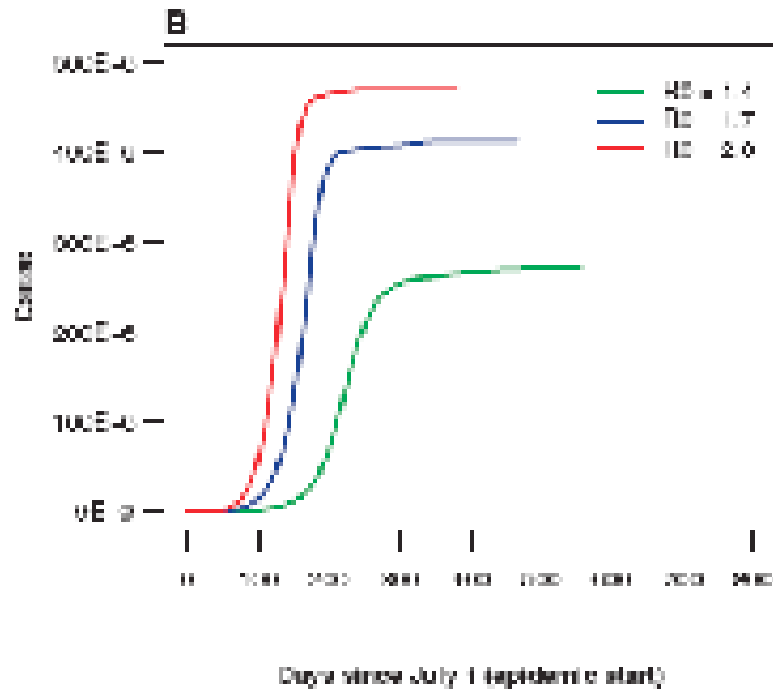


London Start



Worldwide Metro Cases

For various values of R_0 , the reproductive rate of the disease: the number of secondary cases from a single infectious individual introduced into a completely susceptible pool



Worldwide Metro Cases

Table 1. Worldwide metropolitan cases, with and without 95% travel restrictions implemented sequentially after the first 1,000 cases have been identified in each city, for an epidemic with $R_0 = 1.7$.

Location and Time of Initial Cases	Travel Restrictions Implemented	Total Metropolitan Cases Worldwide after 8 Months		Total Metropolitan Cases Worldwide after 12 Months		Total Metropolitan Cases Worldwide at End of Epidemic ^a	
		mean	sd	mean	sd	mean	sd
Hong Kong - Jan 1	no	755,698,209	4,345,852	23,5838,787	4,078,884	336,893,897	1,542,889
	yes	81,551,354	9,783,597	30,1362,274	3,034,716	391,746,710	2,756,226
Hong Kong - July 1	no	425,818,248	4,001,117	414,295,770	258,211	414,188,853	246,489
	yes	192,234,576	9,481,456	42,9218,442	1,974,474	415,947,362	2,463,781
London - Jan 1	no	176,641,756	2,781,862	29,5413,483	2,278,130	347,340,743	1,903,589
	yes	178,529,844	16,690,324	32,1376,868	5,378,466	38,6483,419	9,032,182
London - July 1 ^b	no	22,473,114	37,430,968	61,027,027	194,641,536	62,021,271	194,941,514
	yes	2,144,046	13,293,148	61,349,325	121,863,257	62,074,165	120,688,629
Sydney - Jan 1	no	88,456,144	2,5413,355	38,5489,211	73,281,207	37,5149,462	2,932,185
	yes	22,860,217	10,255,096	32,7274,482	10,734,621	40,6587,417	5,940,307
Sydney - July 1	no	298,429,177	6,494,197	41,2769,112	4,84599	41,1276,458	416,499
	yes	64,823,751	13,494,412	48,6239,486	2,046,870	41,2366,614	2,130,810

^aThe end of the epidemic is determined when there are no further cases worldwide.

^bThese data represent mean and standard deviation for all 100 runs, including the runs in which the disease did not develop a pandemic curve and did not reach the US.

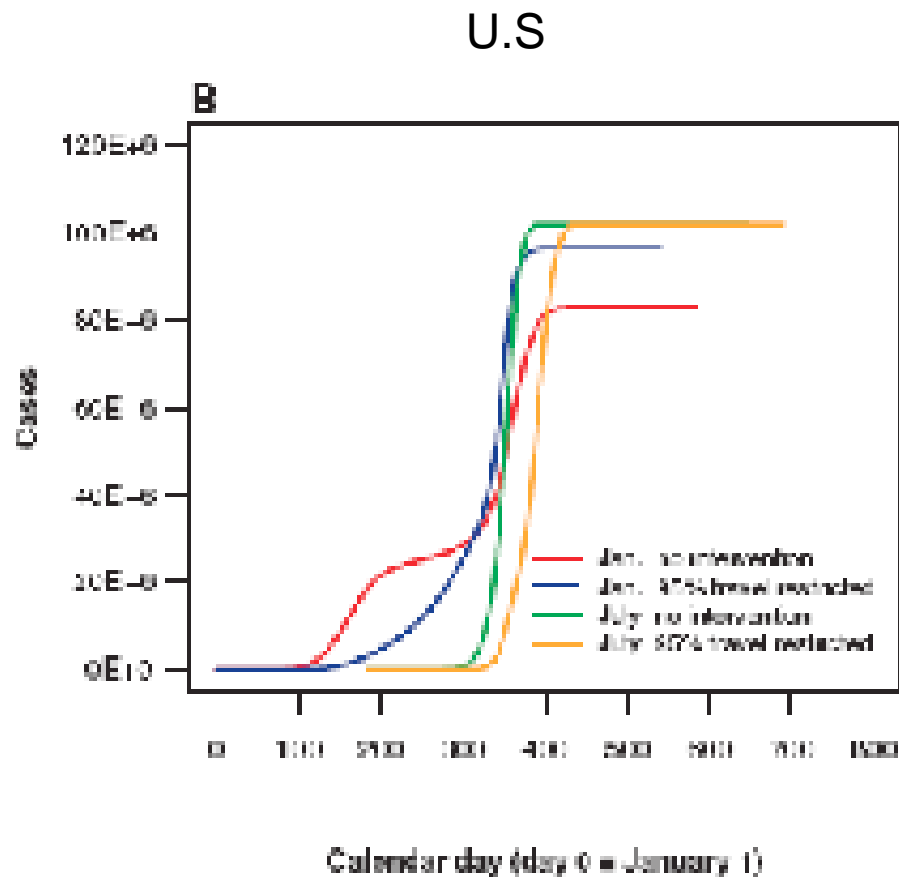
Note: The data are presented for only the 152 major cities, not the entire world population.

doi:10.1371/journal.pone.0240120.t001

Containment Application: International Air Travel Restrictions

- Delay global propagation
 - Buy time for vaccine development, distribution, and nonpharmaceutical interventions
 - Shouldn't make the epidemic *worse* for any country...right?
-

Wrong: Restrictions Can *Increase* Cases!



