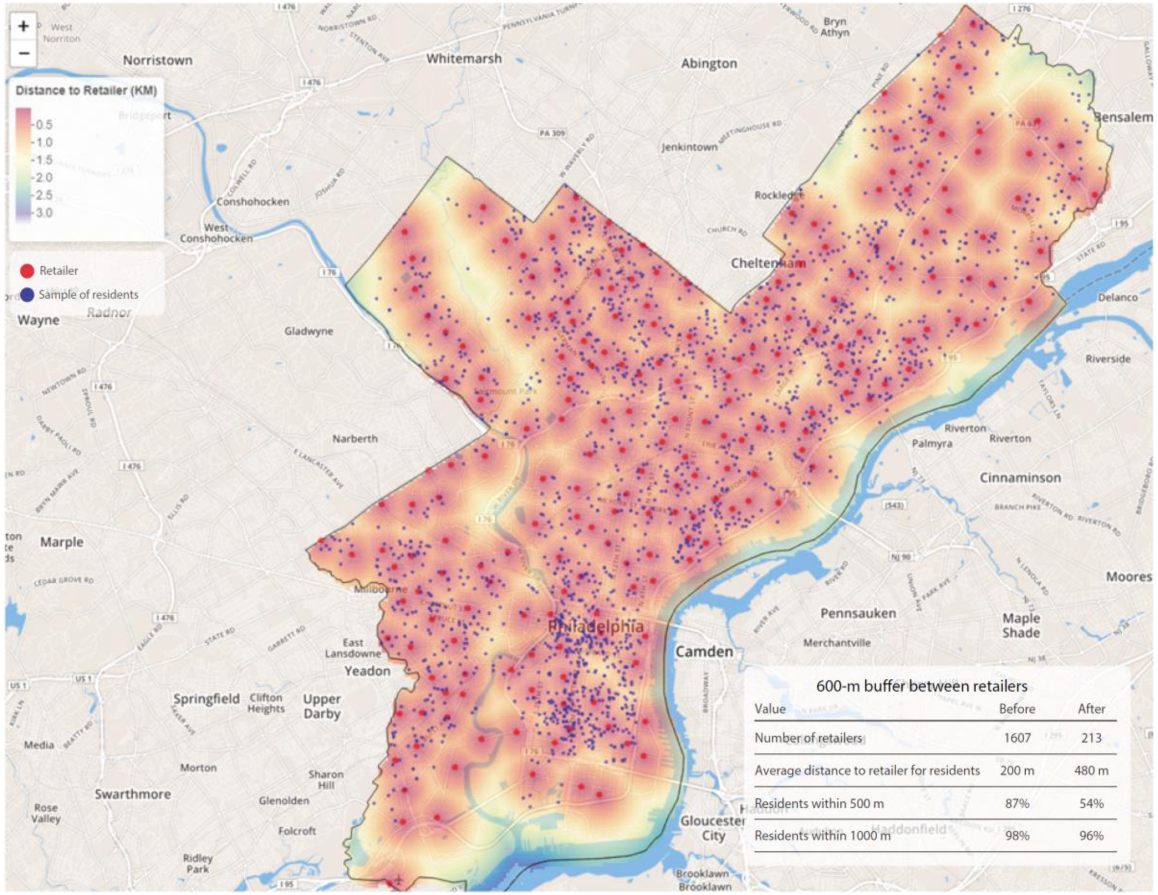
- Distance traveled differs at baseline
- Different policies = different effects



