How Drug Control Strategies Should Vary Over the Course of an Epidemic

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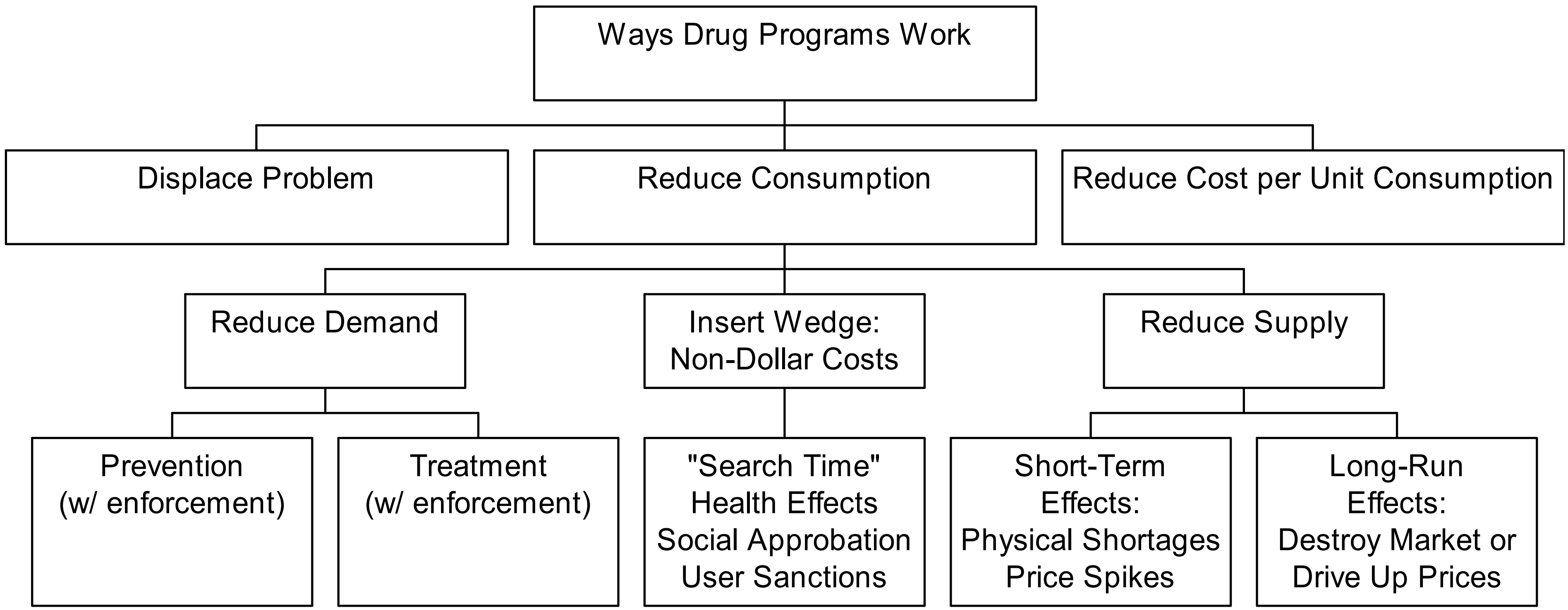
RAND, Drug Policy Research Center

Outline of Talk

- Sample insights from “static” CE
  - Treatment
  - Prevention
- Key points concerning “dynamic” CE
  - Drug-related phenomenon change rapidly
  - Some “facts” we know about epidemics
  - Sources of nonlinear feedback
  - Typology of epidemic models and implications
  - Key insights from some “Vienna” models

Framework for Understanding Intervention's Effectiveness: Mature Epidemic Case



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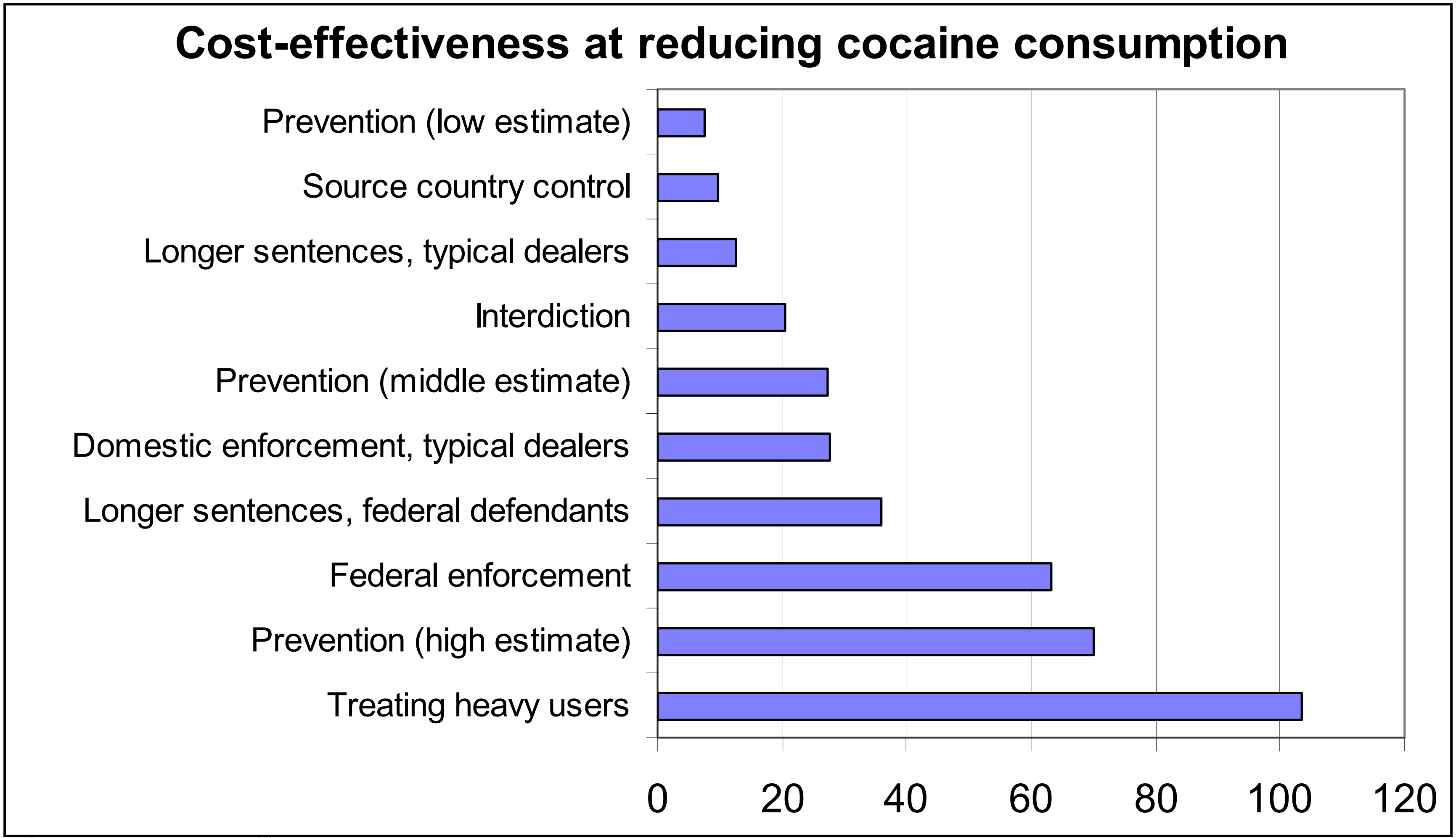
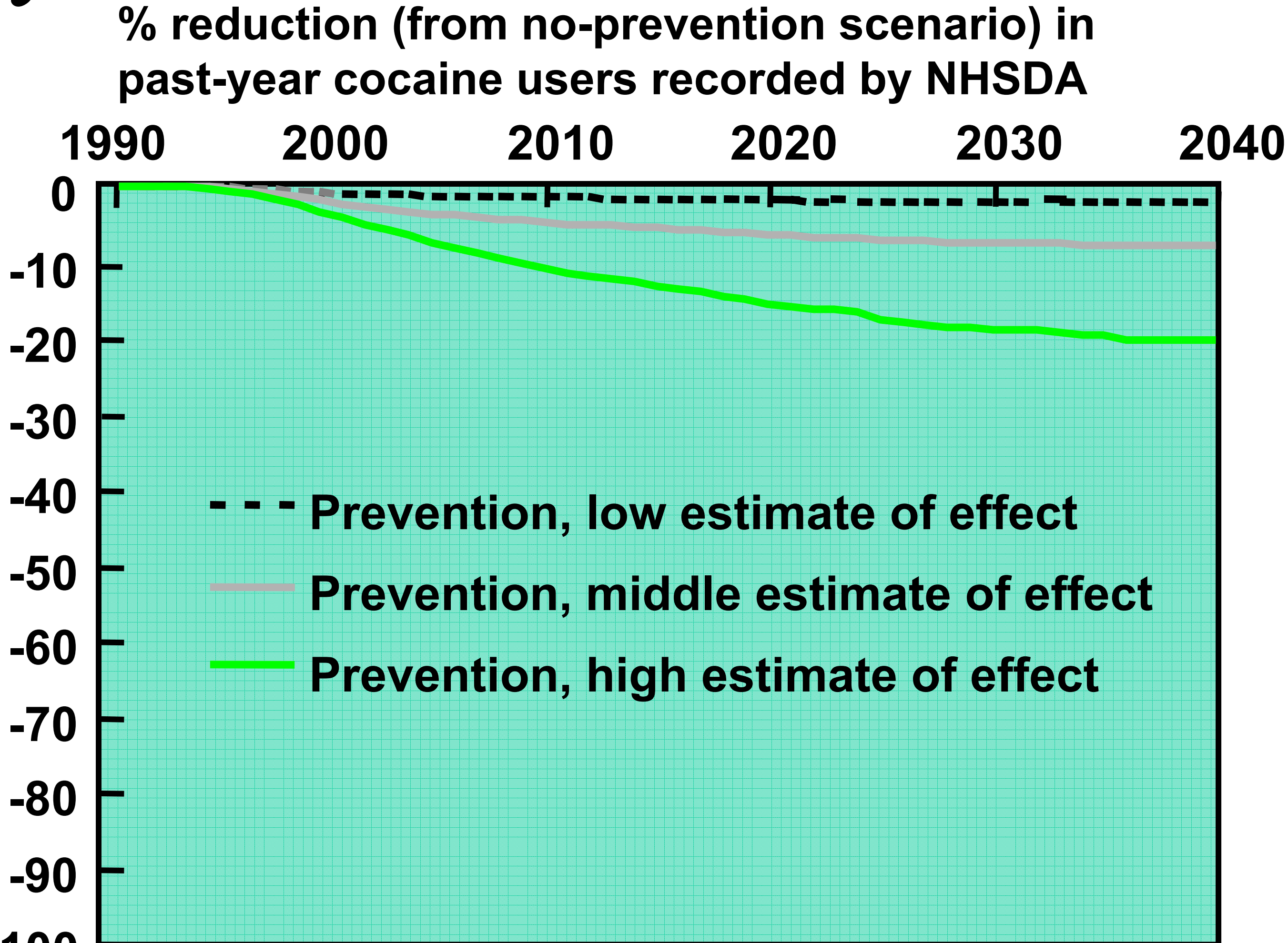
Horse Race Results of Cost-Effectiveness Studies



Insights Concerning School-Based Drug Prevention

– **Prevention is cost-effective but not very effective**
– Drug prevention is not primarily about preventing drug use
– You need to do prevention 15 years before you know you need to do it
– Only one-quarter of program's impact on cocaine use comes from preventing participants from initiating cocaine use.
– Most uncertainty about cost-effectiveness is not due to uncertainty about cost or the evaluated effectiveness

Prevention Circa 1992 Couldn't Greatly Affect # of US Cocaine Users



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Prevention's Cost-Effectiveness

	Coc-aine	Mari-juana	Ciga-rettes	Alc-ohol
Units of Use	grams	grams	packs	SRD
F1: Baseline Use per Initiate	350	560	8900	640
F2: Proportion Initiating	18%	62%	78%	58%
F3: Discount Factor	0.53	0.58	0.42	0.49
F4: Short-term Effectiveness	10.9%	16.0%	16.8%	12.8%
F5: Reduction in Lifetime Use per Unit of F4	27.6%	19.4%	14.0%	17.3%
F6: Correl.-Causation Ratio	0.9	0.9	0.9	0.9
F7: Scale-Up Factor	0.6	0.6	0.6	0.6
F8: Social Multiplier	2.0	1.0	1.0	1.0
F9: Market Multiplier	1.3	1.0	1.0	1.0
F10: Social Cost per Unit of Use	$215	$12	$8	$98
Social Benefit/Participant	$300	$20	$300	$210
Total	$840 per participant			

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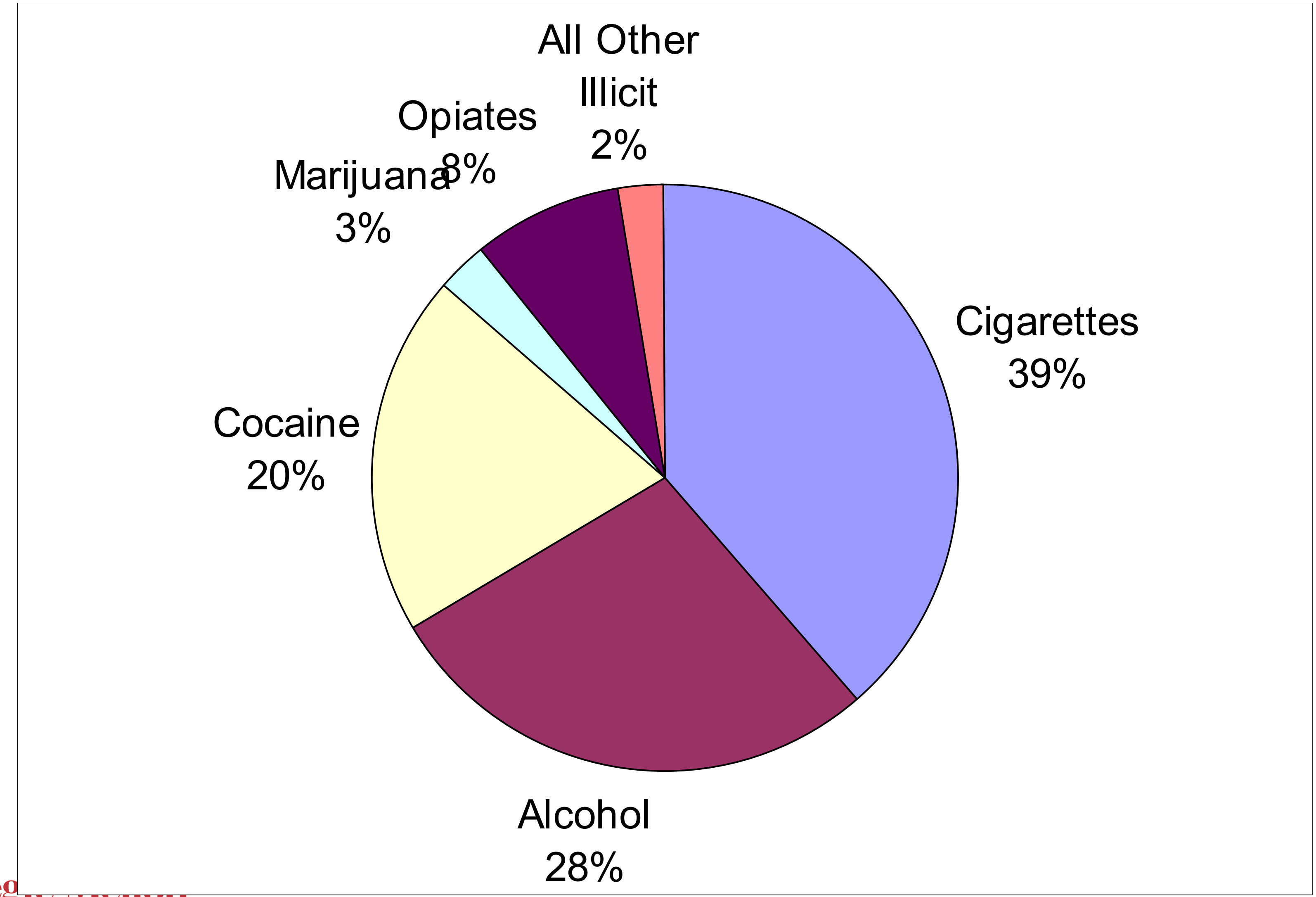
Benefits Not Just from Illicits



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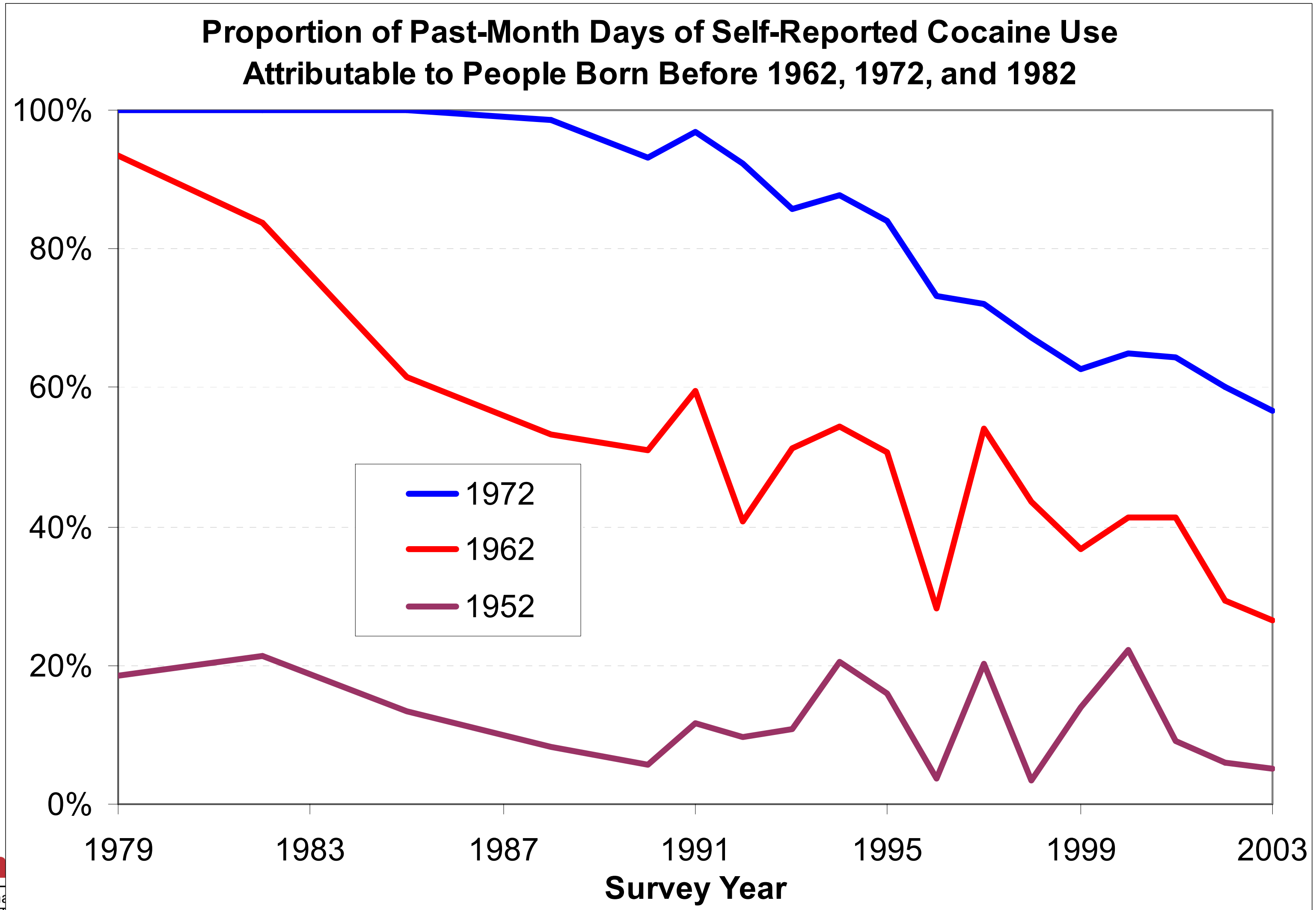
Perfect SB Prevention Starting in 1985 Could Cut Household Cocaine Prevalence