Counterintuitive:

- Restrictions can make it worse.
 - Why?
 - Better mixing (a la classical ODEs)?
-

-
- Nah...too few people fly
 - So, why?

Seasonality

- Seasonality!
 - Suppose Hong Kong outbreak starts in US low season.
 - Restrictions do delay introduction into the US
 - But can delay until peak is in US high season...so it's worse!!
 - Must have a global model with planetary dynamics to catch this.
 - Quite a useful thing to know before imposing restrictions.
-

-
- We've gone from playground to planet.
 - Shift gears and think about social networks.
-

Example 5. An Agent-Based Model of Smoking

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Mr. Jon Parker

Center on Social and Economic Dynamics

The Brookings Institution

The Legacy Foundation

April 20, 2007

An Agent-Based Smoking Model

“As Simple as Possible, but no Simpler” *Einstein*

**We want a *simple but revealing* model
of the decision to smoke or not.**

- **Simple**

If $U = \text{Utility}(\text{Smoking}) > 0$, then Smoke;

Otherwise Do Not Smoke.

- **Revealing**

$U = F$ (Networks, Messages, Psychology, Biology)

Build Up Decision Function

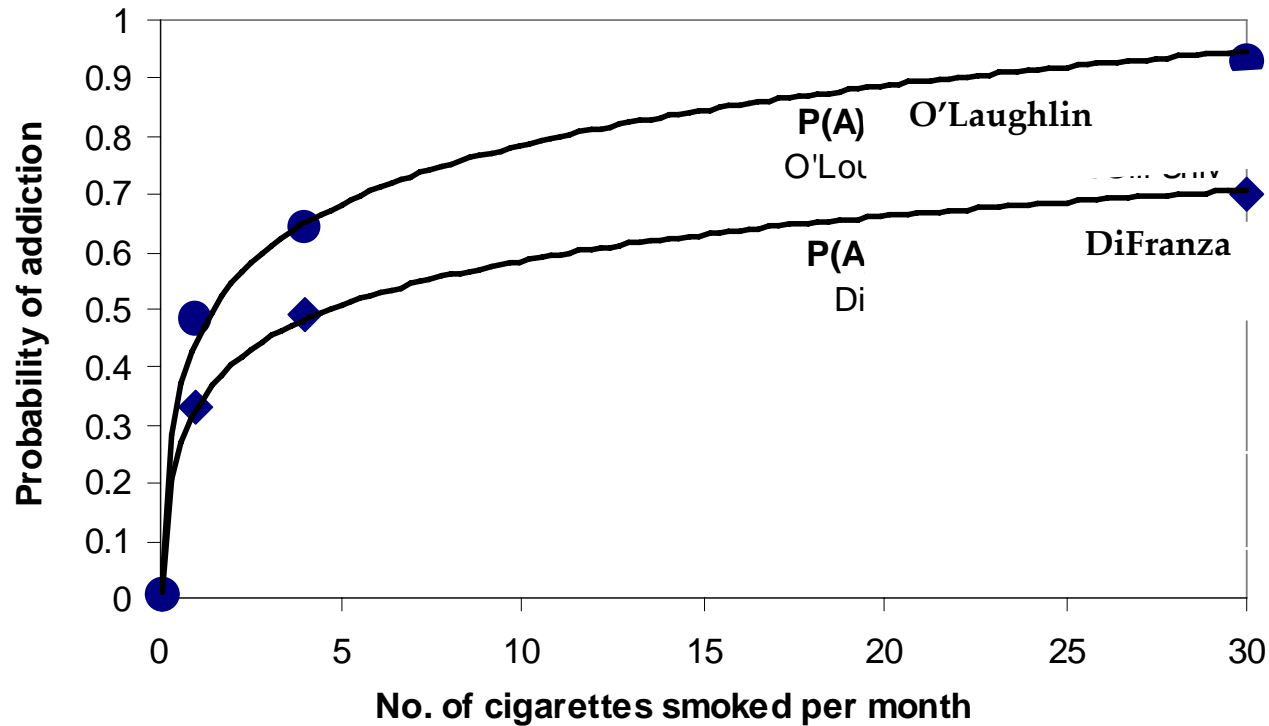
- Individual Biology
 - Addiction Function
 - Individual Psychology
 - Reactance
 - Skepticism
 - Social Network(s)
 - Weighted
 - Information
 - Messages
-

Physiology: factors leading to addiction

$P(A)$ =probability of being addicted

- $P(A)$ depends on smoking rate, genetic predisposition, other factors
 - Smoking is dynamic; genetic predisposition is fixed
 - Data from two studies
 - DiFranza *et al.* (2002)
 - O’Laughlin *et al.* (2003)
-

F



- Discrepancy likely due to male/female ratio: [1:2, 1:1]
- Girls achieve symptoms of addiction in a median of 21 days.
- Boys achieve symptoms of addiction in a median of 183 days.

Social networks: friends and leaders

- The USC (Valente) data

Who are your five best friends?

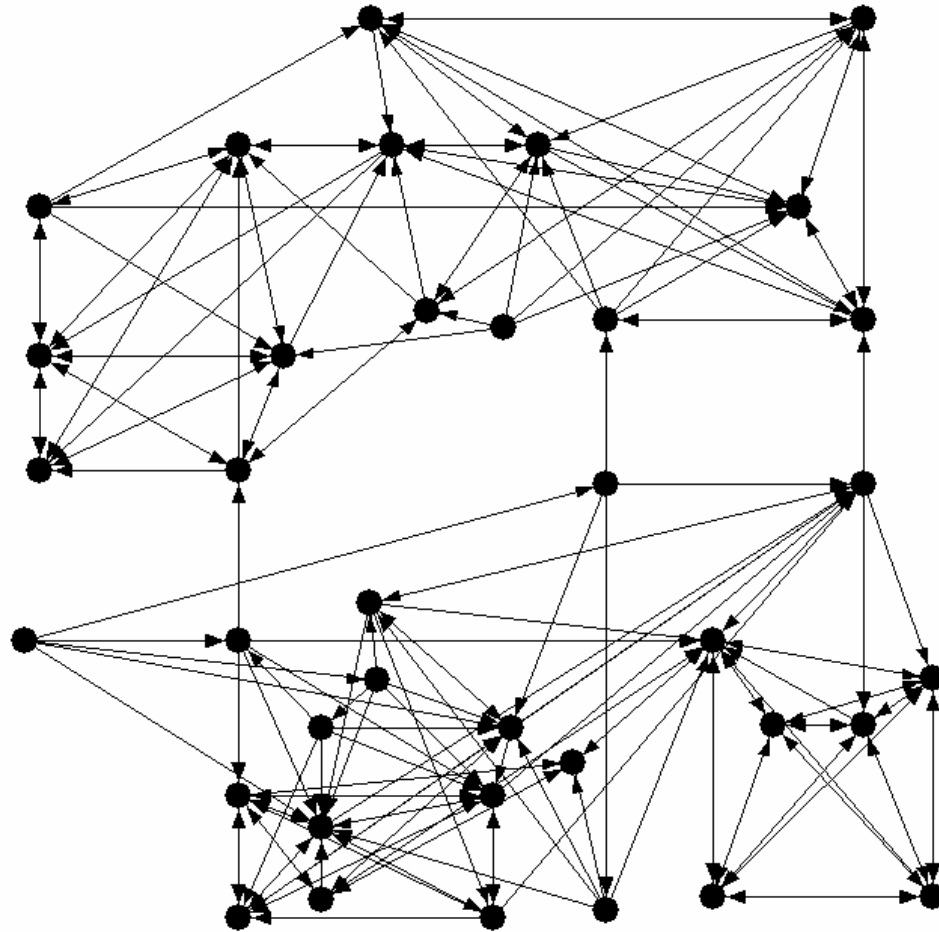
Who would be the best candidates to lead a class project?