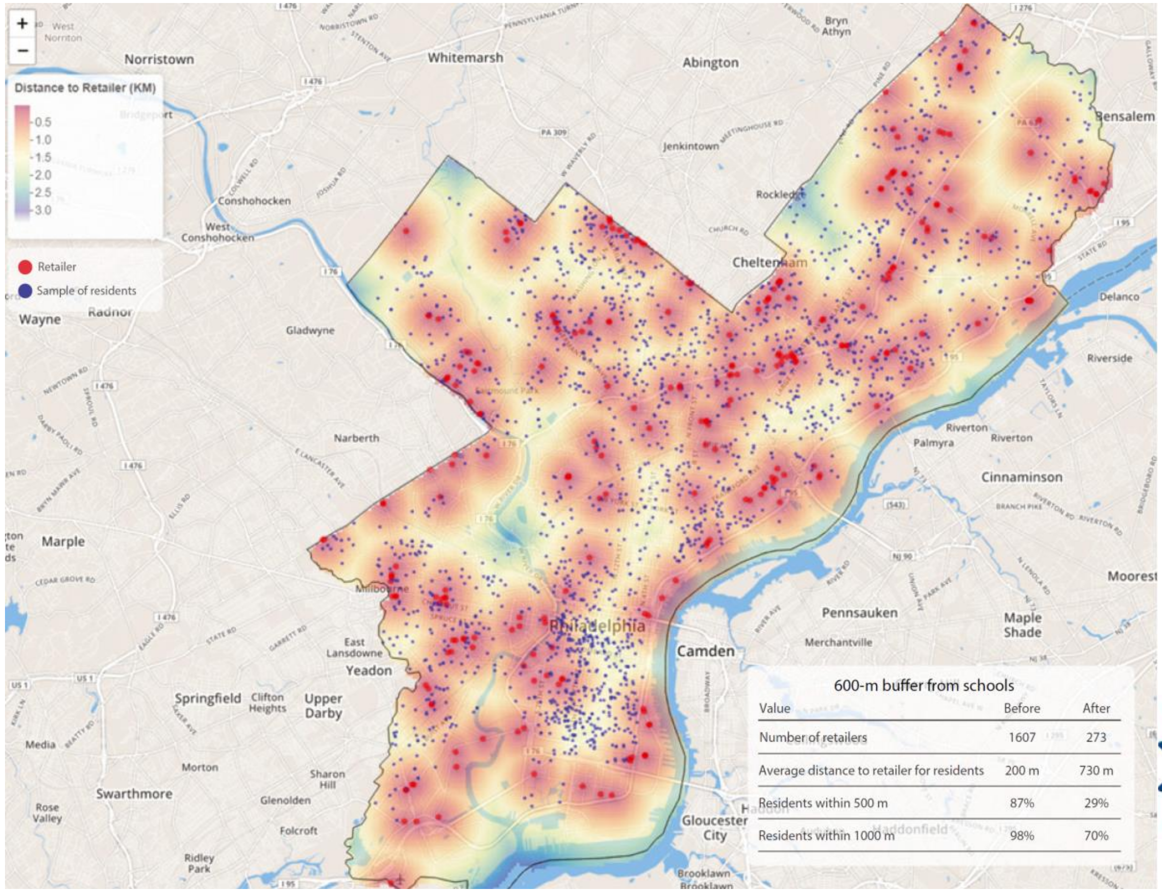


Density and proximity are not the same

- 600m retailer buffer:
  - Density: **4.5 → 0.60** retailers/km^2
  - Proximity: **200 → 480m** avg. distance resident→retailer



- 600m school buffer
  - Density: **4.5 → 0.76** retailers/km^2
  - Proximity: **200 → 730m** avg. distance resident→retailer



Causal mechanisms open many doors

1) By understanding how policies or interventions actually work, we can design more effective polices/interventions with less guesswork
2) This type of knowledge allows us to argue more persuasively about which programs should be maintained, and which should be deimplemented
3) Offers a new way to understand health disparities, by focusing on the processes and dynamics that lead to disparities, rather than simply documenting disparities

From models to community tools

Developing dashboard tools that can be used by community partners to explore effects of retailer reduction policies