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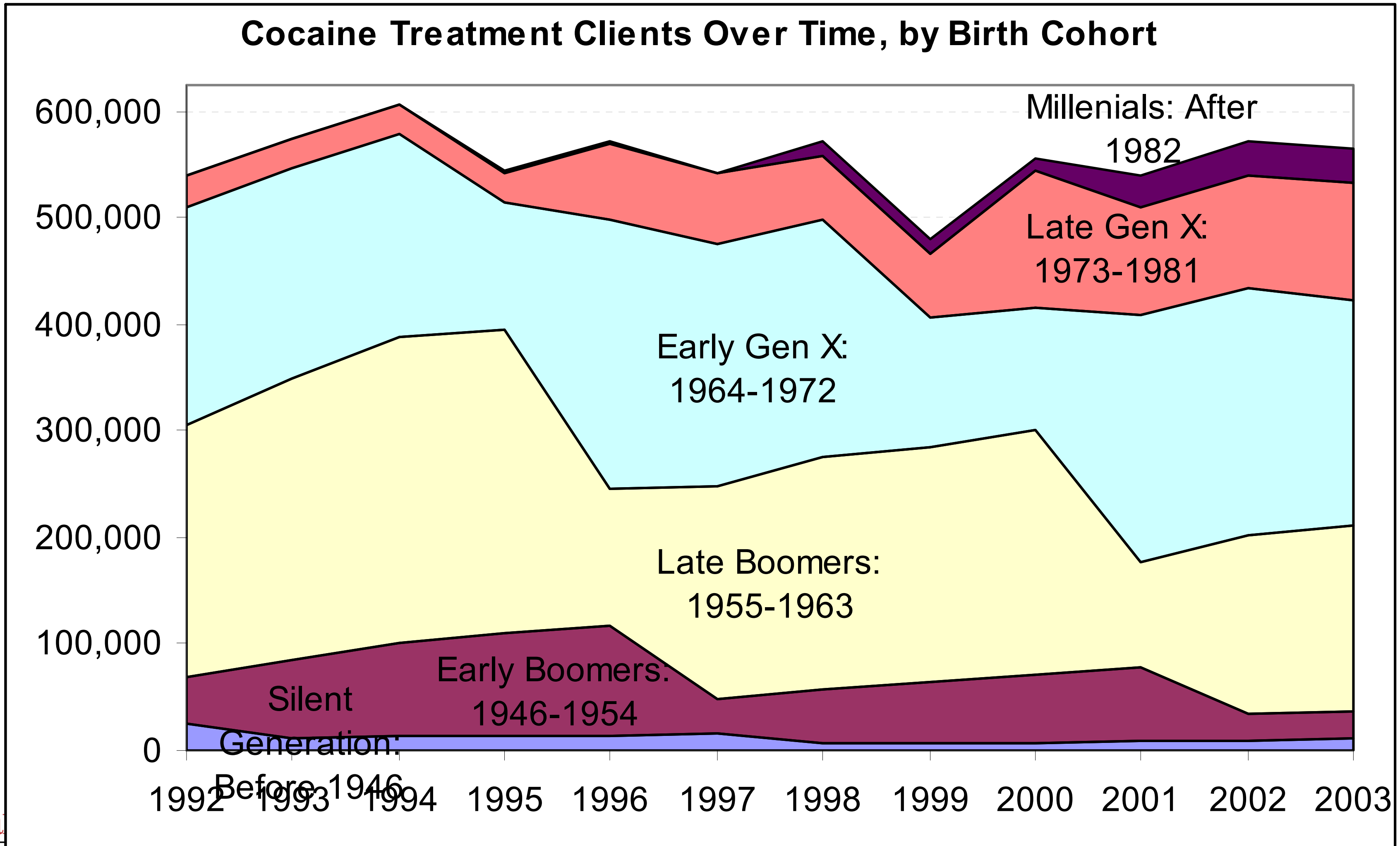
But Would Have Only Modest Effect on Problematic Use



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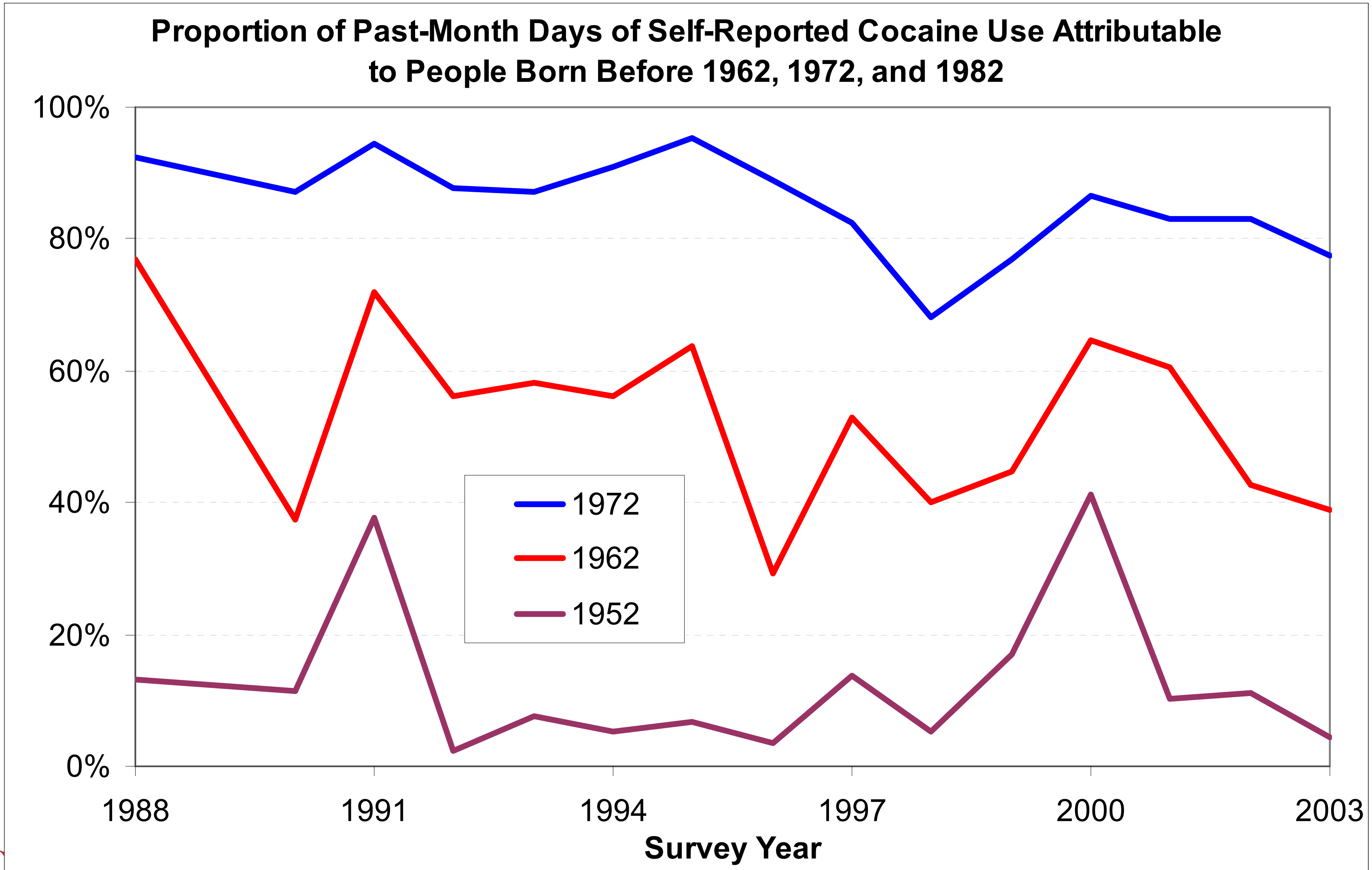
And Even Household Crack Use



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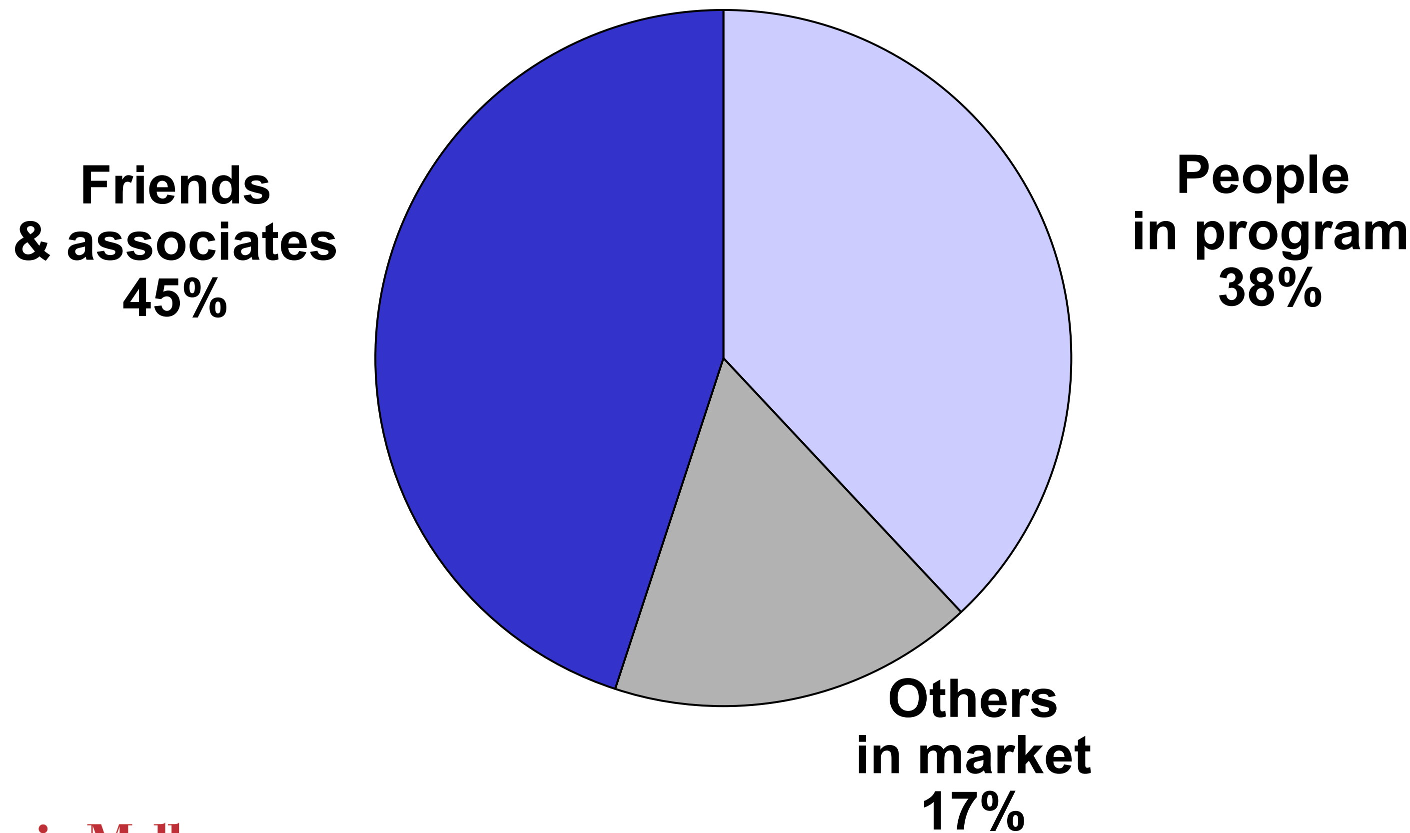
Focusing on Program Participants Overlooks Most Benefits of Prevention

Sources of prevention's reduction in cocaine use



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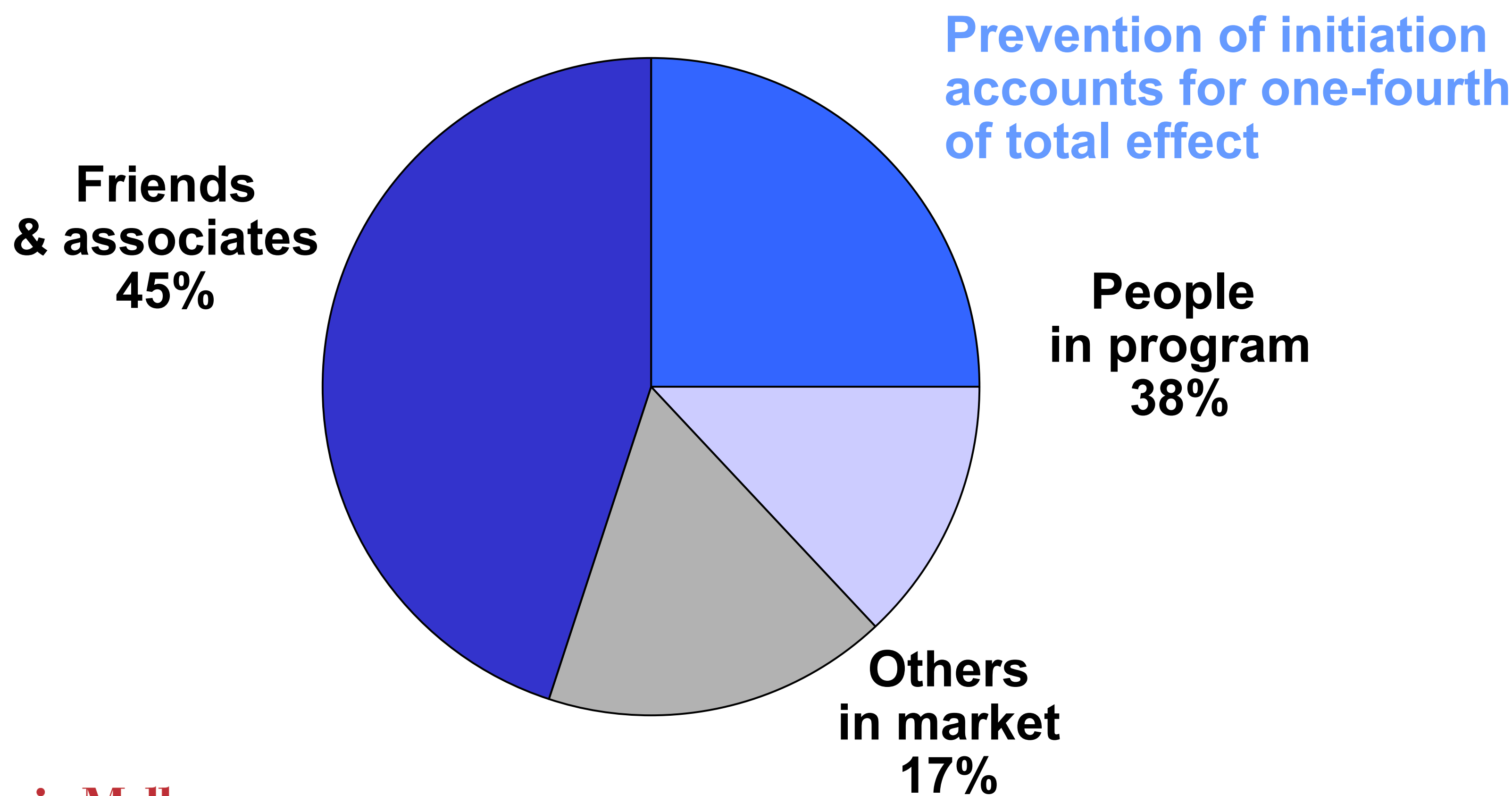

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School-Based Prevention's Cost per Participant Is Modest

Cost Category	**Cost**
Curriculum and training	**$ 2**
Curriculum, training, and teacher time	**$ 70**
Curriculum, training, teacher time, and facilities	**$150**

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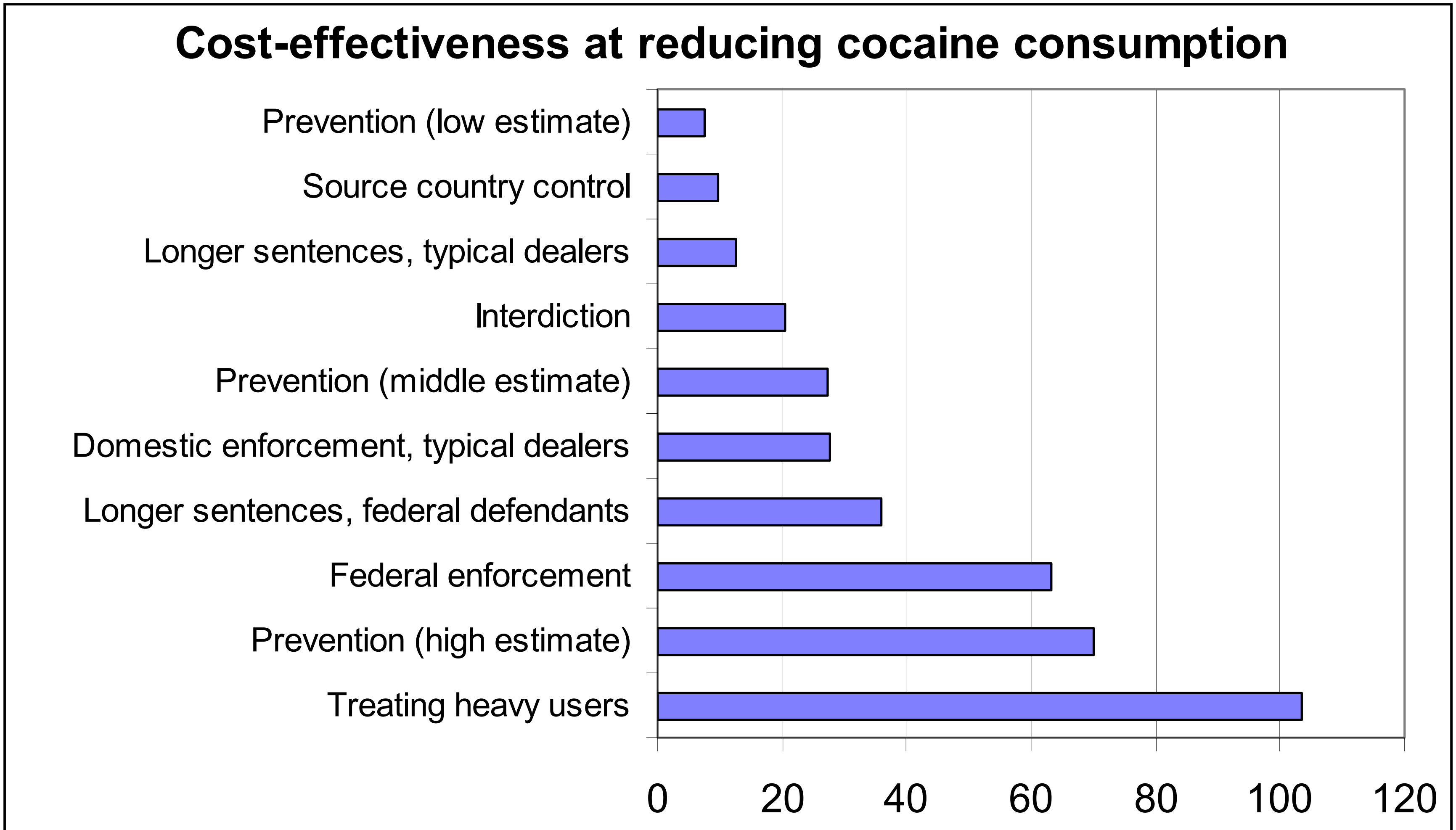