- Know network for each of 86 classrooms
-

Network characteristics

- Friend and leader networks have different structures
 - Leader networks have superstars
 - Friend networks are more homogeneous
 - Both networks exhibit clustering of boys and girls
-

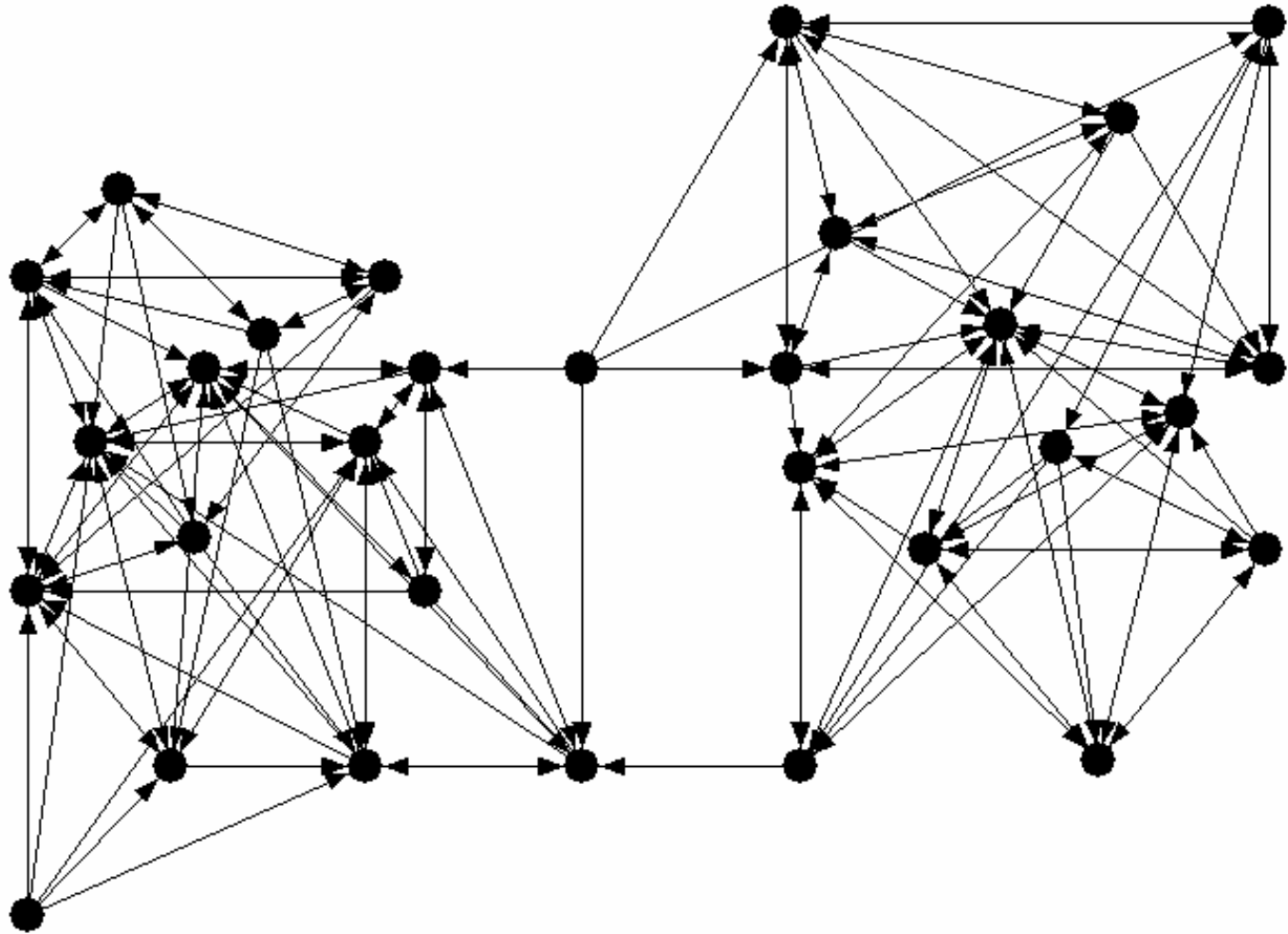
A friends network from the survey



Synthetic networks

- People with similar characteristics are more likely to be friends.
 - Factor analysis determines the most relevant characteristics.
 - Networks are generated by a probability model calibrated from the data.
-

A synthetic network



Social networks

- What are my friends doing?

$$\mathit{socialCoefficient} * \sum_{i=1}^n \mathit{weight}_i * \mathit{friend}_i$$

Messages and risk aversion

- **What message am I getting from “authorities?”**

Normally $[-1,0]$, no positive smoking message possible

$$message \in [-1,0]$$

- **To what degree do I believe it?**

$$message * (1 - skepticism)$$

- **How risk averse am I?**

$$risk_aversion * message * (1 - skepticism)$$

Reactance

“Assail my sense of personal control by telling me I cannot do something and I will want to do it all the more” (Phares, 1991)

Reactance generally causes:

- increased desire for proscribed behavior (“forbidden fruit”)
 - increased tendency to try (or to increase frequency of) the behavior
 - tendency to engage in even more extreme behavior
 - tendency to persuade “peers” to engage in the behavior
 - adoption of opposite/extreme view (“boomerang”)
-

Reactance: empirical evidence

- ❑ Studies confirm basic theory, and link reactance to:
 - age (adolescents maximally susceptible to reactance responses)
 - particular personality types; measurable personality trait itself

 - ❑ Public health studies focus on persuasion & “forbidden fruit”
 - substantial evidence on reactance and teen alcohol use
 - (on smoking , see Burgoon *et al.*)
-

Messages and reactance

- What message am I getting from “authorities?”
- What is my reactance level?