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From Epstein, 2008; *Why Model?*
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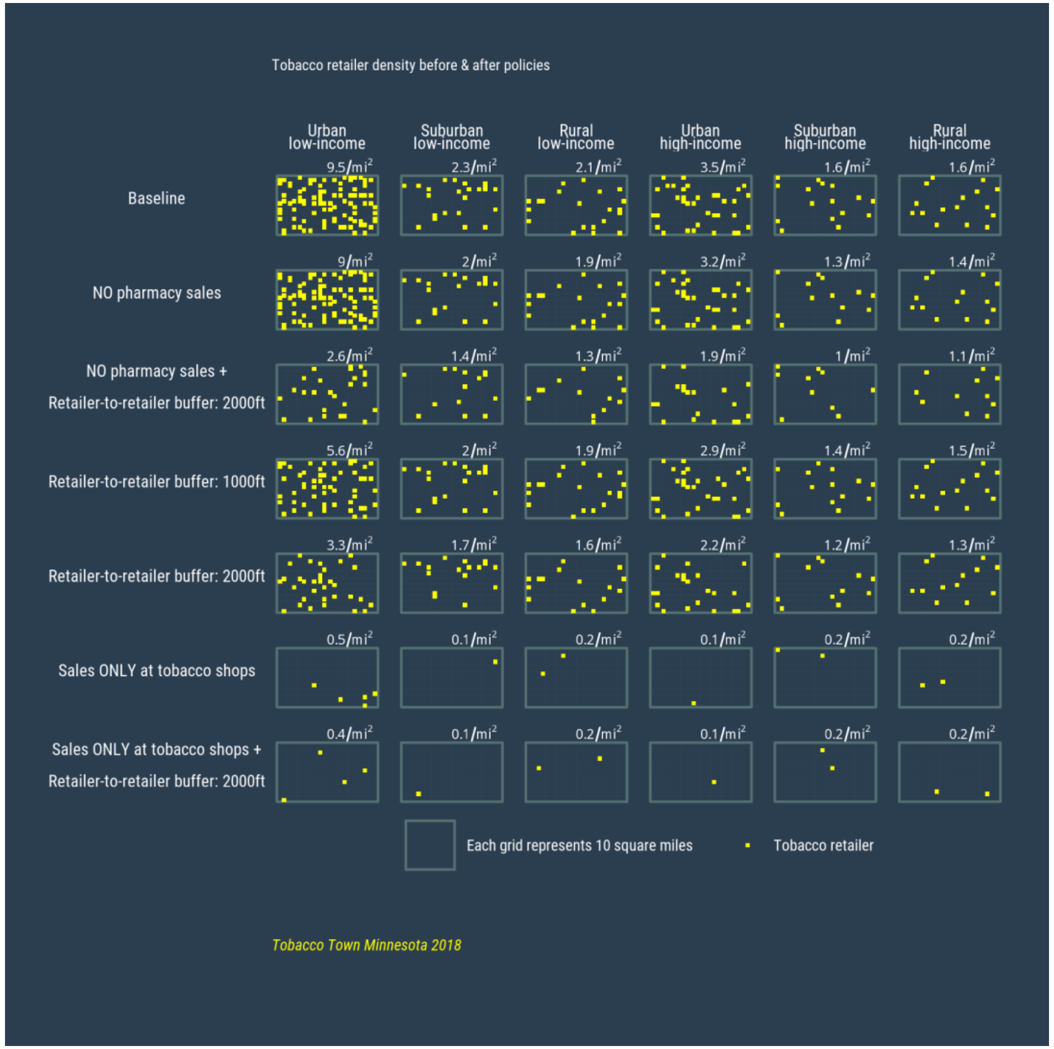
Policy effects depend on context