Major Limitation of Early Cost-Effectiveness Analysis

- Most analysis focuses on drugs that are the biggest problems
- Drugs that are the biggest problem (cocaine in the US; heroin in Europe) have mature, stable patterns of use
- No reason to think relative CE of different interventions is the same at different stages of an epidemic

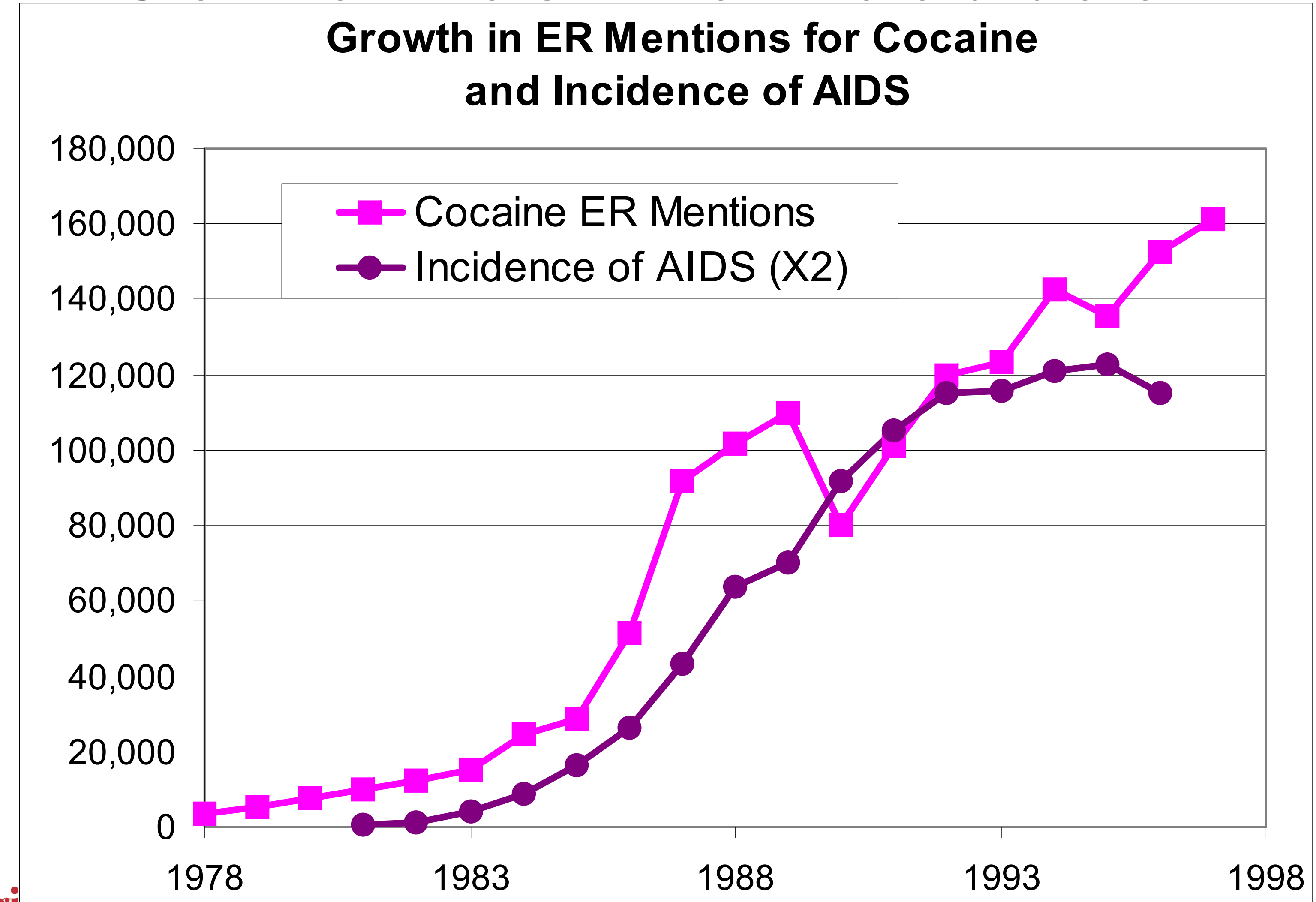
Major Points Concerning Dynamic Drug Policy Analysis

- Some facts concerning drug dynamics
  - E.g., drug-related phenomena change rapidly (faster than "root causes")
- Theory suggests drug "system" has nonlinear dynamic feedback
- Typology of epidemic models & policy implications
- Key insights from "Vienna" models

Observations Concerning Drug Dynamics

- Rapid, ***convex*** growth
- Overshoot
- Subsequent undershoot – sometimes
- Ongoing oscillation?
- Price matters
- Policy variation not main driver
  - Definitely for demand-side
  - I believe generally true for supply-side

Use Can Explode: There is Some Positive Feedback



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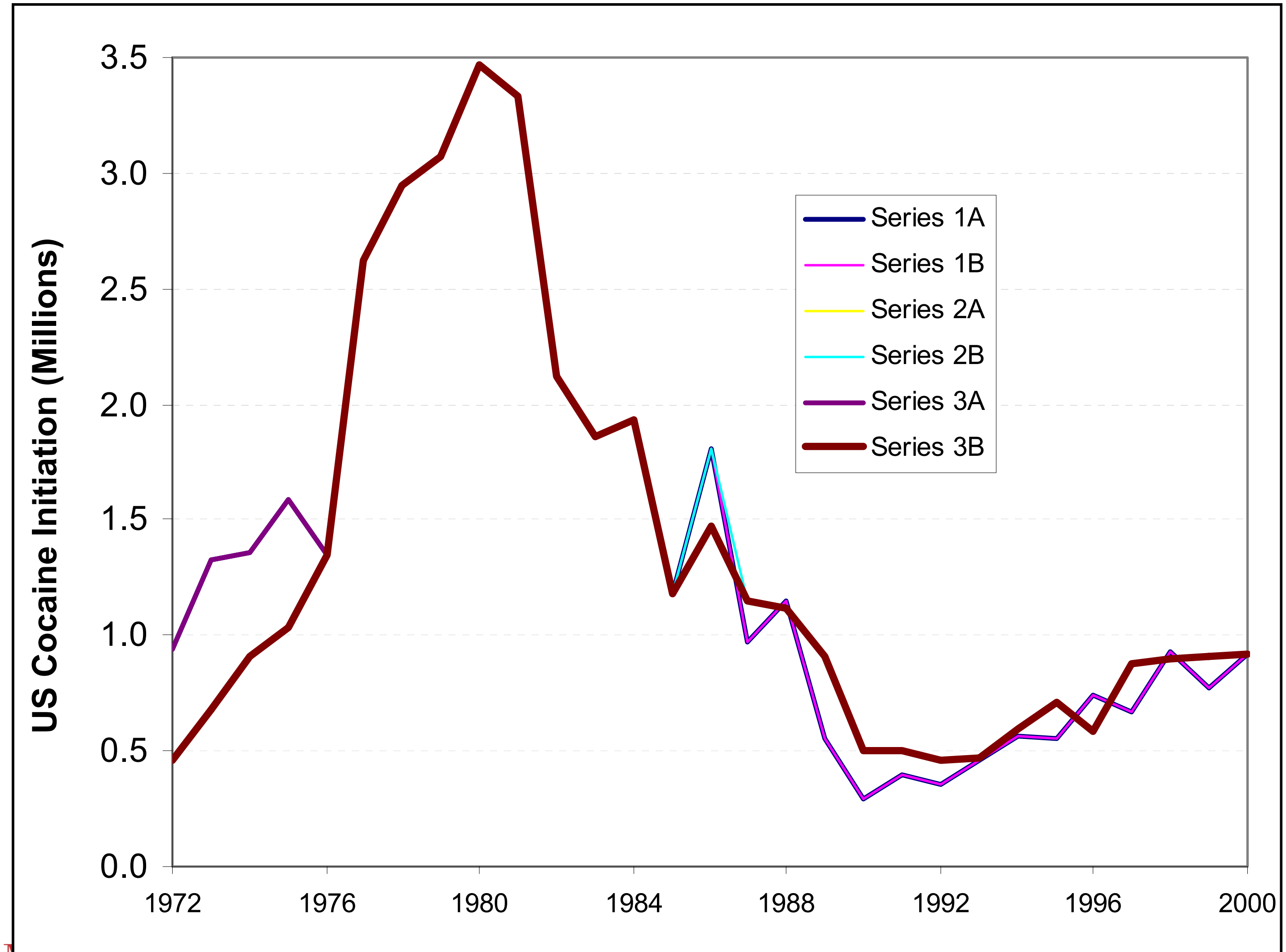
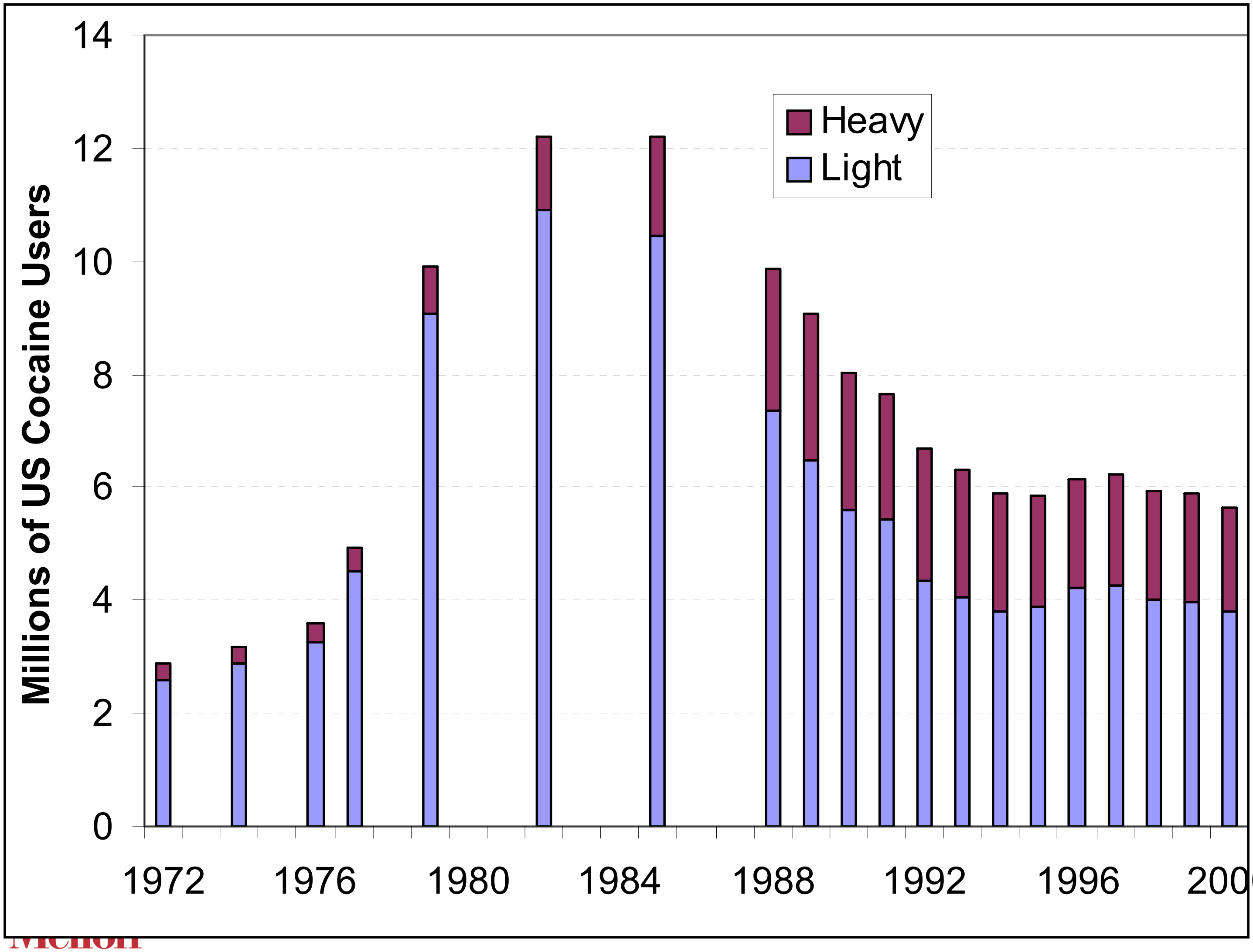
Convex Growth

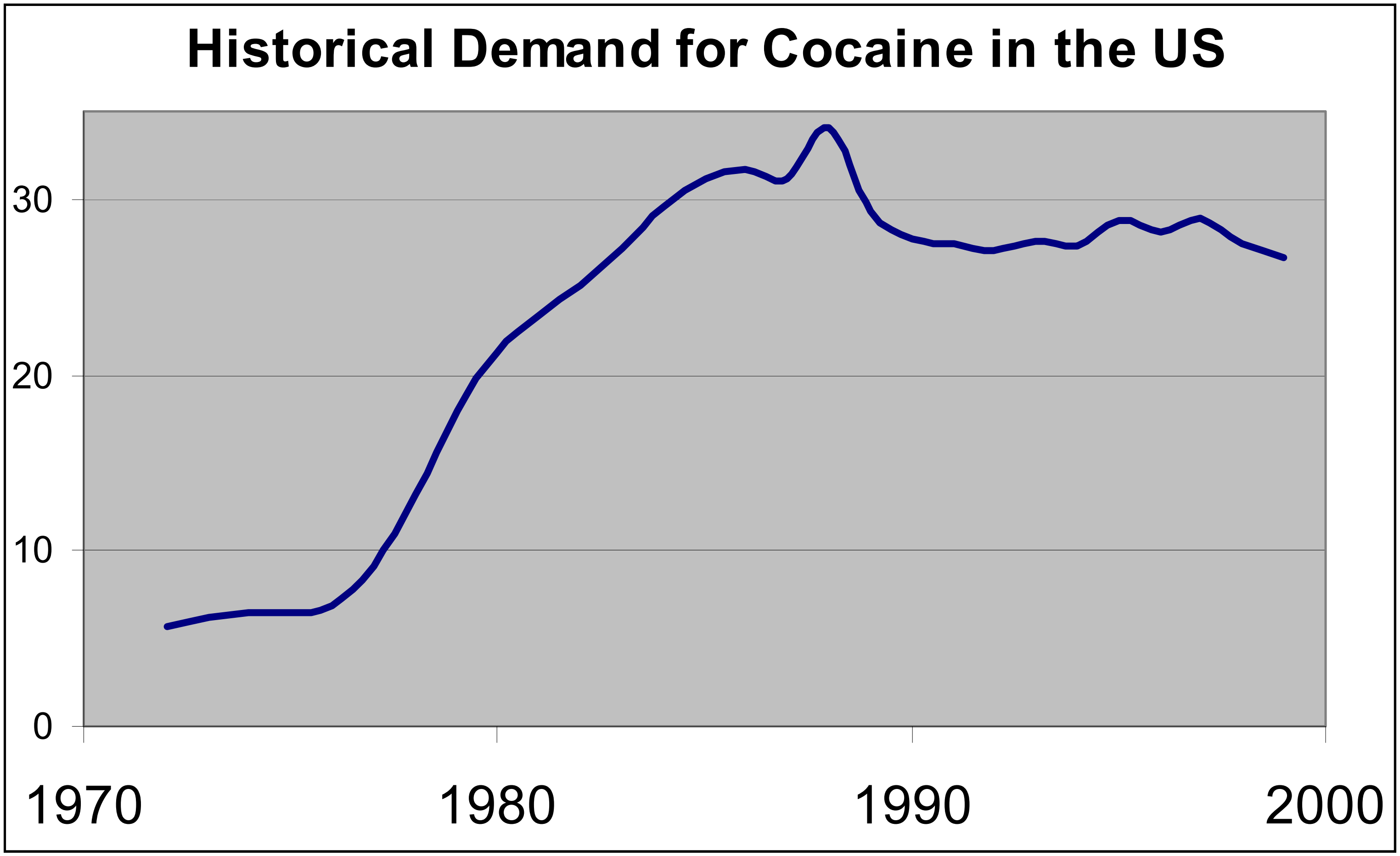


Overshoot



Millions of US Cocaine Users
14
12
10
8
6
4
2
0
Heavy
Light
1972
1976
1980
1984
1988
1992
1996
2000

Sometimes Peak Leads to a Plateau (& Slow Decline?)