*message*reactance*

If *message* = -1 and *reactance* = 1, this term equals -1
and *ceteris paribus*, I gain utility from smoking

Putting it all together

- $U = F$ (Networks, Messages, Psychology, Biology)
- Utility = (social_coefficient)(weighted sum of network) - (message)[(1-skepticism)(reactance + risk_aversion)] + pleasure.

If $U > 0$, agent decides to smoke;

Otherwise, agent decides to not smoke.

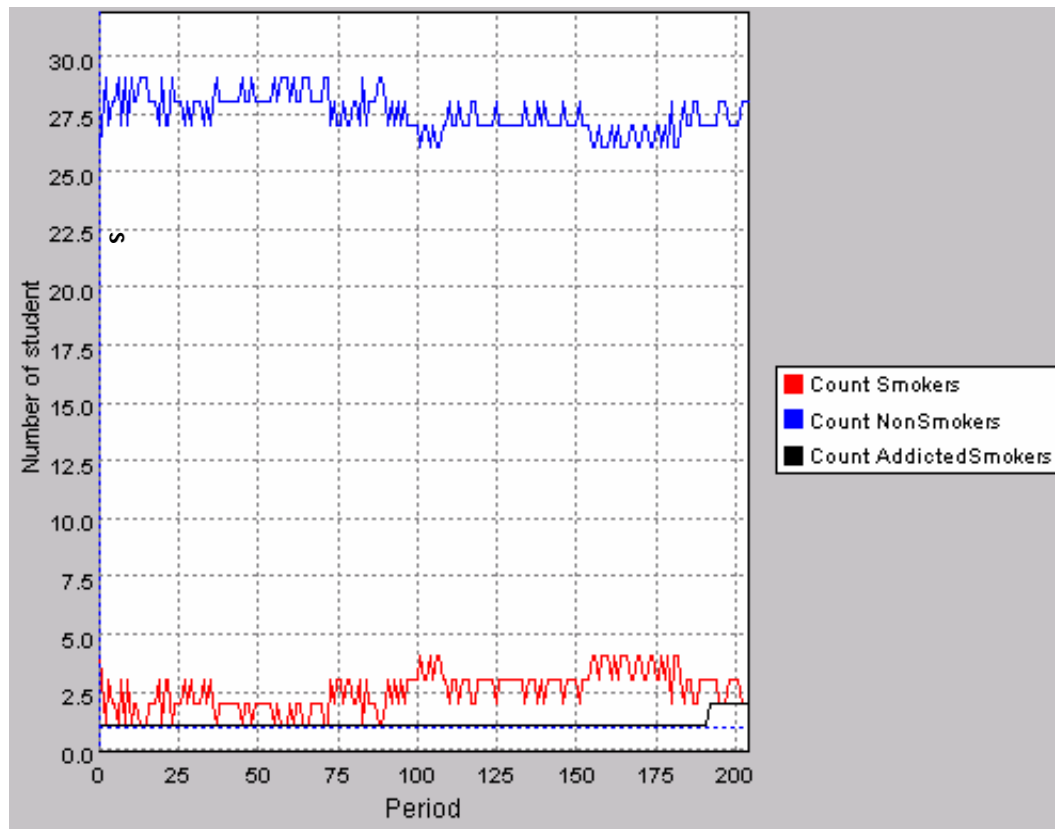
Runs on network data

- ❑ We've collected a large body of school network data.
- ❑ Reactance distribution on that data has big impact on message effectiveness.

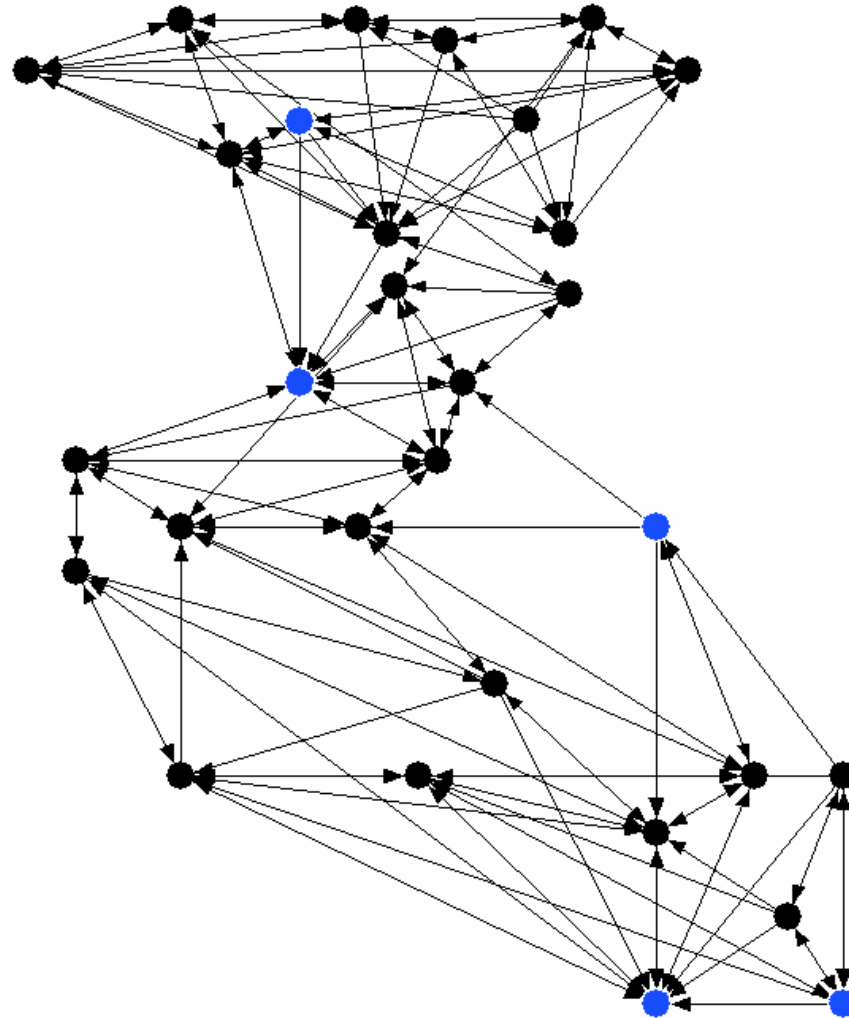


Zero Reactance.