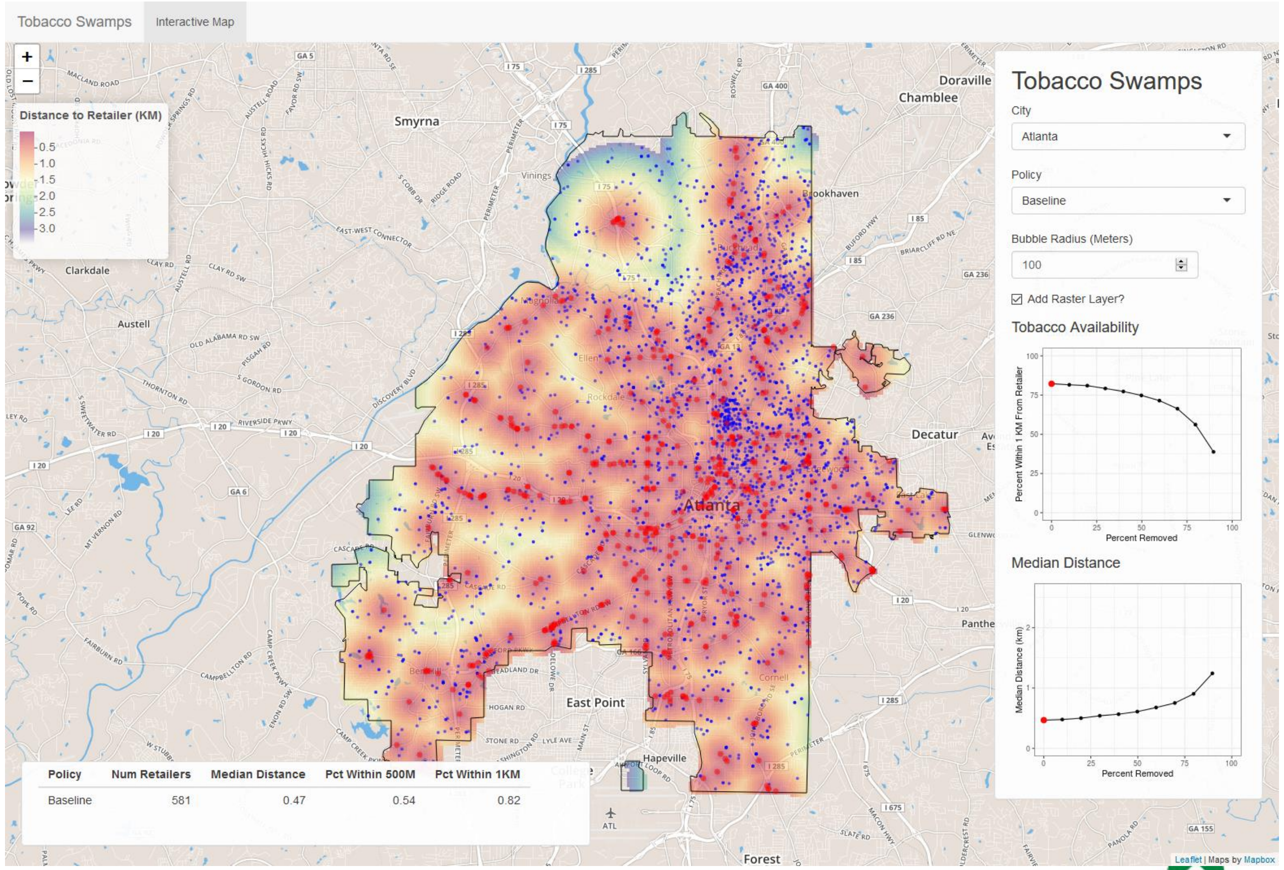
- No ‘one-size-fits-all’ policy
- Layering of policies may help remove community disparities



Tobacco Town Minnesota; https://tobaccotown.shinyapps.io/Minnesota/

Dissemination – Systems tools for stakeholders

- Design for dissemination (Brownson, Dearing)
- Systems science results are very amenable to stakeholder discussions and action
  - Interactive community dashboards
- *Tobacco Swamps* examples
  - tobaccotown.shinyapps.io/Minnesota
  - Tobacco Swamps (ASPiRE)



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