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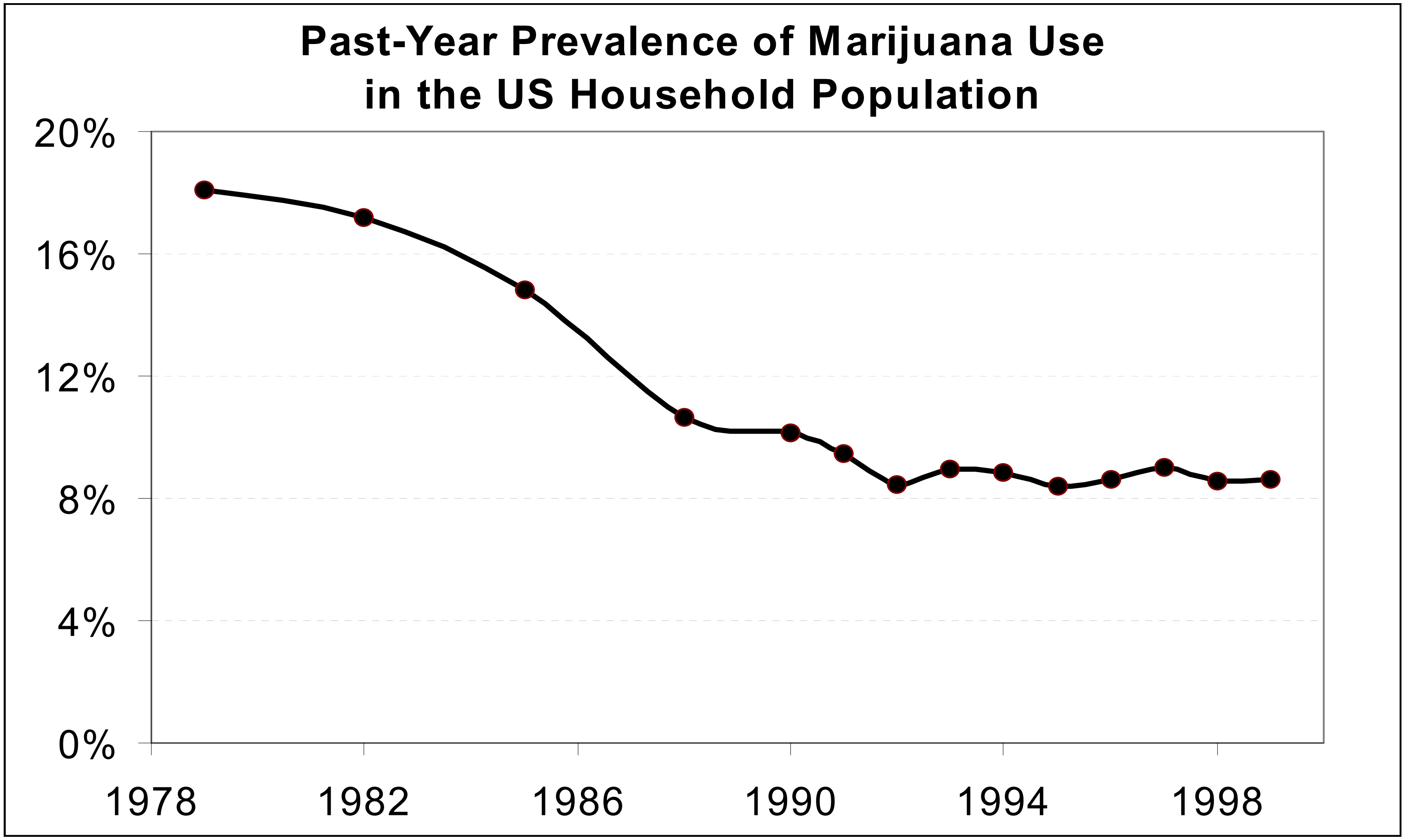
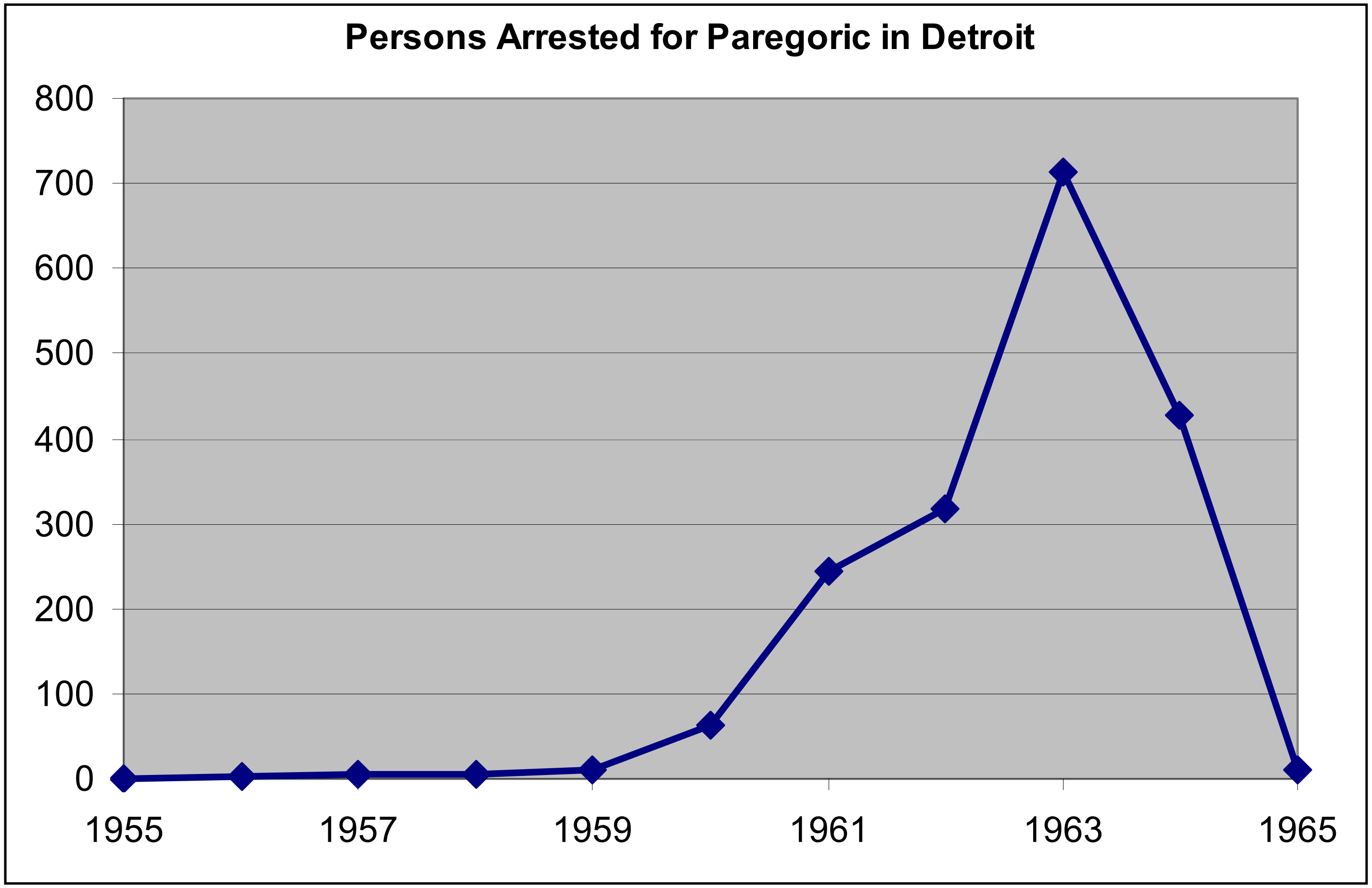
Sometimes Peak is Followed by Significant Decline



Sometimes Use Drops As Fast As It Rose



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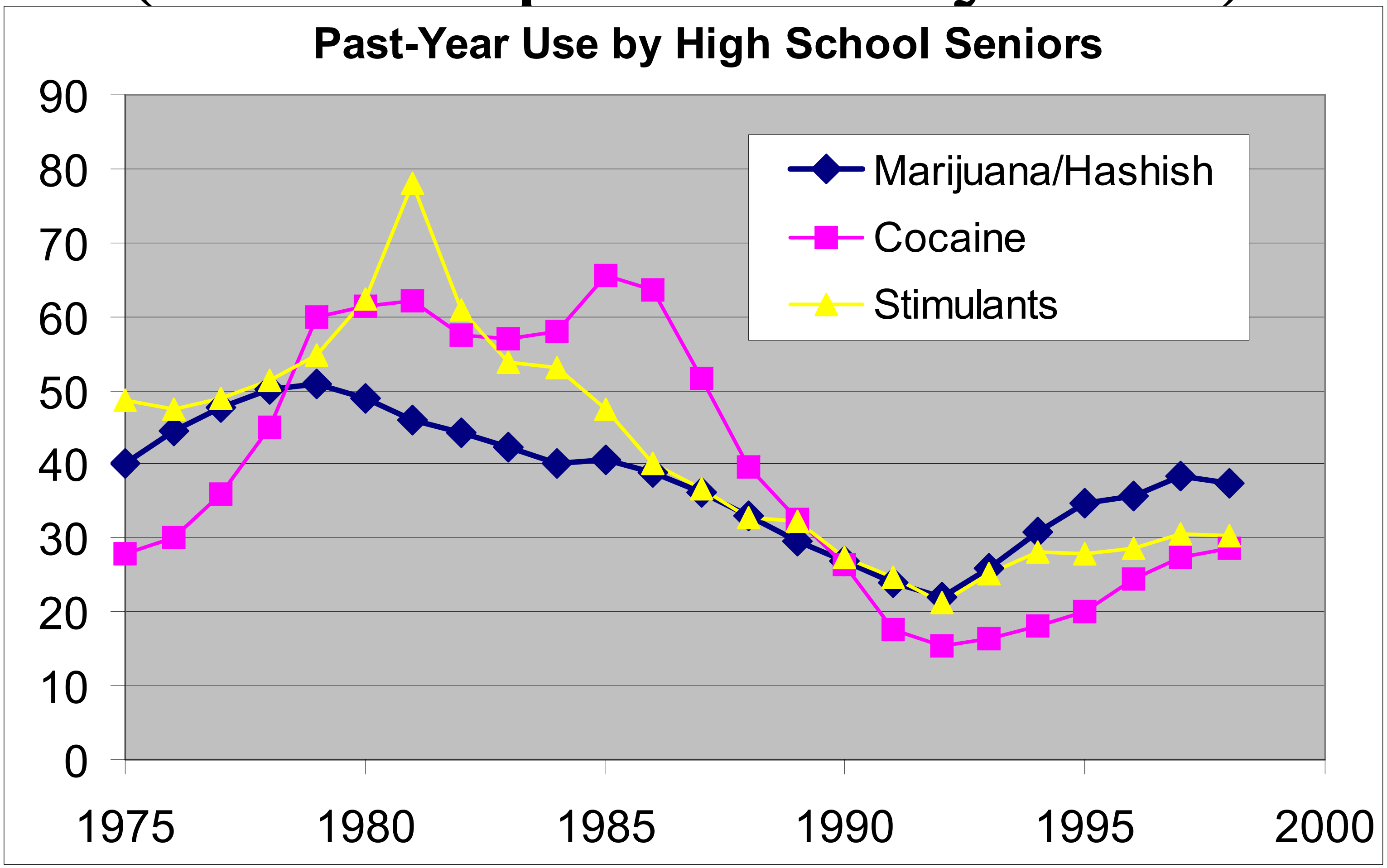
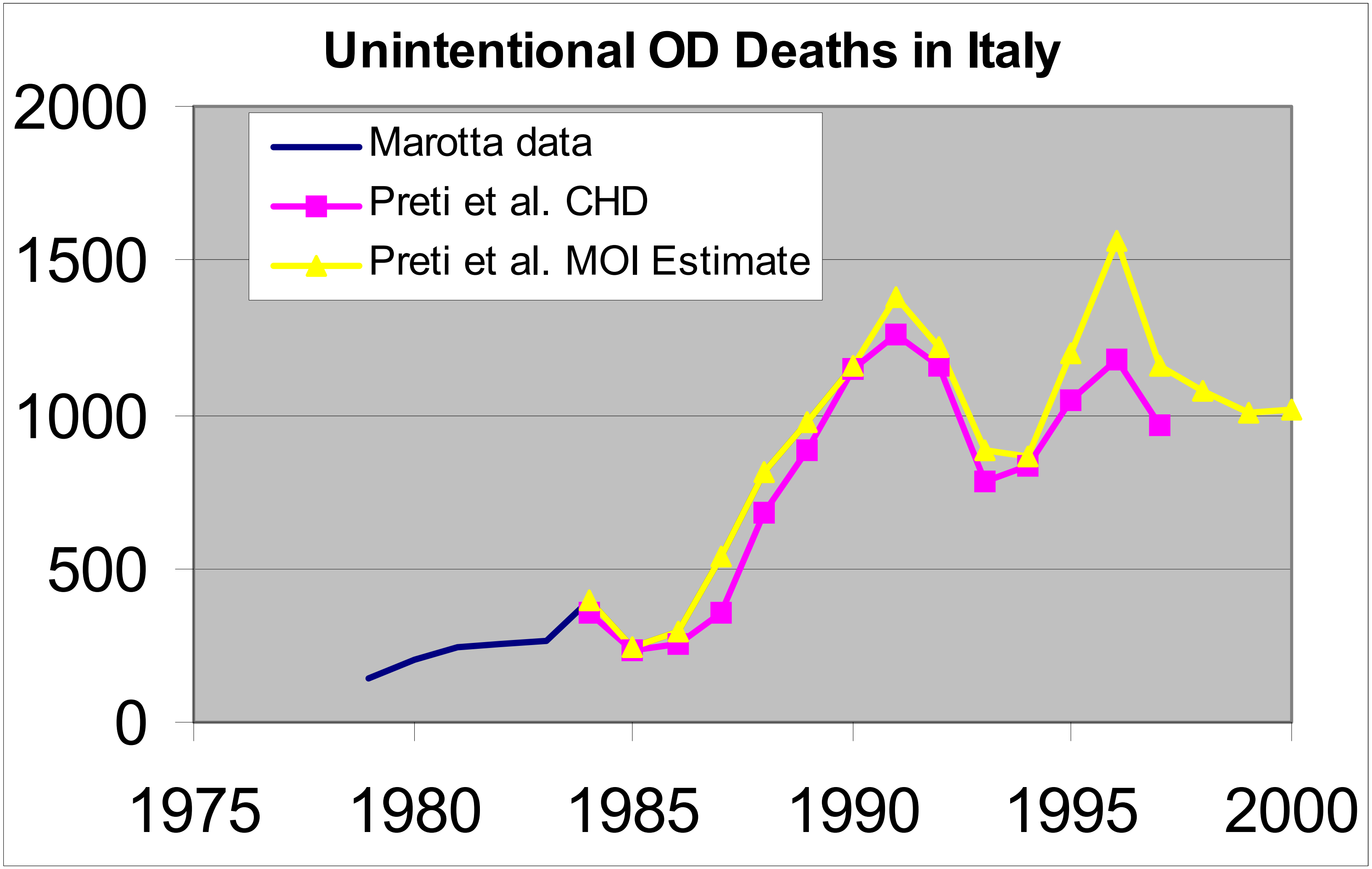
Evidence of Undershoot (or Perhaps Even Cycles?)



More Evidence of Cycles?



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Linear Adjustment Dynamics Can't Explain This

- Suppose
  - $\hat{Y} = f(X; u)$
  - $\dot{Y} = A(\hat{Y} - Y) = A\ (f(X;u) - Y)$
- Then
  - $Y(t) = f(X;u) + (Y_0 - f(X;u))\ e^{-At}$
  - Exponential chasing of slowly moving f(X;u)
- Can't explain
  - Convex growth, overshoot, undershoot, or cycles
  - Unless they are driven by X(t), but amplitude and time constant of variation in Y(t) doesn't match that of X(t)

Alternative Paradigm

- Focus on endogenous nonlinear dynamics
- $\dot{X}$ = f(X; u)

Nonlinear Feedback Effects

- Friends initiate friends
  - Positive feedback from light use to initiation
- Musto effect
  - Knowledge of adverse consequences suppresses initiation
  - Negative feedback from heavy use to initiation
- Enforcement swamping
  - Market participants respond to incentives, such as enforcement intensity
  - Enforcement intensity is amount of enforcement per person exposed to that enforcement
  - So $dN/dt = f(E/N)$

More Nonlinear Feedback

- State-Dependent Demand
  - Demand today = f(Q consumed yesterday)
  - At individual level, have three states with different time constants of decay
    - "Addiction" (Dependence)
    - Tolerance
    - Intoxication
- Learning by doing
  - Supply today = f(Q consumed yesterday)

Nonlinear Feedback Effects

- Network externalities
  - Dense markets more efficient
  - Density of use modulates reproductive rate
- Geographic spread
- Reputation via “generalized other”
- “Barriers to exit” (from dealing)
- Drug control budgets/efforts
- Stigma swamping
- Musto effect beyond initiation
  - Knowledge of consequences suppresses escalation and/or encourages desistance

Typology of Epidemic Models: Models That Ignore Dynamics

1) No important internal dynamics; “root causes” determine use and control has little effect on use.
2) No important internal dynamics; use is a direct reflection of success (or failure) of drug control efforts.

Typology of Epidemic Models: Logistic Growth Models

3) Use grows exponentially "without bound", unless constrained by control.

4) High-levels of use are the only stable state. Low-levels observed only as transients. Control is futile.

5) Tipping models with stable low- and high- volume equilibria. Control's value depends on state.

Mathematically, these can be seen as variations on the same basic theme.

Typology of Epidemic Models: Endogenous Initiation Declines

6) Explosion from naïve state unavoidable, but epidemic ebbs as susceptibles are exposed and become resistant. Regardless of control policy, everyone uses, but most soon quit of their own accord.

7) Use can grow exponentially but internal, lagged negative feedback brings use back down. Well-timed control efforts are very valuable.

8) (New) Prevalence-dependent infectivity generates overshoot and tipping, with or without reputation feedback

Typology of Epidemic Models

	Endogenous Dynamics	Control's Effect on Drug Use
Symptom of root causes	ignored	minimal
Random walk	ignored	all determinative
"Unbounded growth" absent control	logistic, but high equilibrium is effectively "out of bounds"	our only salvation
Unstoppable, but bounded growth	logistic once triggered	none
Tipping models	logistic above threshold	can keep Pandora's box closed, but not close an open box
All infected, few addicted	SIR structure	minimal
Musto models	immediate positive feedback + lagged negative feedback	depends on timing

"Vienna" Approach

- Build simple mathematical models of drug use and feedback effects
- Solve as optimal dynamic control problems
- Note whether and how optimal mix of interventions varies over time
- Draw tentative inferences about policy

Some “Vienna Models”

- One-state model (A(t) = # of “addicts”)
- Two-state LH models
- Three-state LHY and LHE models
- Four-state LMHQ model
- Age-Distributed Models
- Susceptibility as stable personality trait
- SA/SLH models

Basic One-State Model

$$Min \;\; J = \int_0^\infty e^{-rt} \left(\kappa\, \theta\, A(t)\, p\big(A(t), v(t)\big)^{-\omega} + u(t) + v(t) \right) dt$$