Extreme Message (-1)Effective



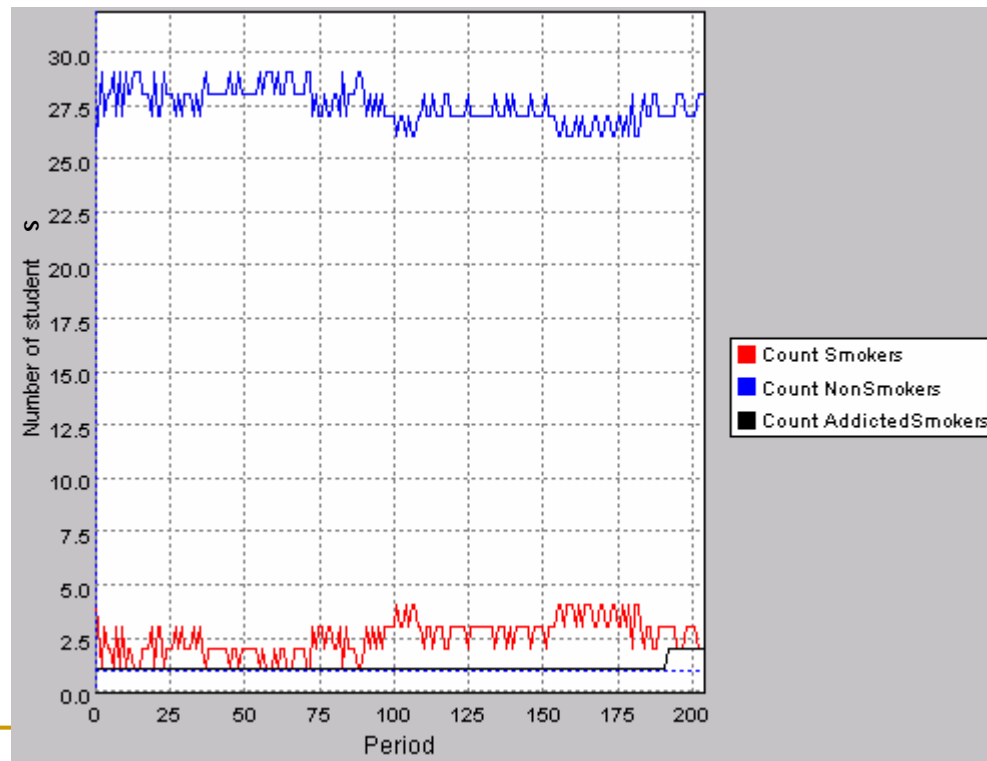
Case 1: Dispersed reactance



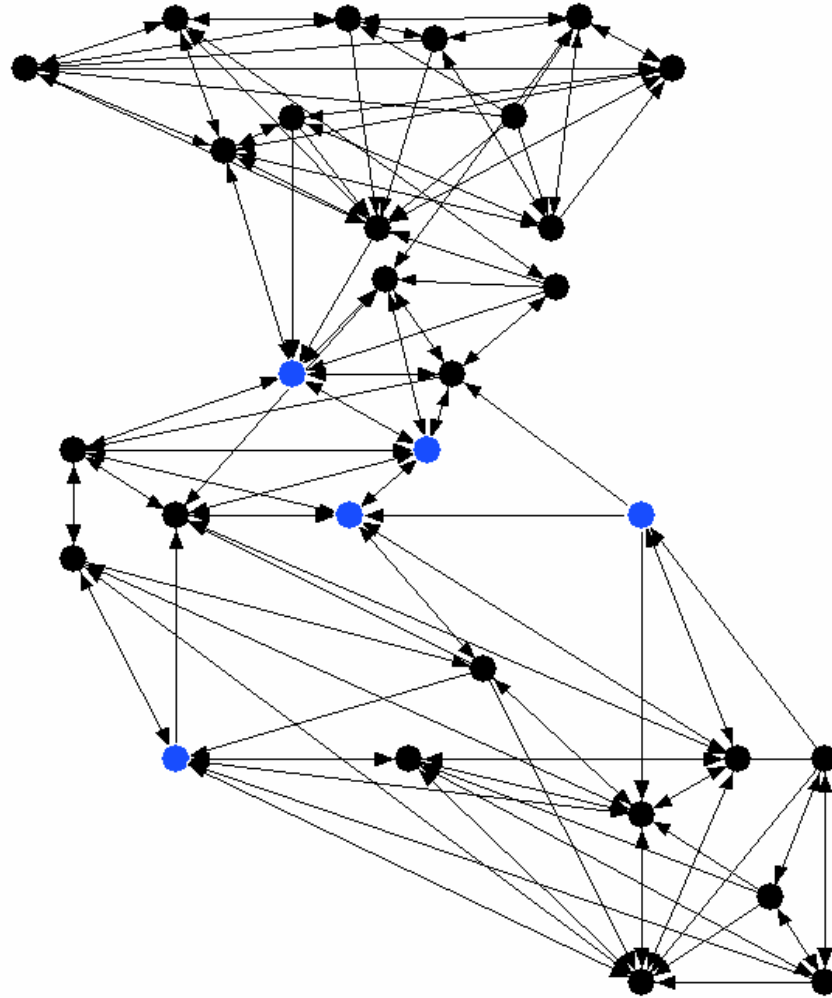
Case 1: Dispersed Reactance

Extreme Message (-1) Neutral

With reactant kids dispersed through the network (not concentrated in a clique), the extreme negative message $m=-1$ neutral.

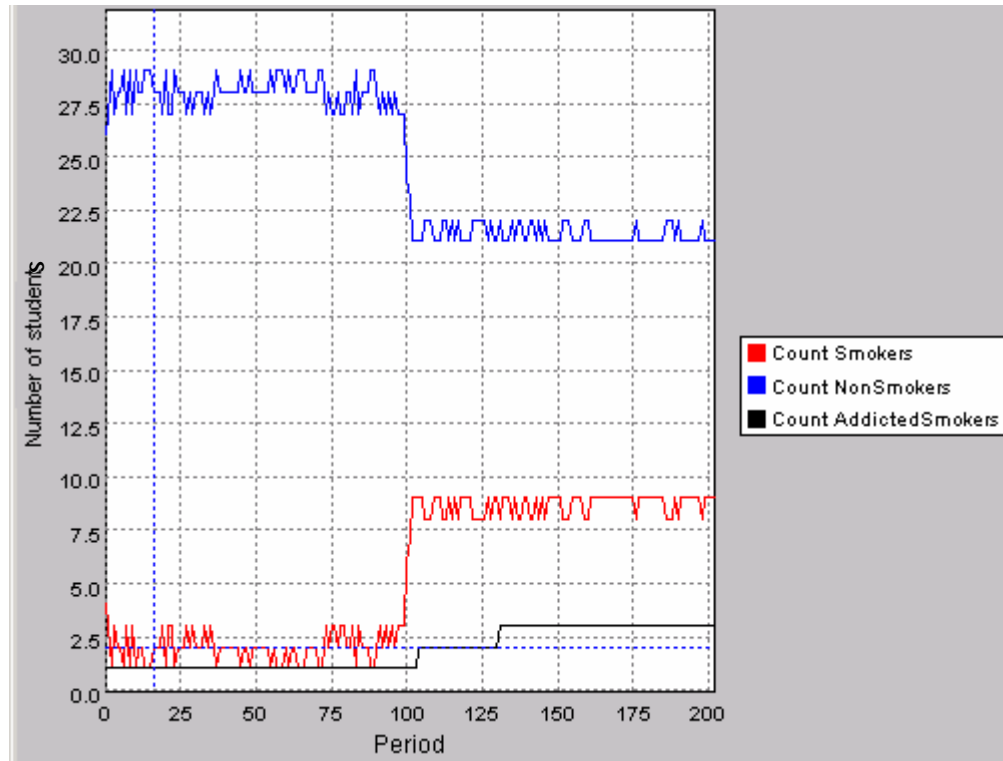


Case 2: Concentrated reactance



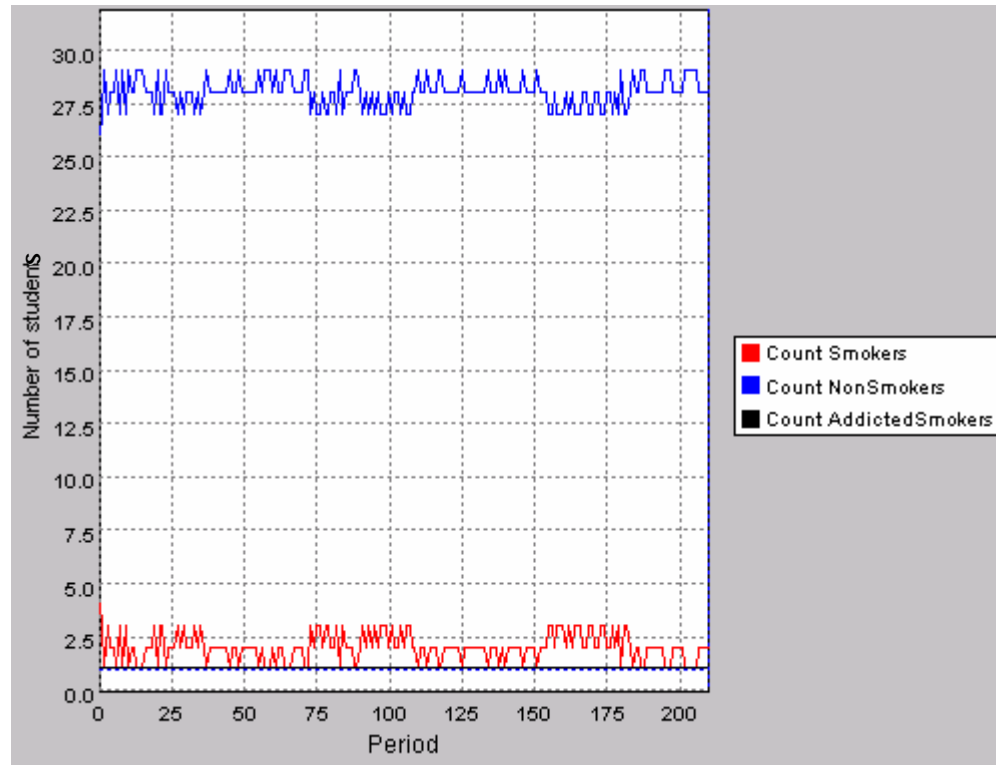
Case 2: Concentrated Reactance $M=-1$

However, the same extreme message backfires if reactant kids are concentrated in the network.



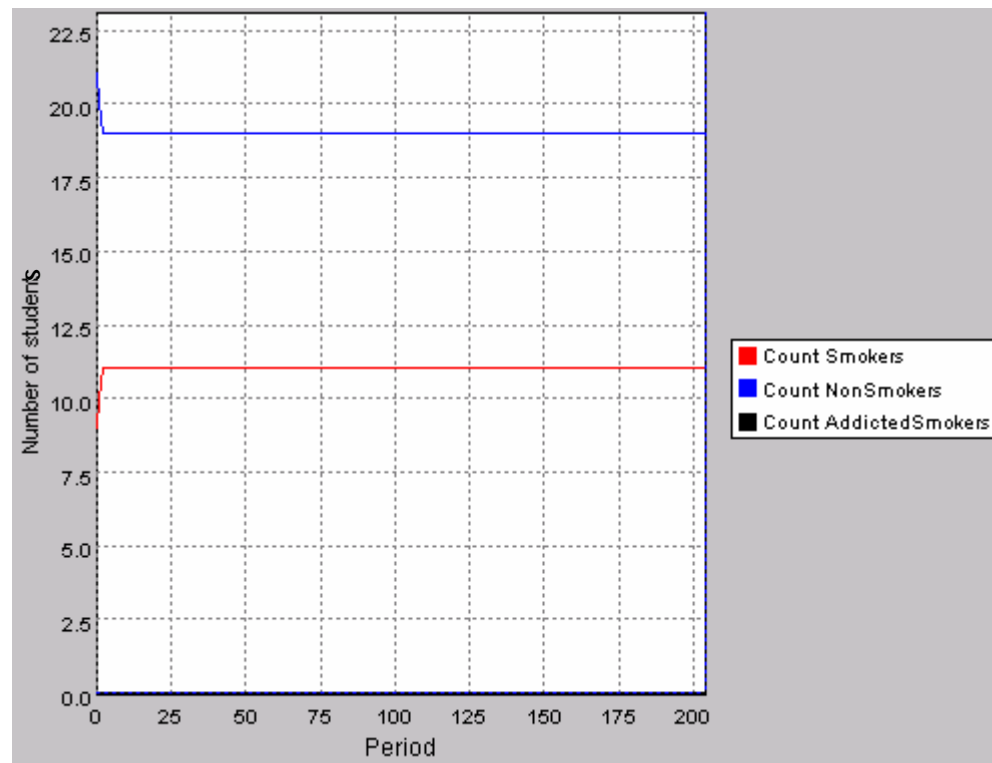
Case 3: Concentrated Reactance $M=-0.25$

With concentrated reactance, a weaker message does NOT backfire...no epidemic.



Case 4: Dispersed Reactance $M=-0.25$

With dispersed reactance (Case 1), this weaker message is as effective as the extreme one.



Extreme messages can backfire.

- ❑ In networks where high reactance kids have high weight and high degree, a message of -1 can *increase* smoking.
 - ❑ In networks where low reactance predominates, or where high reactance kids are low weight and/or low degree, the same message of -1 will be far more effective.
-

Finding the “Sweet Spot”

Suppose message of $-.25$ is strong enough to dissuade Tim, but that he cares about his peer network. Suppose this is dominated by high reactance kids. The -1 message sends the reactant kids into smoking, and Tim goes along through network effects.

By contrast, a message of $-.25$ is still strong enough to deter Tim, and weak enough to avert the reactance catastrophe.

The Policy Goal

Find the message strong enough to deter Tim and NOT strong enough to induce the reactance epidemic. This is the “sweet spot.”