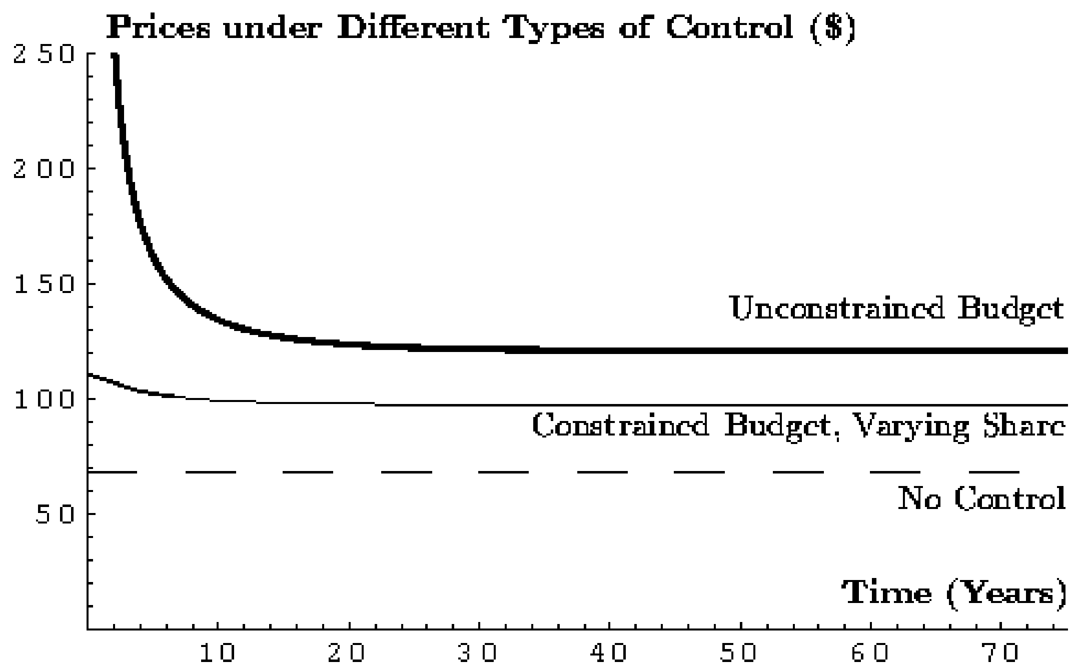
$$u(t), v(t) \geq 0$$

$$\dot{A}(t) = k\, p\big(A(t), v(t)\big)^{-a} - c\, \beta\big(A(t), u(t)\big)^{z} A(t) - \mu\, p\big(A(t), v(t)\big)^{b} A(t)$$

$$\beta\big(A(t), u(t)\big)^{z} = \left(\frac{u(t)}{A(t) + \delta} \right)^{z}.$$

$$p\big(A(t), v(t)\big) = d + e \frac{v(t)}{A(t) + \varepsilon},$$

It Can Be Optimal for Prices to Collapse As Epidemic Grows



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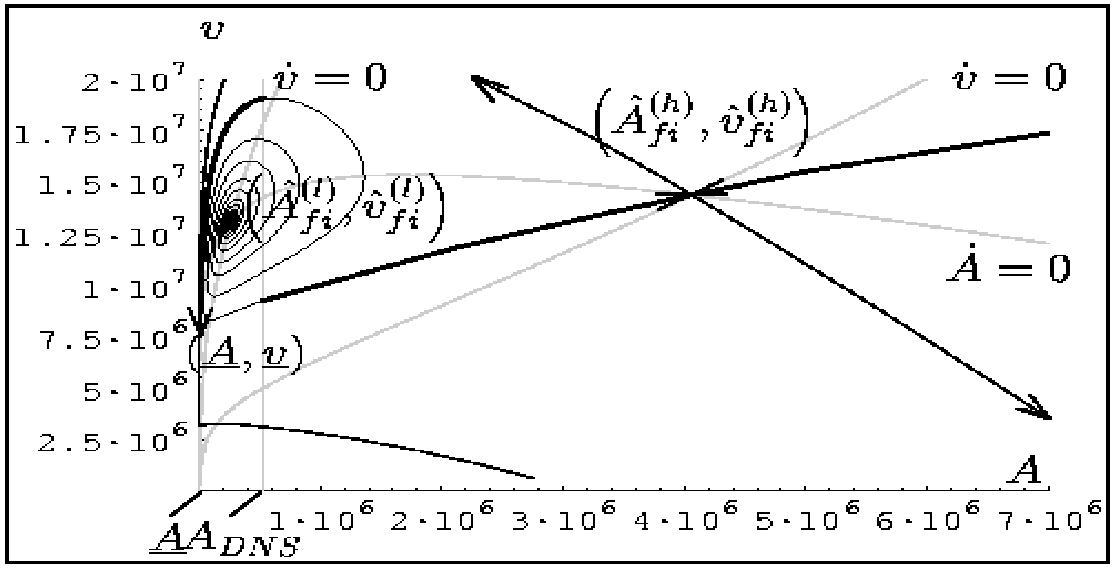
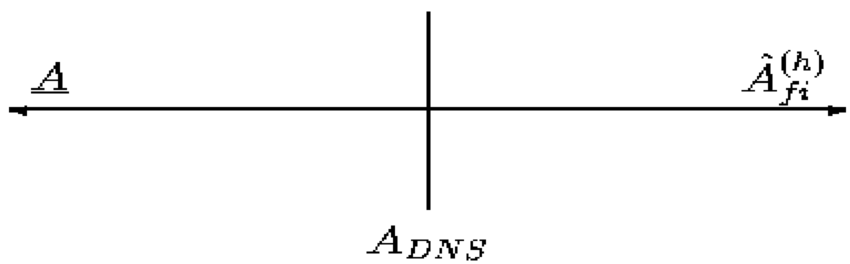
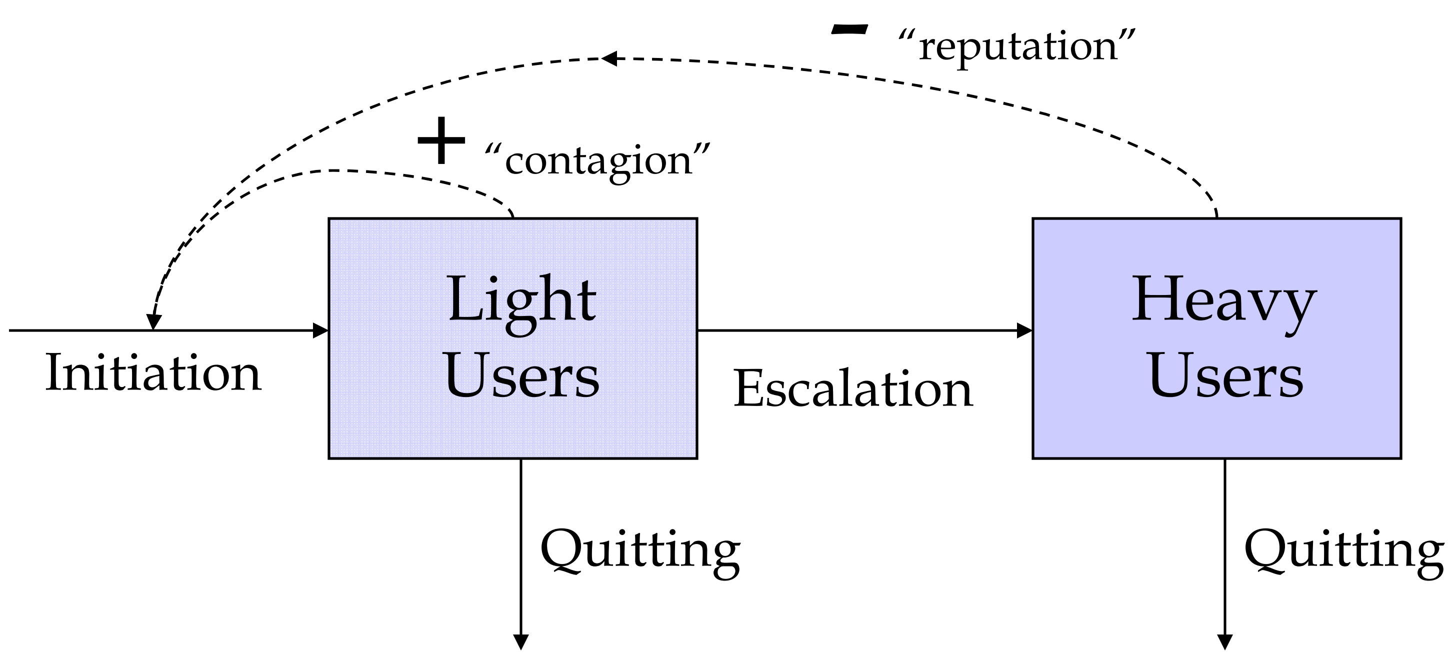
For initial states A_0 below A_{DNS} it is optimal to "eradicate" drug use, while above A_{DNS} a steady state with a high number of users turns out to be optimal



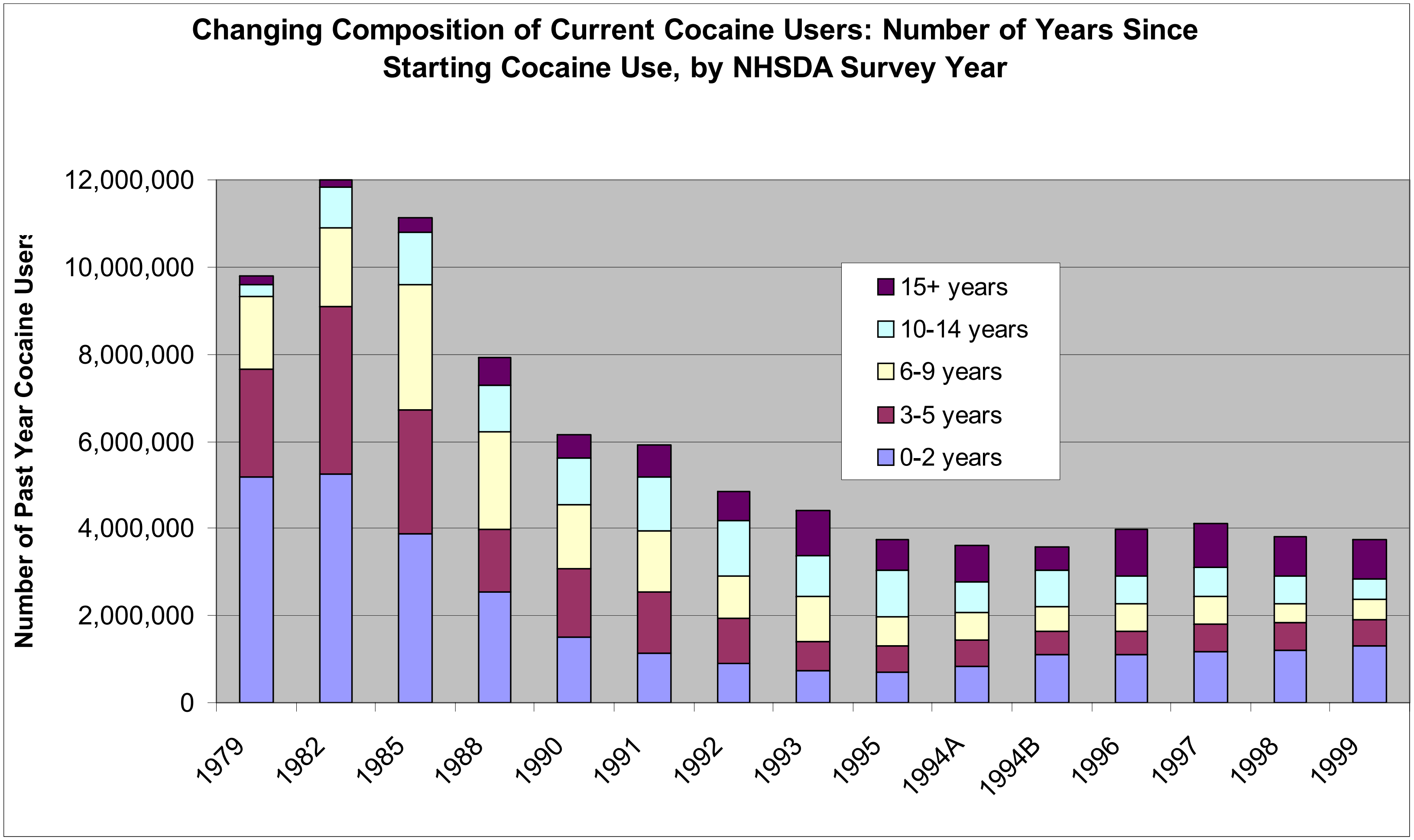
A_{DNS} ... *Dechert-Nishimura-Skiba* threshold



Schematic Two-State LH Model of "Musto" Dynamics



Knowledge Base Concerning Cocaine Really Did Change



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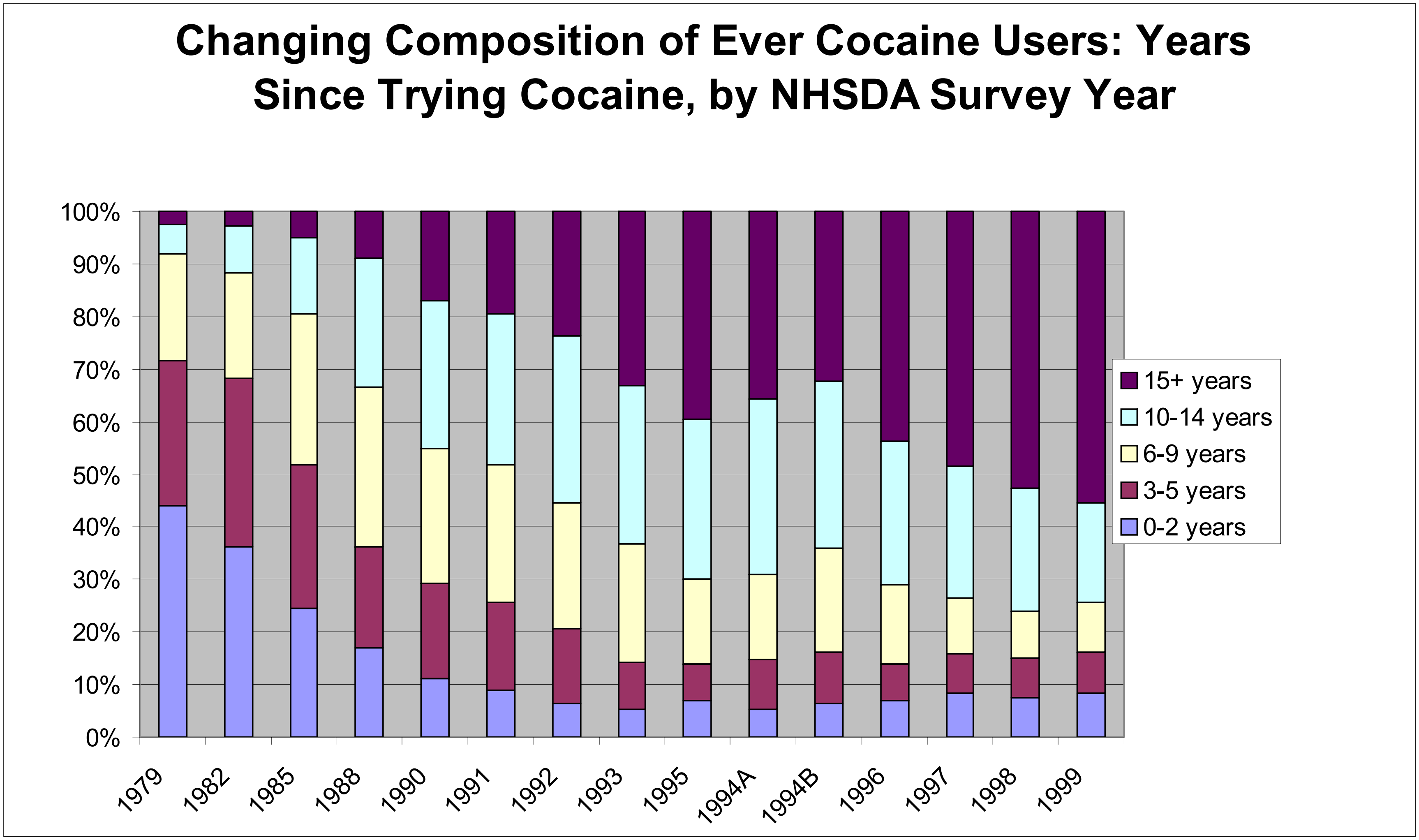
Parallel Graph for Ever Users



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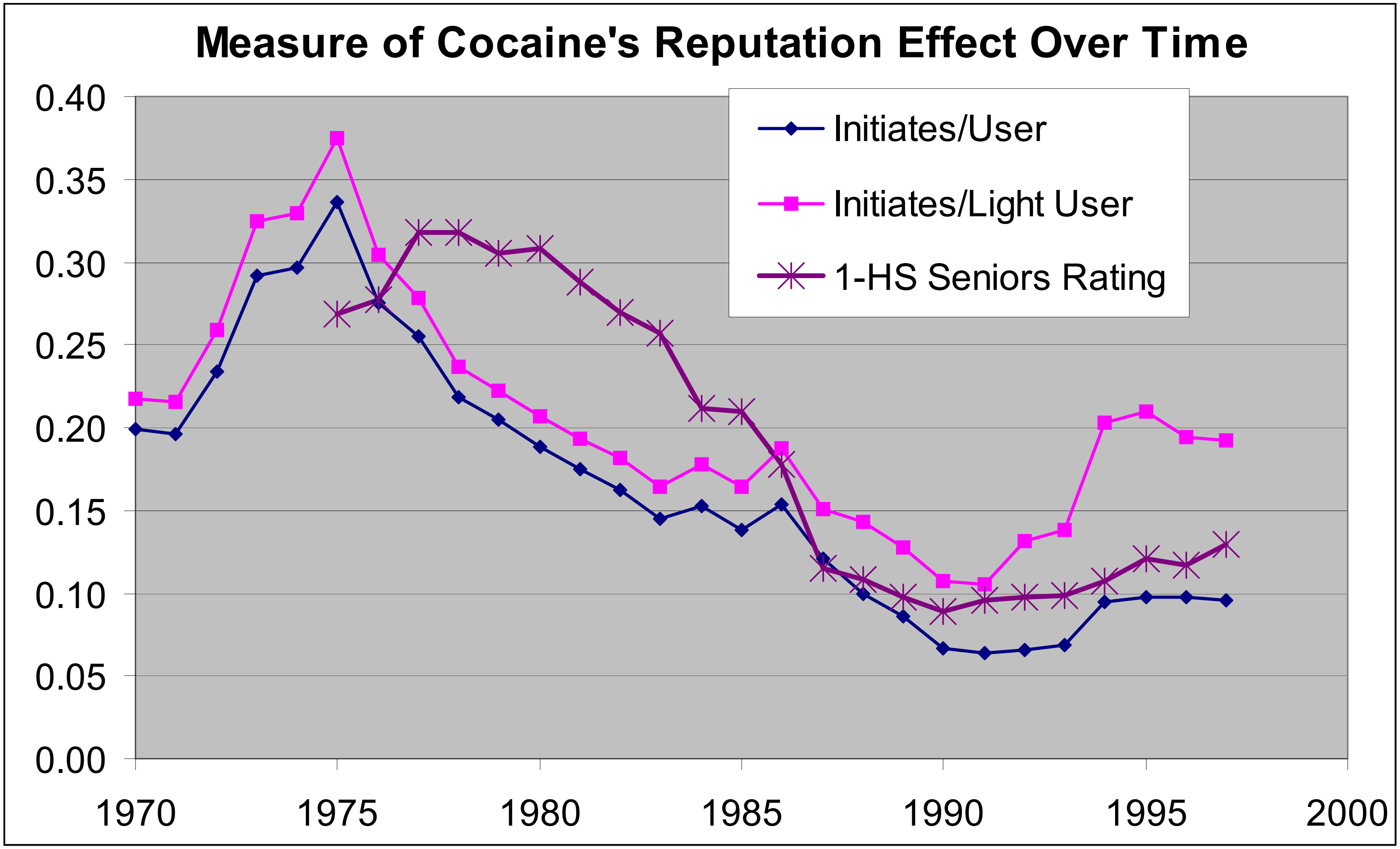
Some Measures of Cocaine's "Reputation Effect" Over Time