Tailored interventions

- The sweet spot will vary among communities, and will depend on:
 - network structure (topology and weights),
 - psychological patterns (skepticism, reactance, risk attitudes)
 - biological patterns (addiction functions).
 - Hence, optimal messages must be heterogeneous, tailored to specific communities, and adaptive over time.
-

Summary

- Social network structure and heterogeneity are critical to understanding the dynamic impact of different forms of intervention.
 - Intervention strategies must be **targeted** to be effective.
 - More empirical studies are needed to determine which policies yield best results for particular groups of individuals.
-

Example 6. Obesity

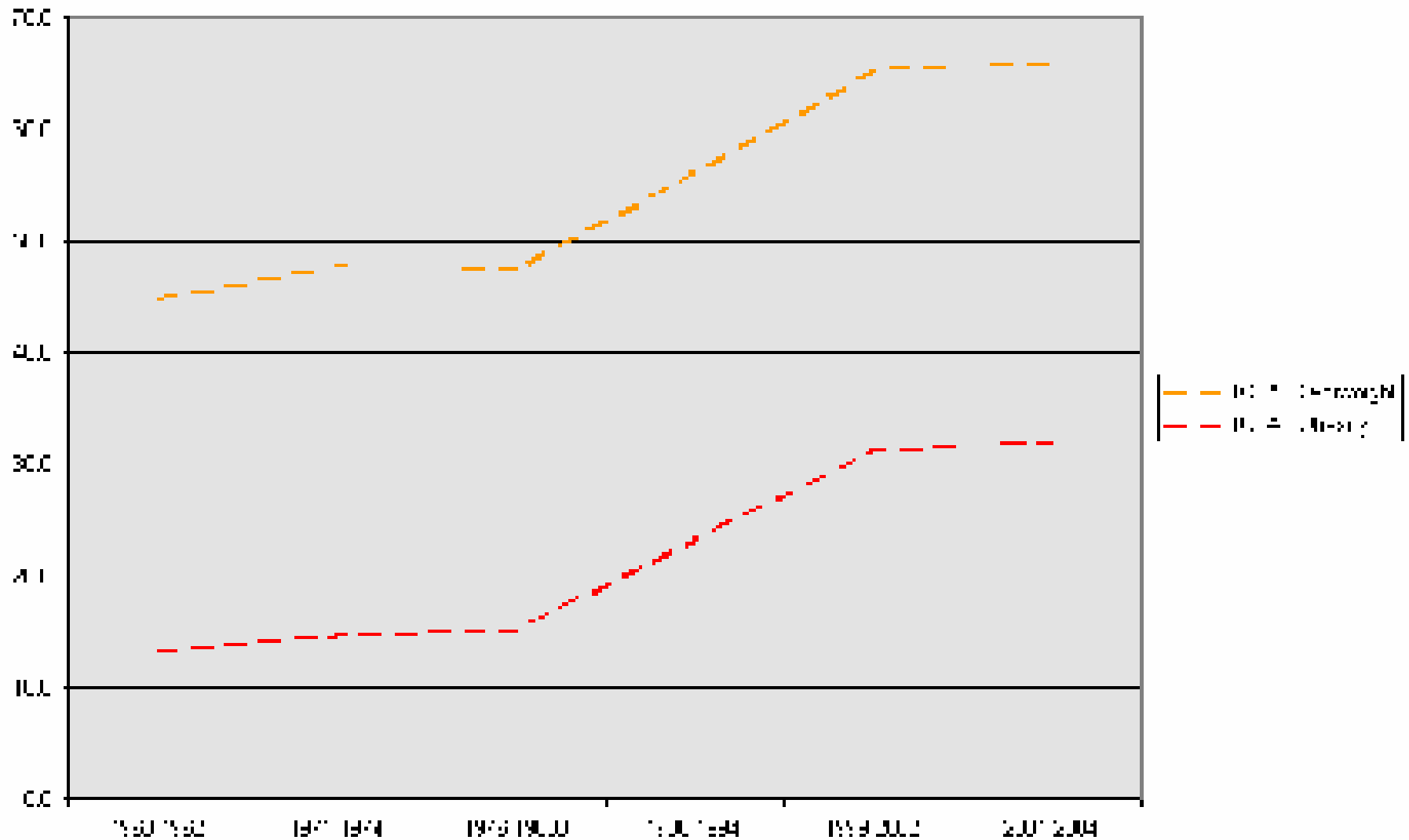
Dr. Ross A. Hammond, Lead

Co-PI. Dr. Joshua M. Epstein,

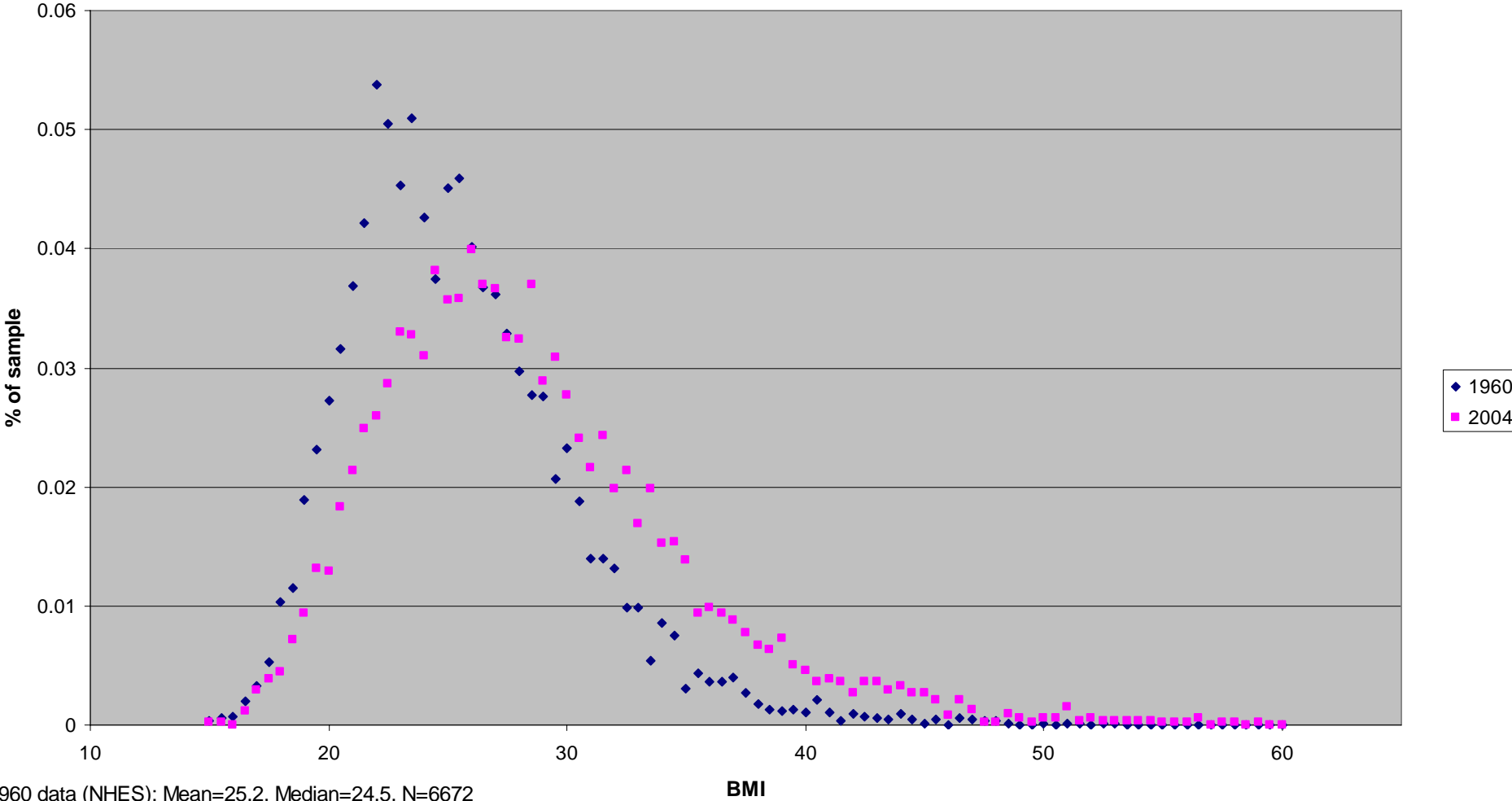
CSED Collaborators: Dr. Peyton Young, Dr. Carol
Graham

Empirical Targets

Overweight & Obese by 1960-2004

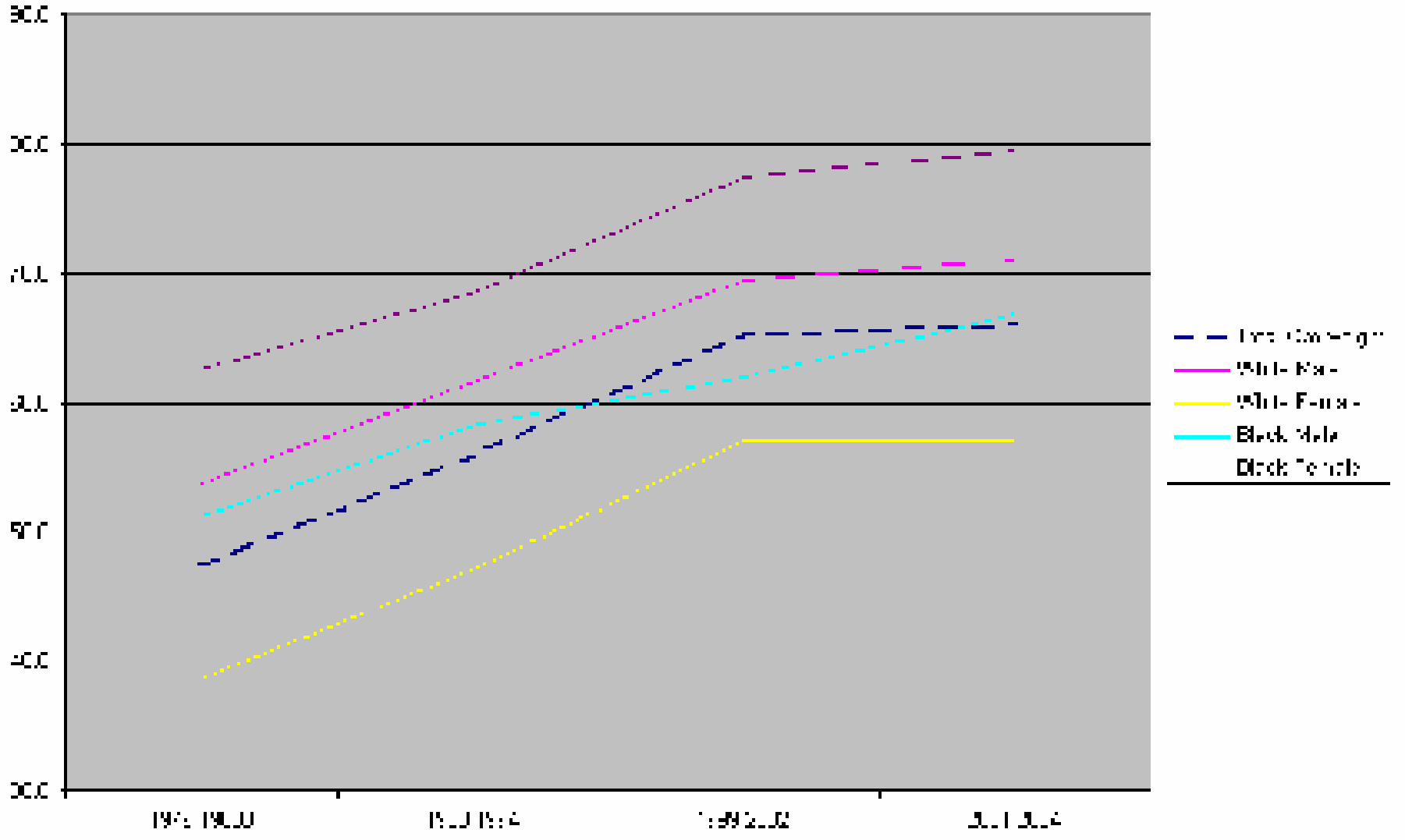


Change in BMI distribution 1960-2004



1960 data (NHES): Mean=25.2, Median=24.5, N=6672
2004 data (NHANES): Mean=28.1, Median=27.1, N=5198

Overweight 1976-2004



An Explanatory Agent Model Should

- Generate the Aggregate Time Series
 - Generate the Distributions
 - Generate the Heterogeneity by Group
 - ...from the Bottom Up!
-

Model components

- Physiology
 - Social influences
 - Individual psychology
 - Media, public health messages, etc.
-

-
- Model in development. Slides deleted.
Please contact author for further information
-

General Bottom Line

- In studying complex social dynamics, there is no alternative to models
 - In policy, there is no alternative to judgment
 - Models like democracy
 - The worst possible system, except for all the others
-

Agent-Based Models

- ABMs powerful for populations that are:
 - Heterogeneous
 - Boundedly Rational
 - Behaviorally Rich
 - Networked
 - Spatially Distributed
 - Locally Interacting
 - Accomodate All Scales
 - from playground to planetary
 - Contagious
 - Smallpox, Flu, TB, SARS...
 - Non-Contagious
 - Chemical release
 - Chronic: smoking, obesity
 - Can be Tested Empirically
-

Concluding Thought

- *“All models are wrong, but some are useful,”*
George E. P. Box
 - Thank you
-