Basic Two-State LH Model

$$J = \int_0^\infty e^{-rt} \left(\kappa\, Q(t) + u(t) + w(t)\right) dt$$

$$\dot{L} = I(L,H) - (a+b)L, \qquad L(0) = L_0$$

$$\dot{H} = bL - gH, \qquad H(0) = H_0$$

$$Q(t) = 16.42\, L(t) + 118.93\, H(t)$$

$$I(L,H) = \tau + sL \exp\left[-q\, H/L\right]$$

$$\psi(w) = h + (1-h)\exp[-mw]$$

$$\beta(H,u) = c\left(u/(H+\delta)\right)^d$$

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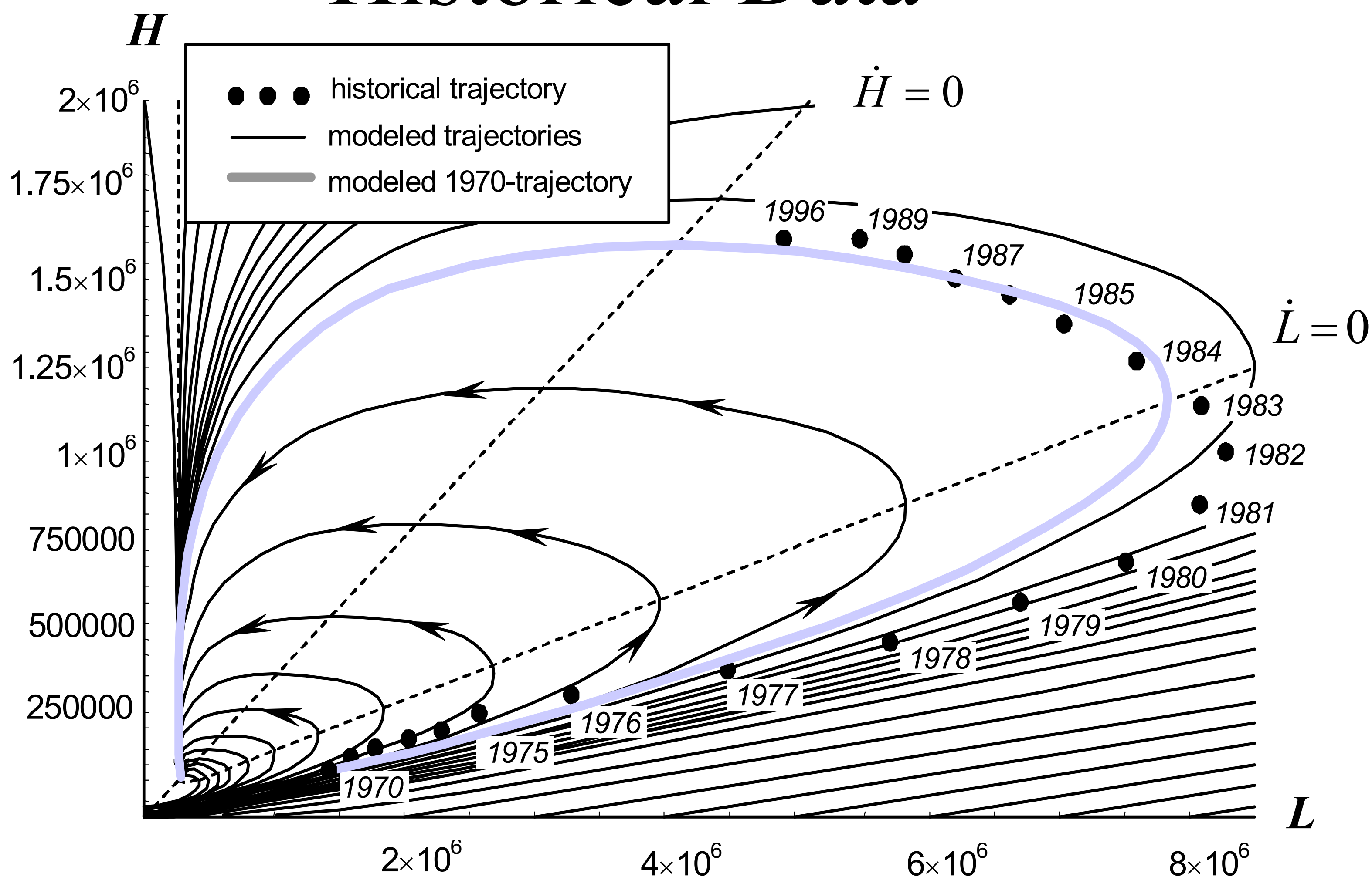
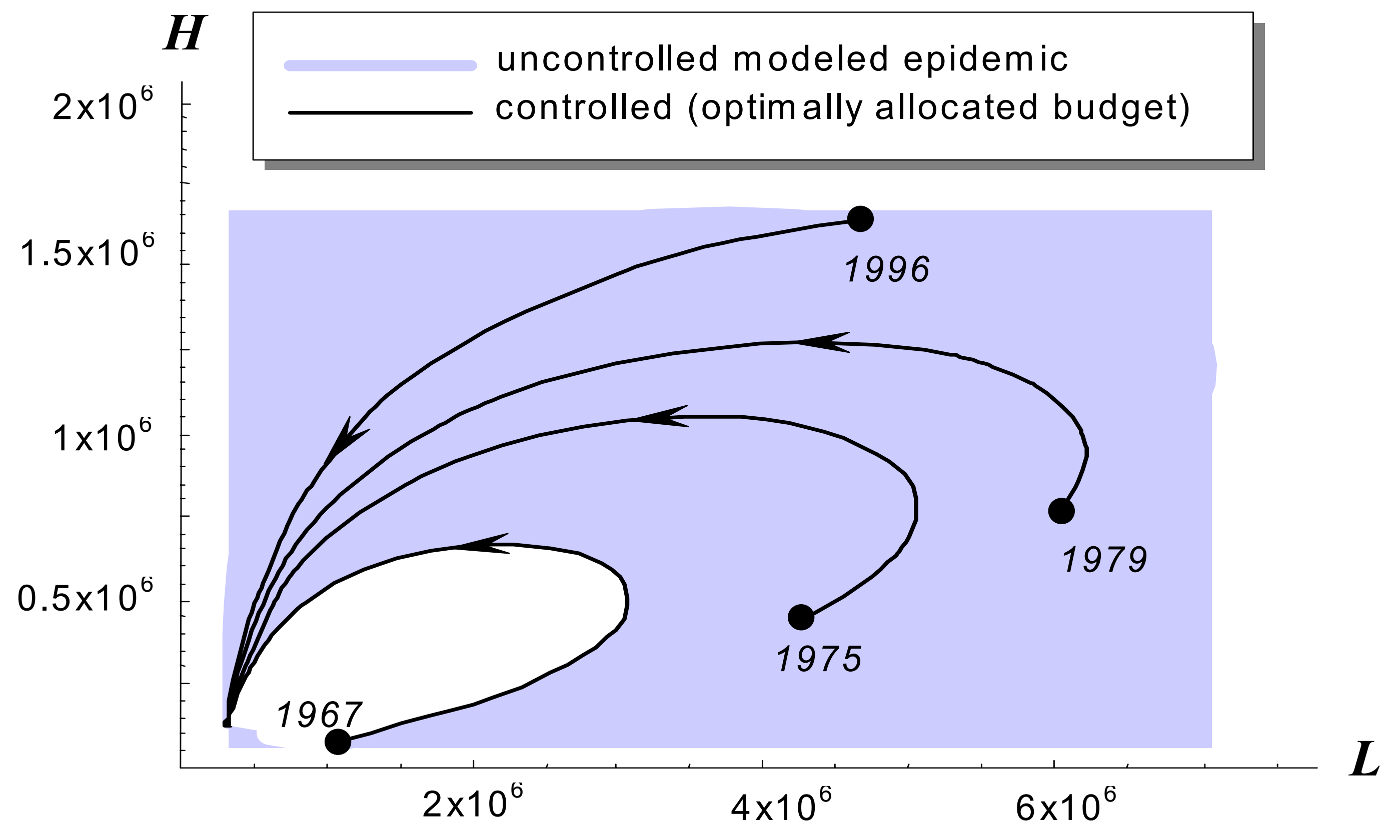
Uncontrolled Dynamics and Historical Data



Early Intervention is Valuable



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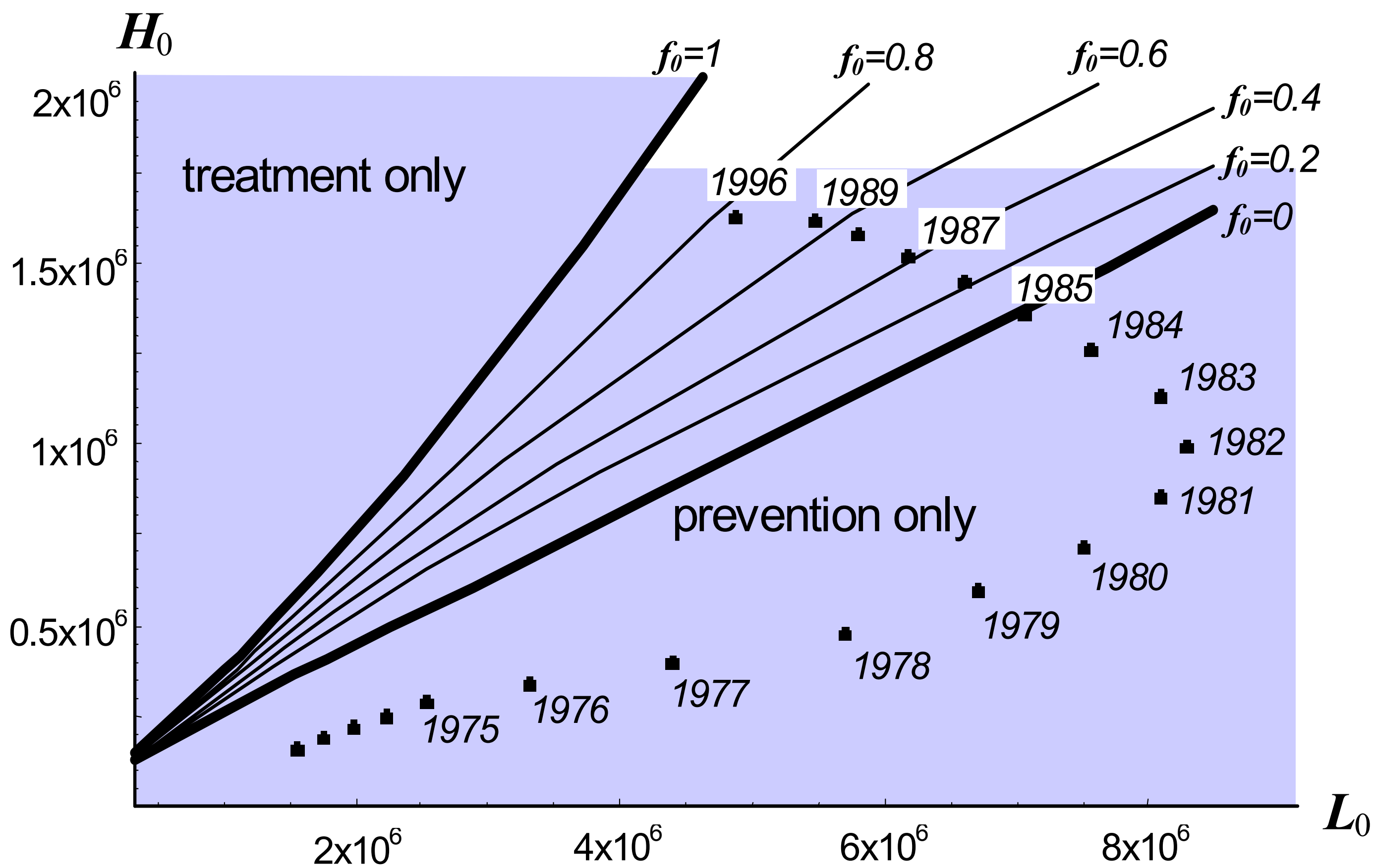
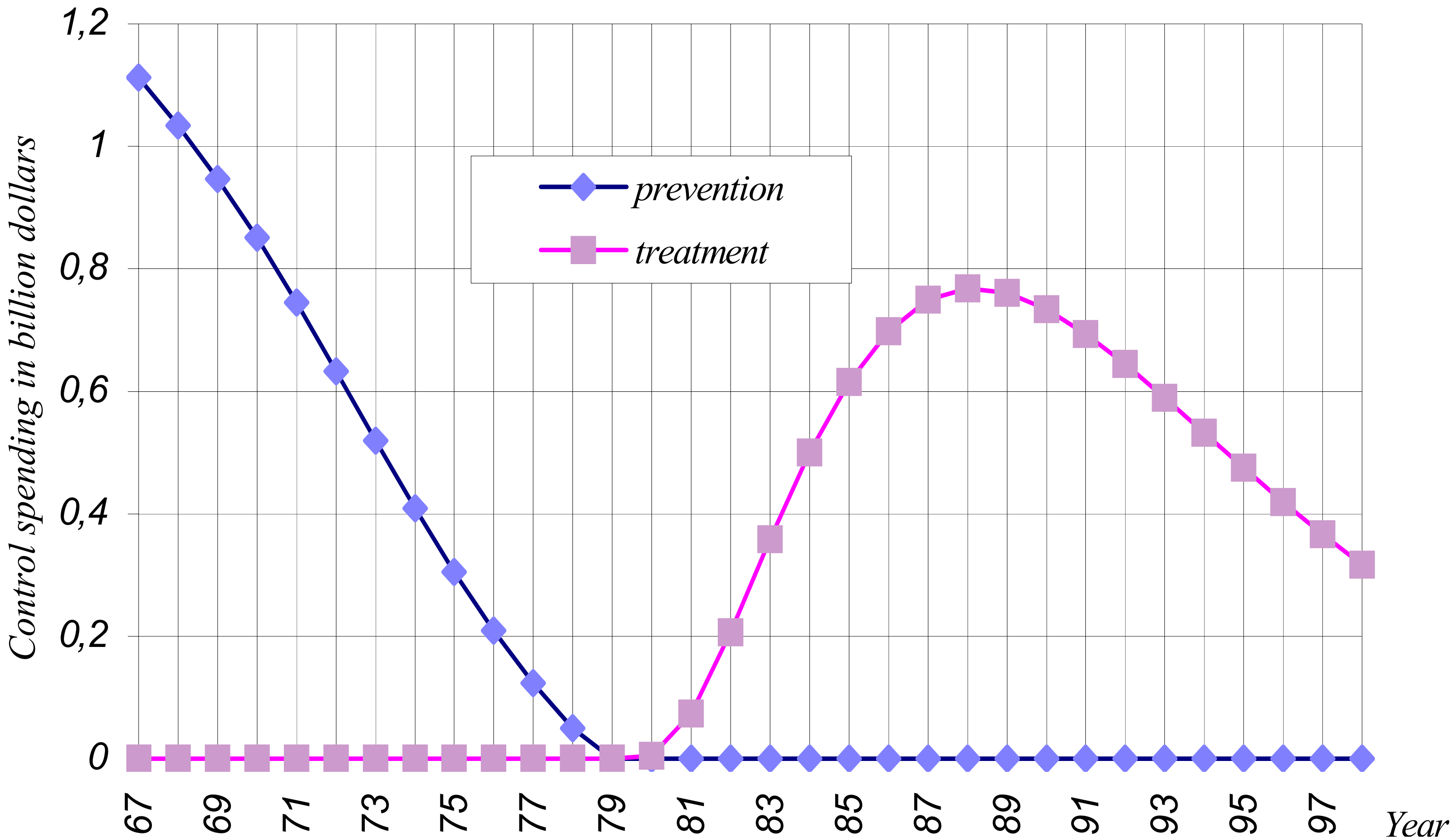
Transition Quickly from All Prevention to All Treatment



Dramatic Result

Treat and Prevent -- But Not at the Same Time



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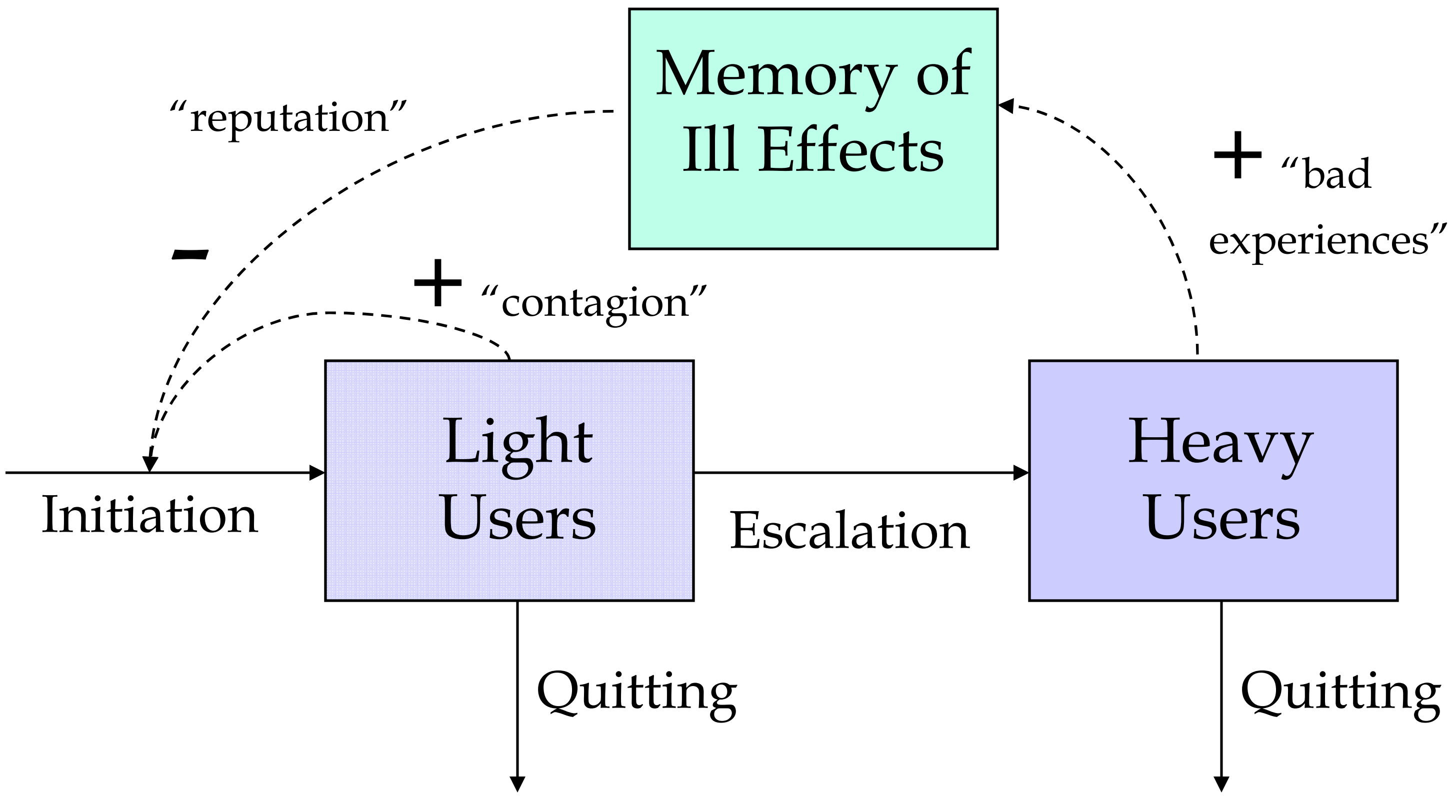
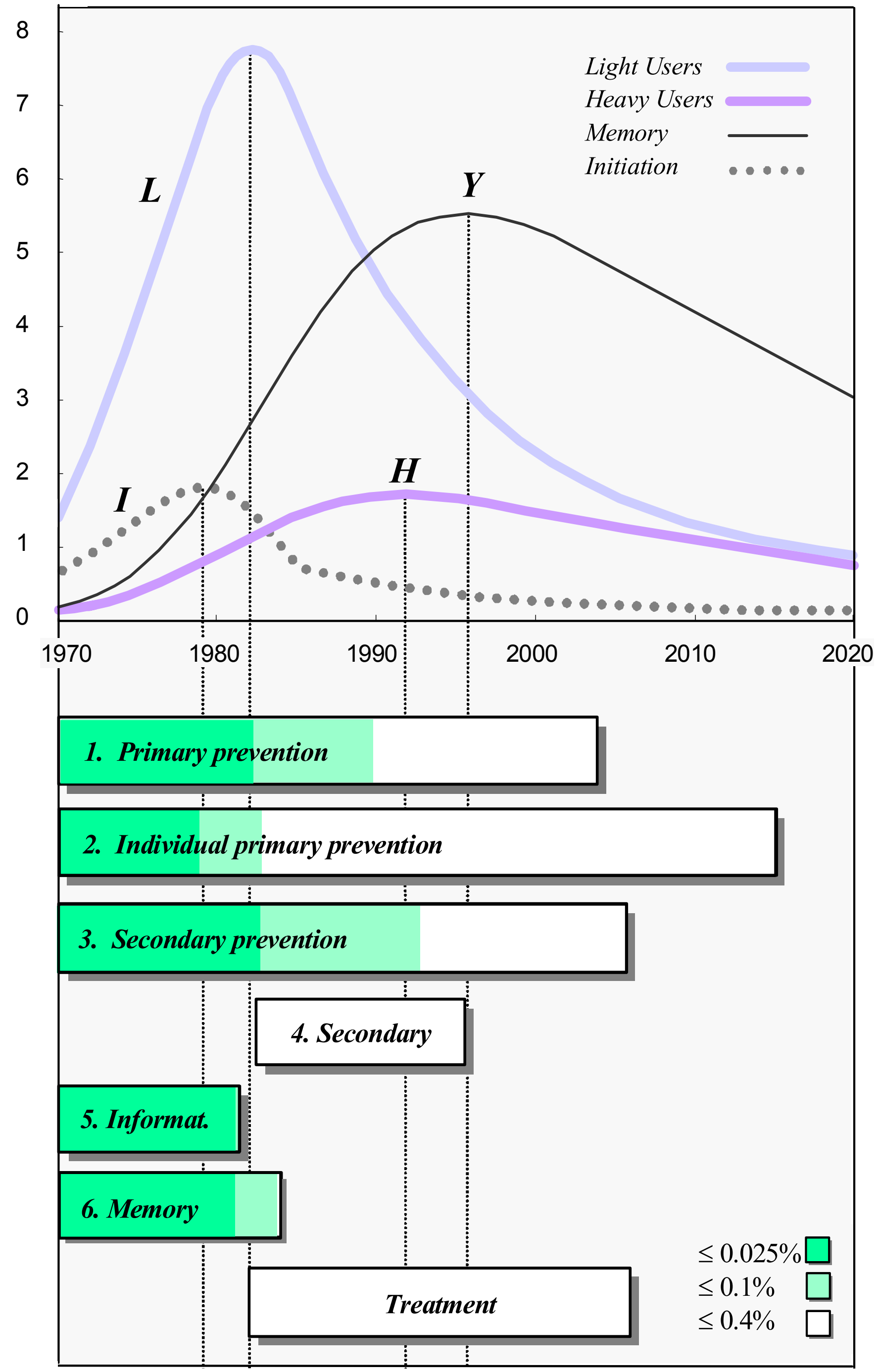
LHY or LHE Versions of Models with "Musto" Dynamics



Estimating the Relative Efficiency of Various Forms of Prevention at Different Stages of a Drug Epidemic



Plot of where prevention is most leveraged (parameter changes of less than $x\%$ yield a pre-specified reduction in future discounted demand).

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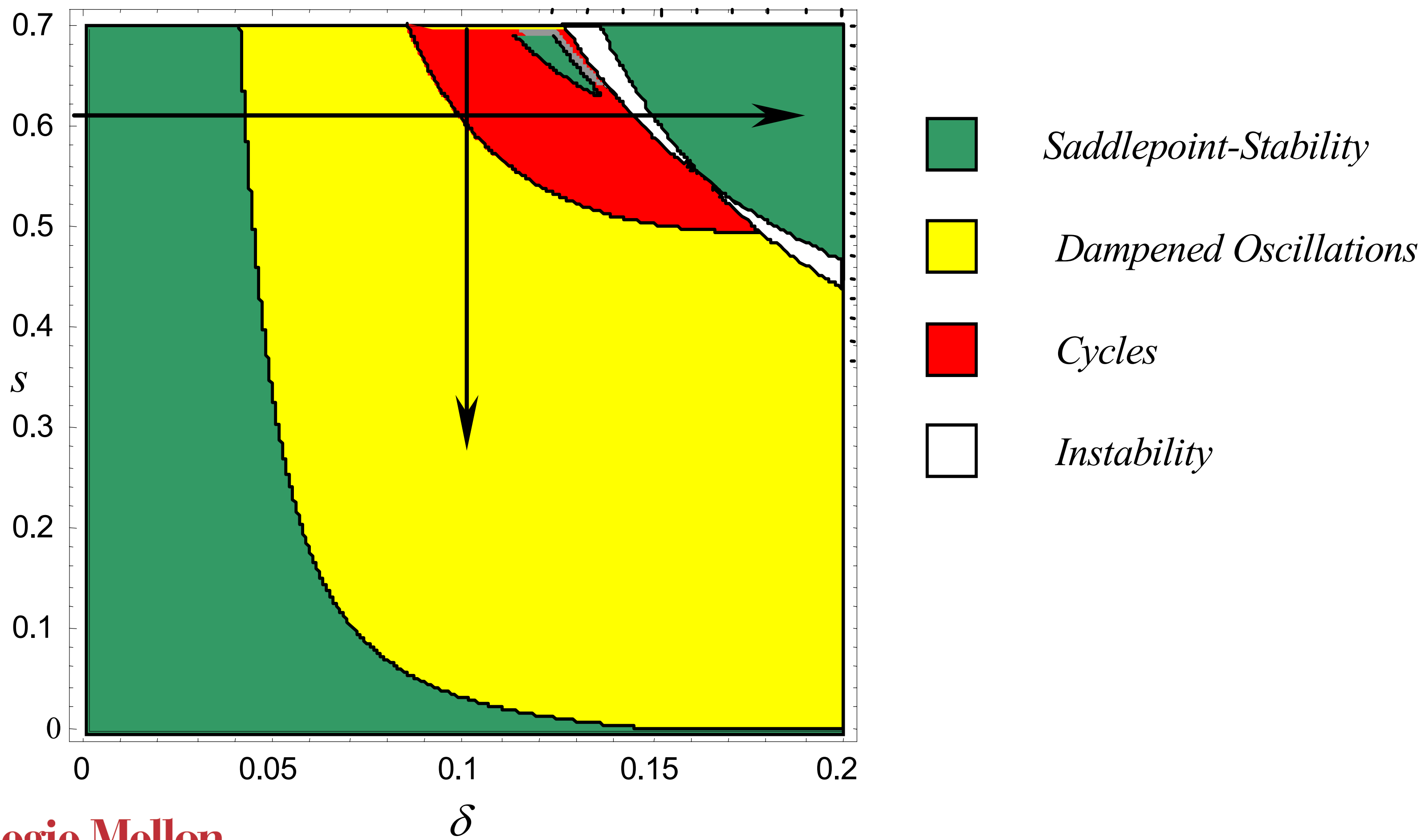
Characterize Types of Drugs that are Prone to Epidemics



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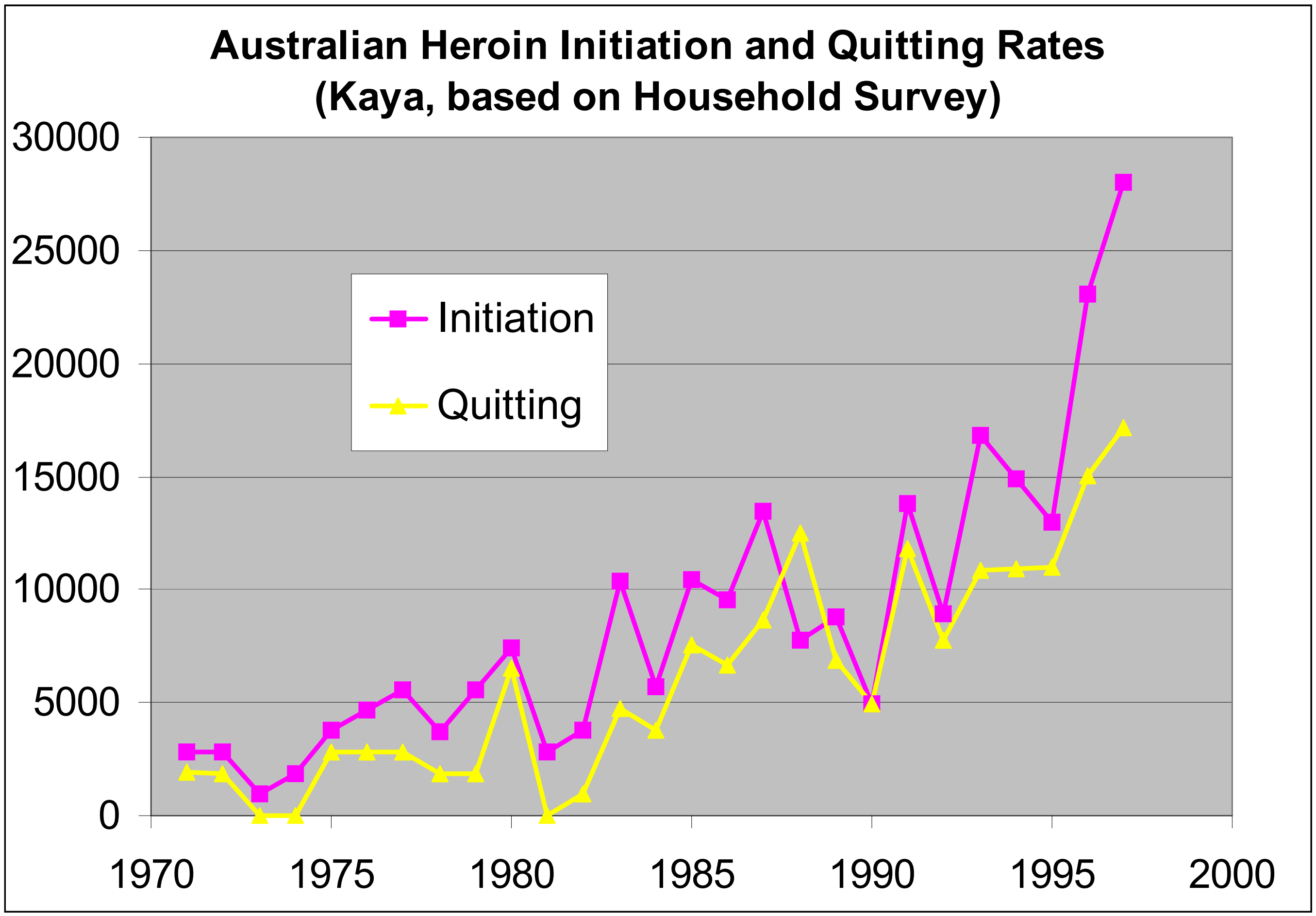
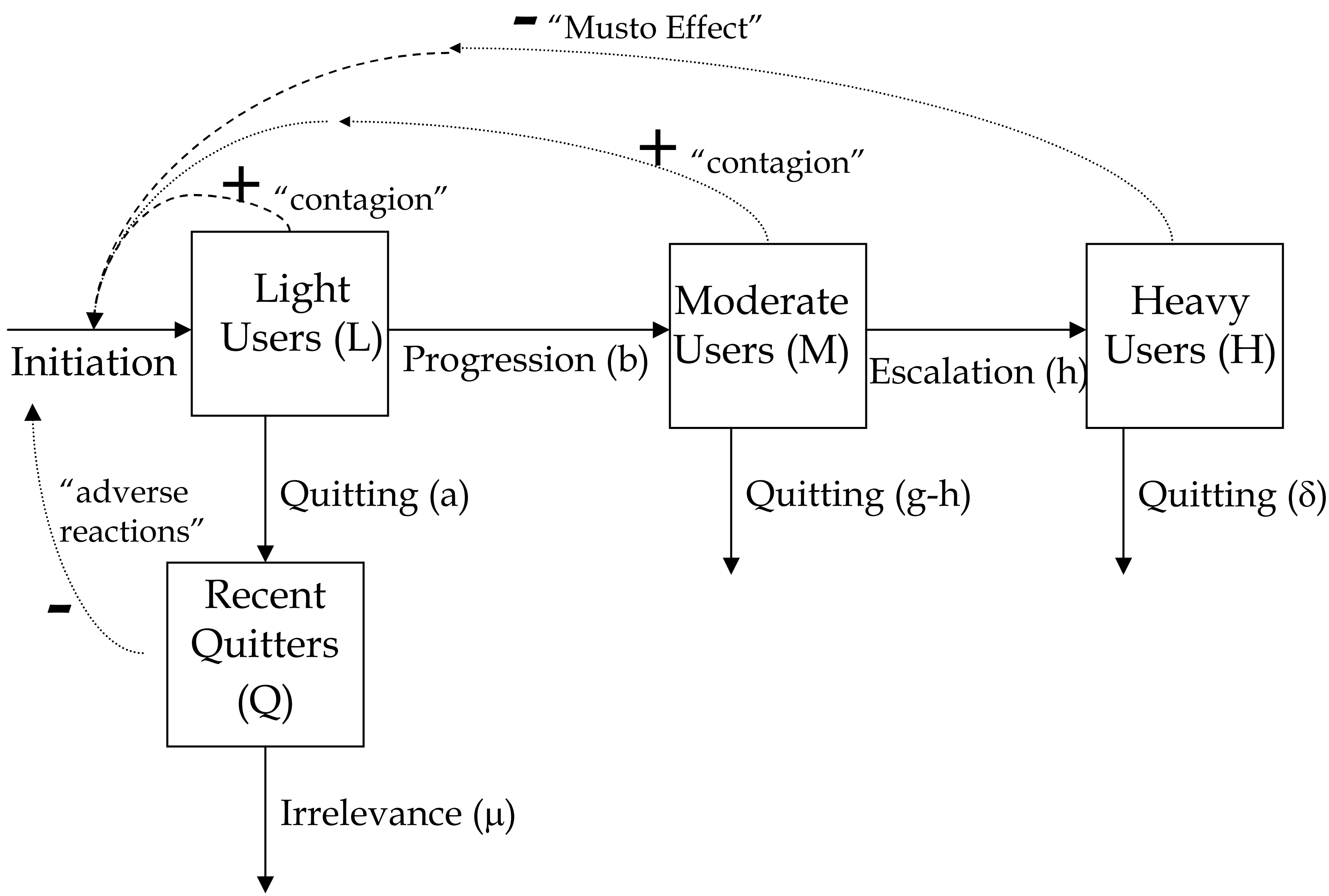
Genesis of LMHQ: Two Distinct Sources of Negative Feedback

- "Musto Effect"
  - Adverse consequences of addiction become known 10 or so years after initiation
- "Adverse Reactions"
  - Adverse reactions can happen much sooner, particularly with novice users who initiated recently
  - Experience of adverse reactions may "disappear" from social environment relatively quickly

(1) Quitting Correlated with Init
(2) Causes Short-term Cycles???



LMHQ Model

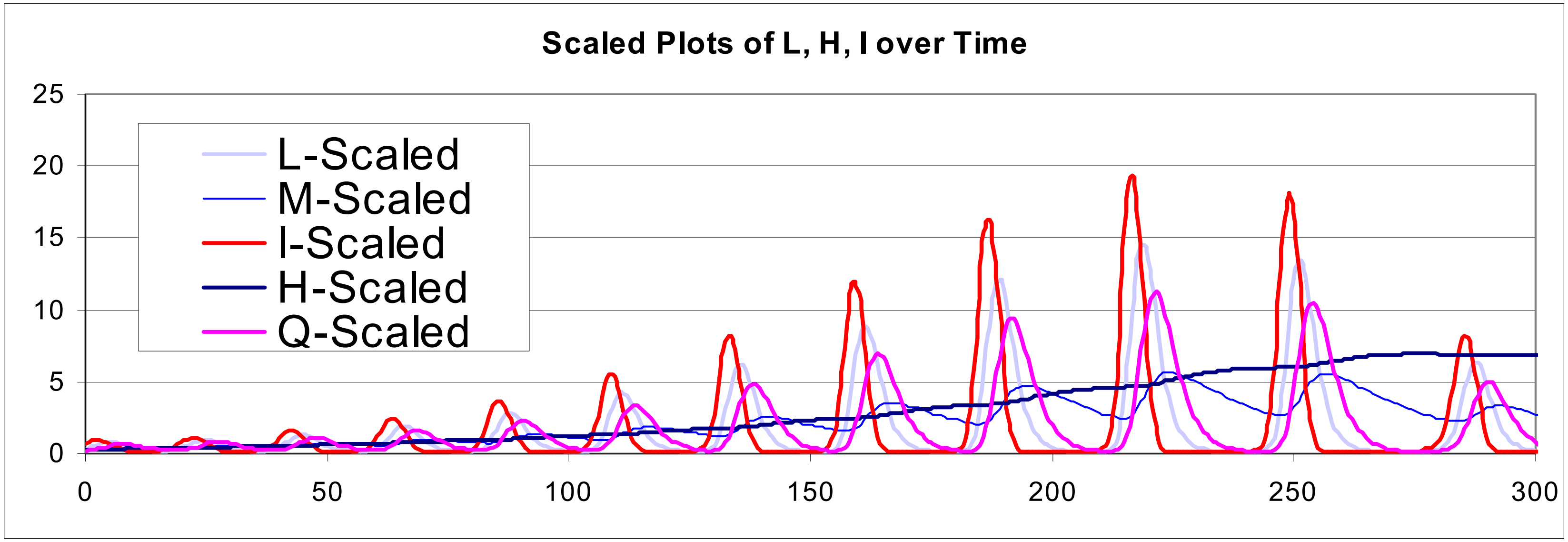

- "Musto Effect"
+ "contagion"
+ "contagion"
Light Users (L)
Moderate Users (M)
Heavy Users (H)
Initiation
Progression (b)
Escalation (h)
Quitting (a)
Quitting (g-h)
Quitting (δ)
"adverse reactions"
-
Recent Quitters (Q)
Irrelevance (μ)

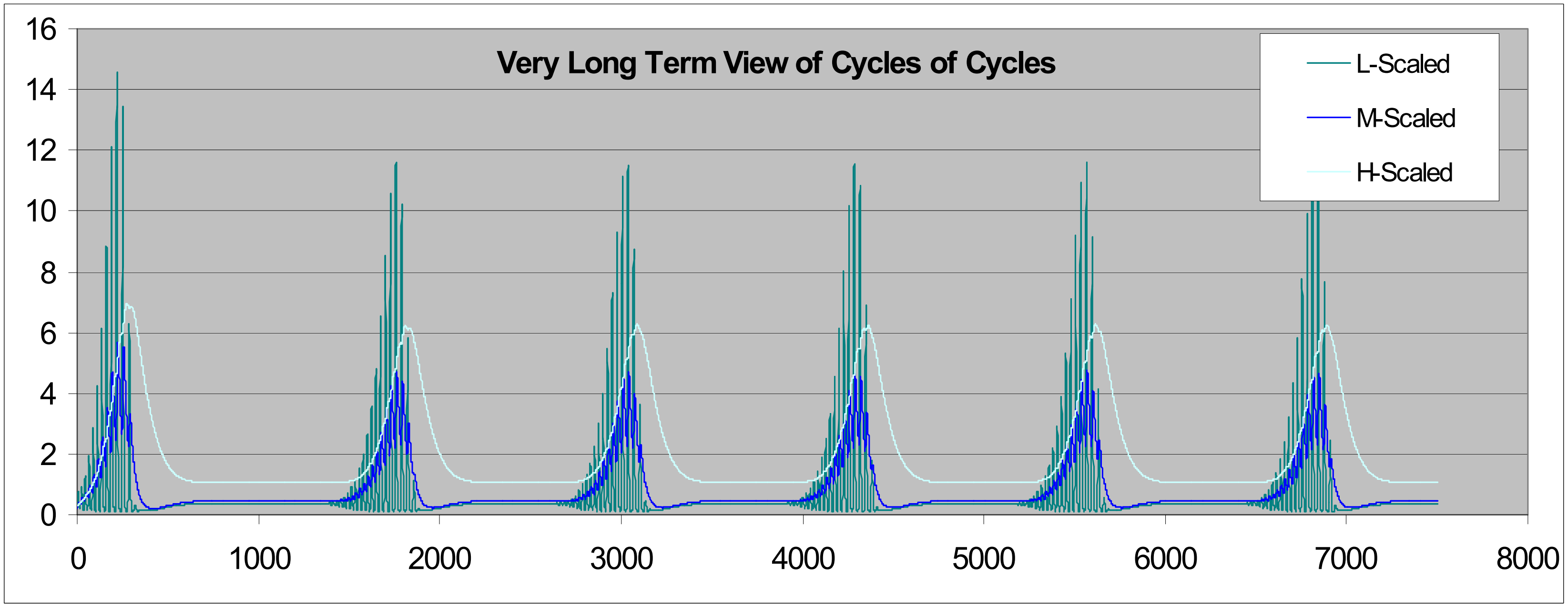
LMHQ Model: Implemented in Discrete Time

- $I_t = \tau + s\,(L_t + \sigma Q_t)\,exp(-q\,(H_t + \alpha Q_t) / (L_t + K))$
- $L_{t+1} = I_t + (1 - a - b)\,L_t$
- $Q_{t+1} = a\,L_t + (1 - \mu)\,Q_t$
- $M_{t+1} = b\,L_t + (1 - g)\,M_t$
- $H_{t+1} = h\,M_t + (1 - \delta)\,H_t$

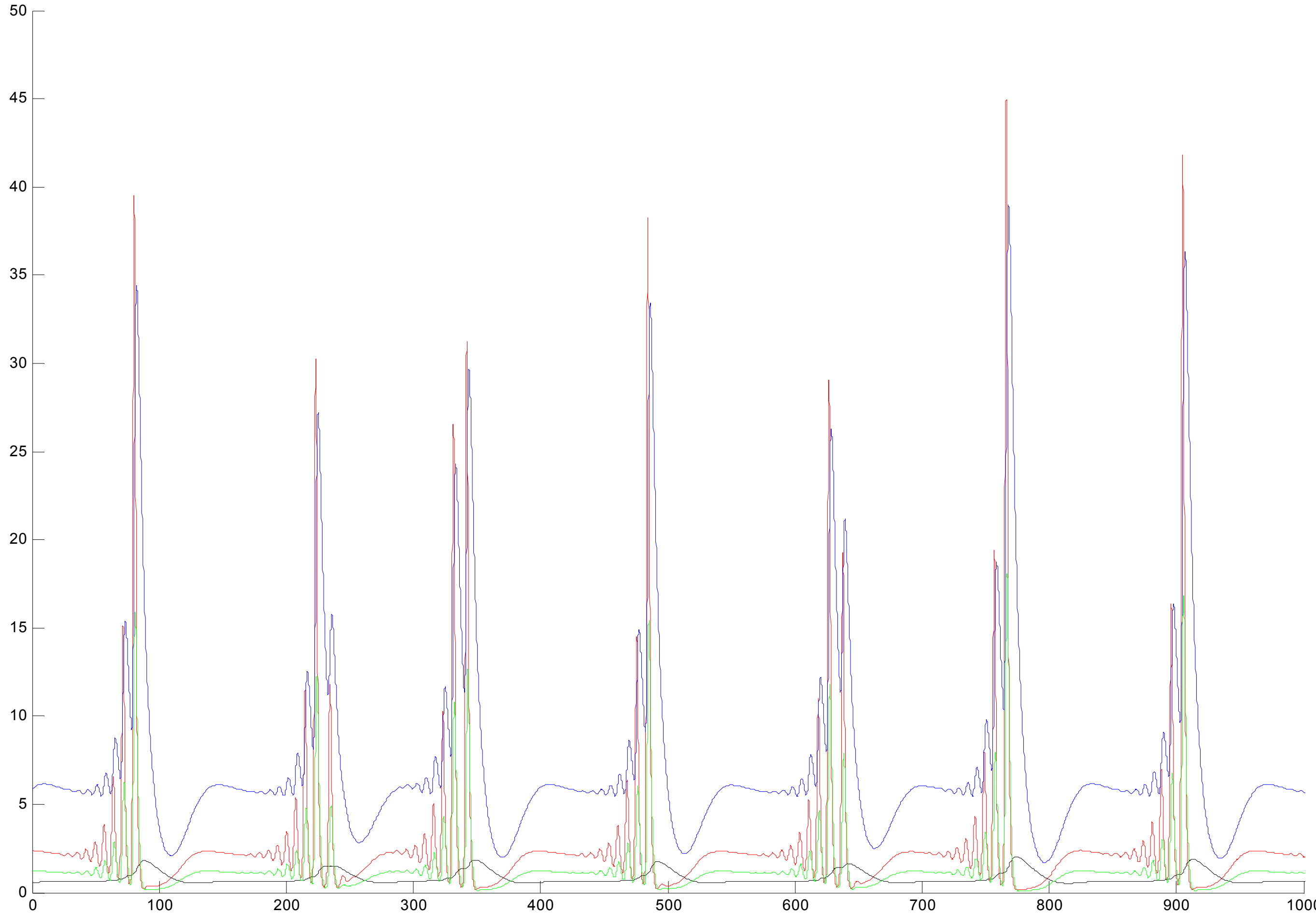
a	0.20	0.20	0.35
b	0.12	0.12	0.25
g	0.04	0.04	0.08
mu	0.30	0.30	0.60
delta	0.01	0.00	0.00
tau	0.20	0.20	0.20
s	1	1	1
q	1	1	2.4
alpha	5	5	1.3
K	1	1	1
h	0.00125	0.00125	0.00010
σ	1	1	1

Can Get "Cycles of Cycles"





Continuous Time Model Has Similar "Toroidal" Behavior



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Almeder et al. Age-Distributed Model of MJ Initiation

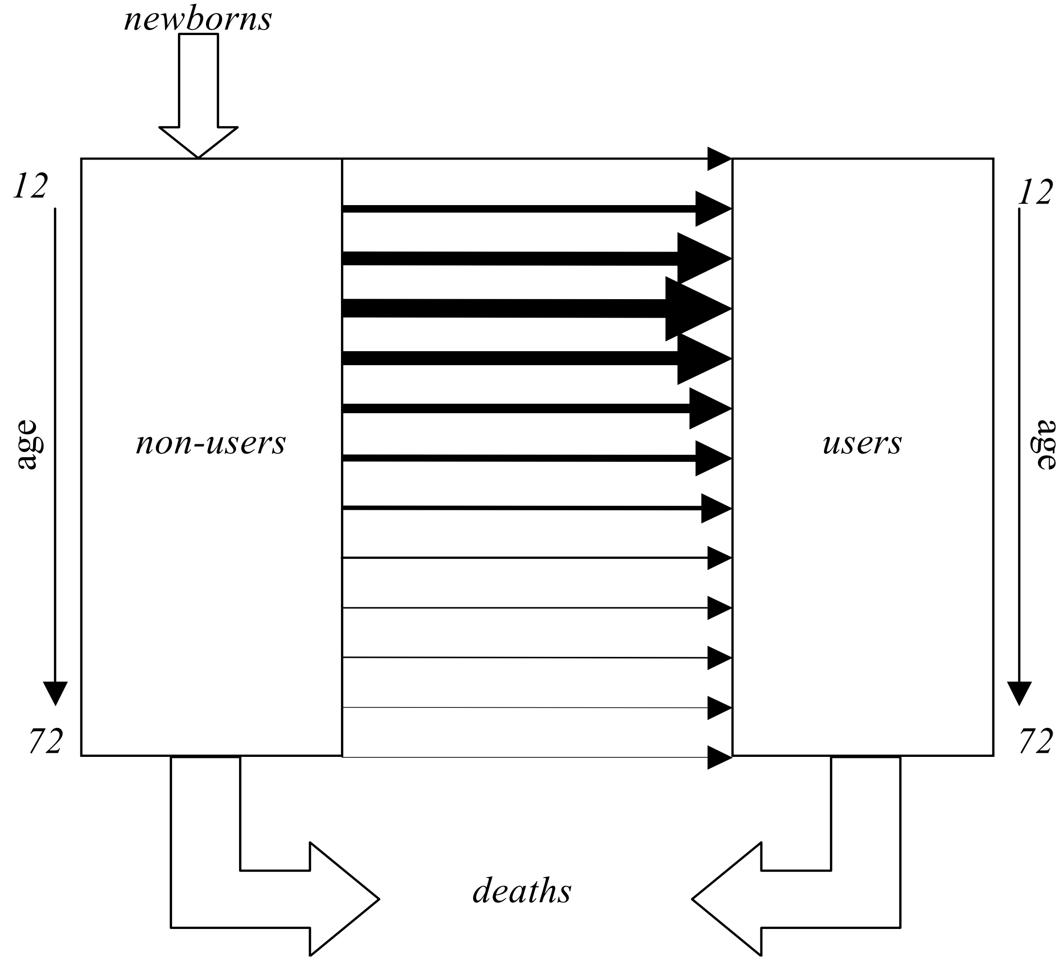


Figure 3: Schematic representation of a simple age-specific model
(thicker arrows indicate higher initiation rates)

Age-Specific Reputational Feedback

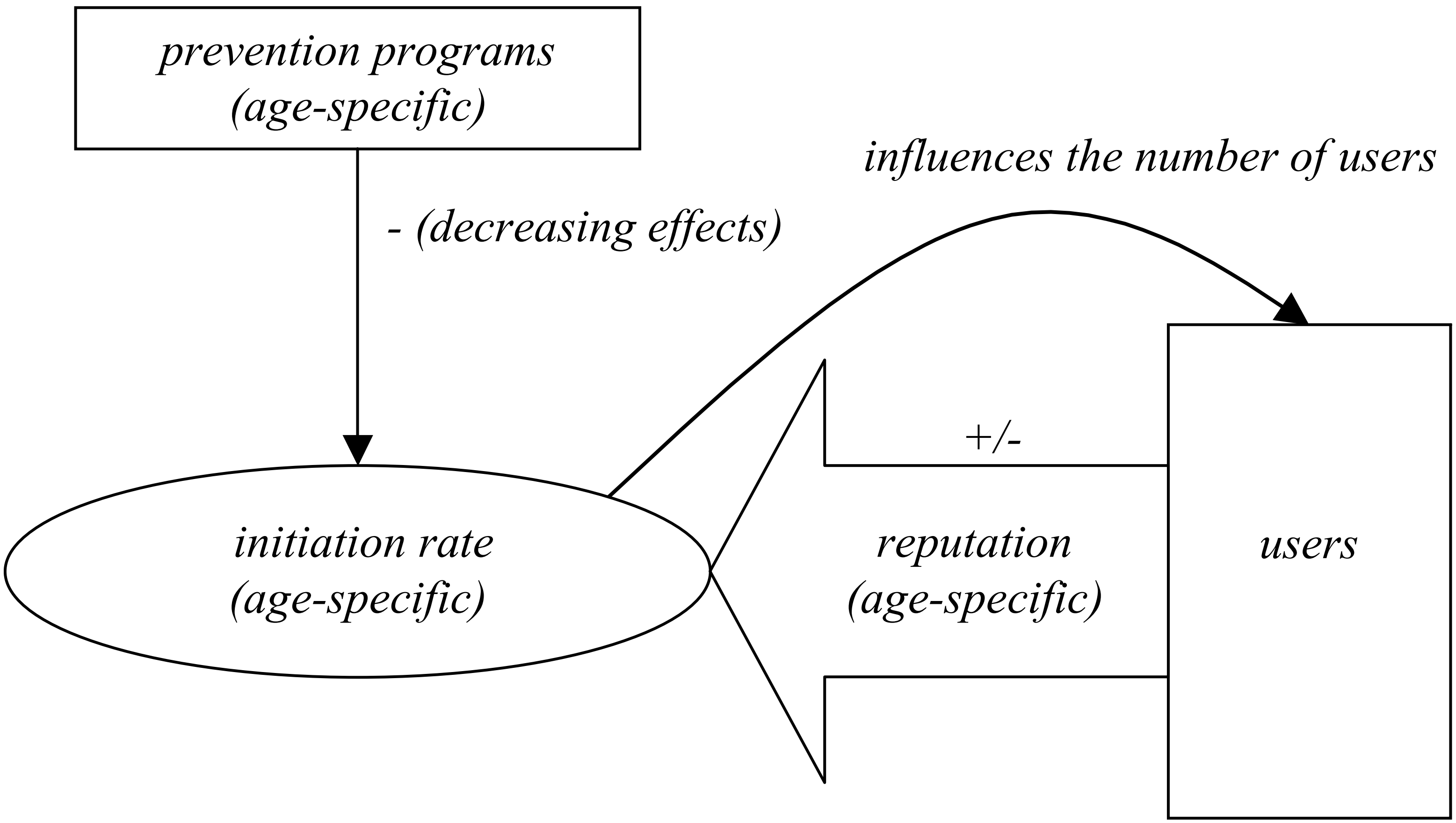
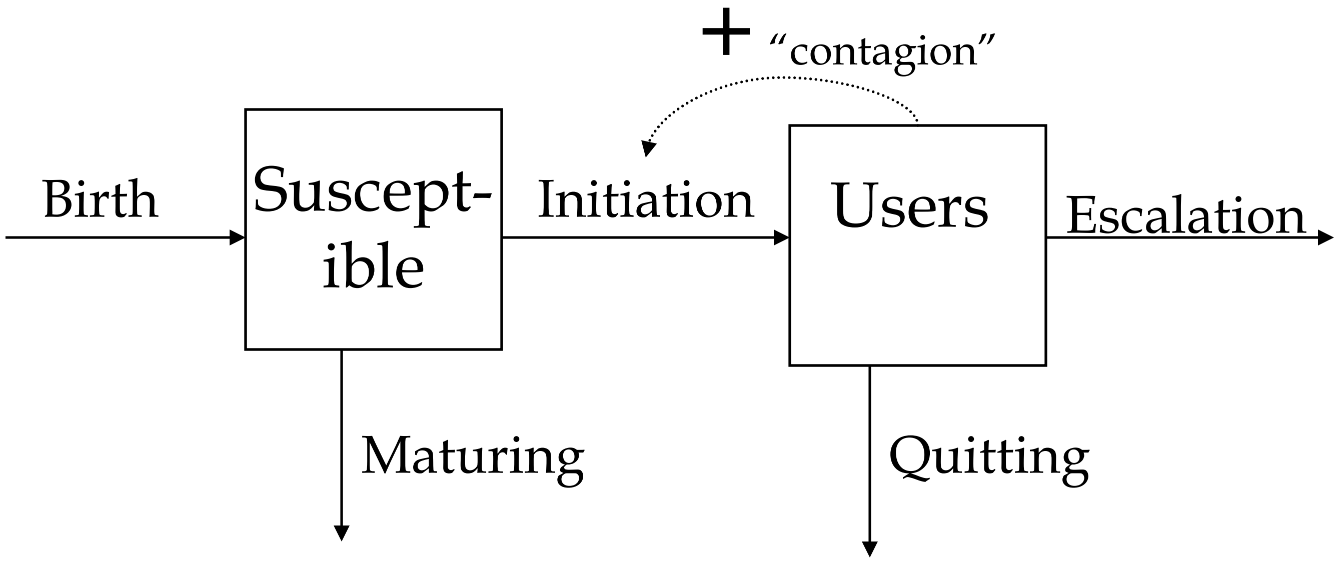


Figure 4: Influences on the initiation rate

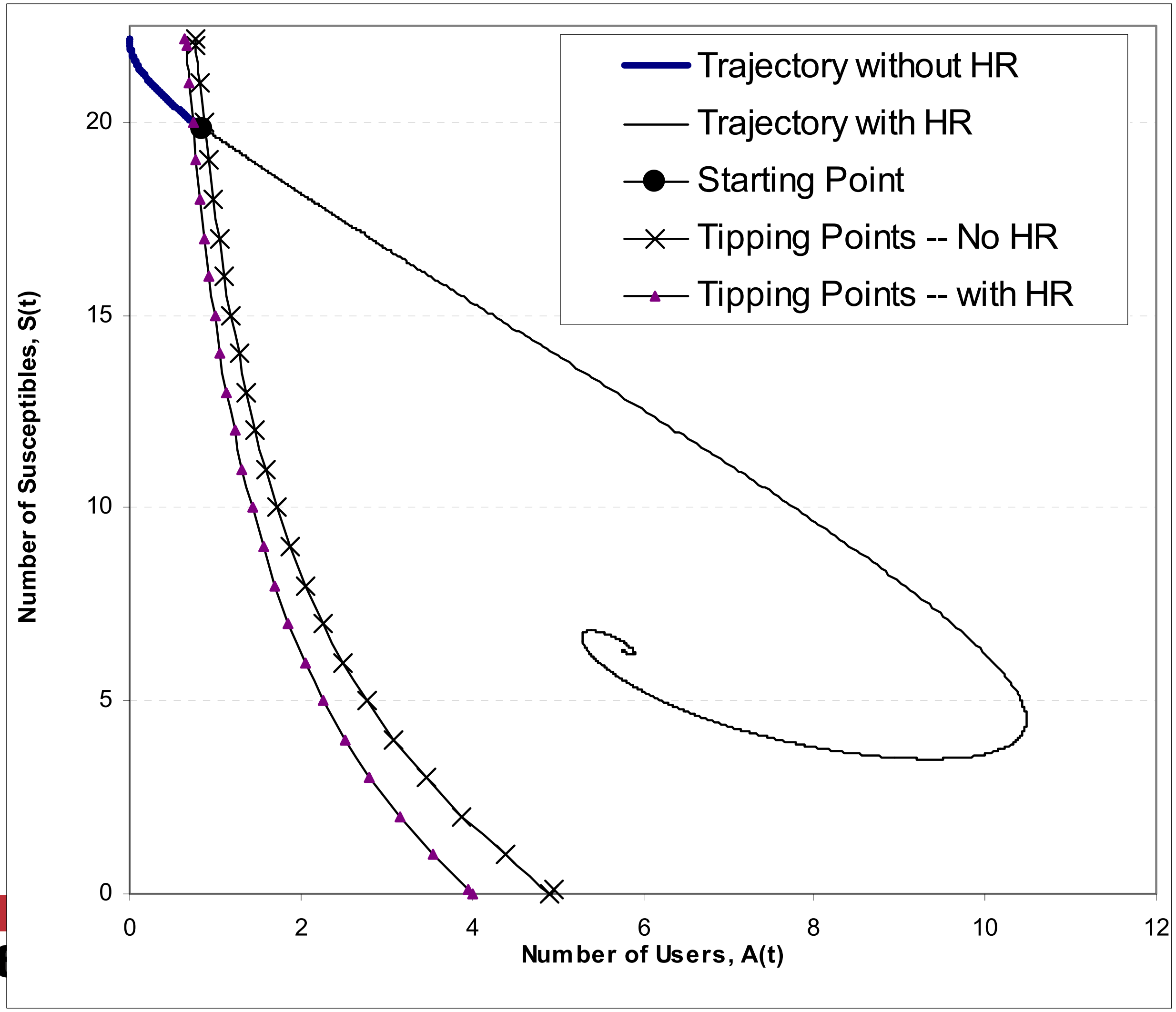
Adding Susceptibles to Models

- Common feedback on work to date is need to model susceptibles explicitly
- Makes sense: pool of susceptibles can be the dry "fuel" that feeds the wildfire of contagious initiation early in an epidemic
- Customarily done as a state of (non) use that is the origin of the initiation flow
- Such models should be pursued, but it may also be useful to model susceptibility as a stable personality trait???

SA Model


+ "contagion"
Birth
Suscept-
ible
Initiation
Users
Escalation
Maturing
Quitting

Implementing HR with Modest Effect on Initiation Might "Tip" Epidemic – only in Certain Circumstances



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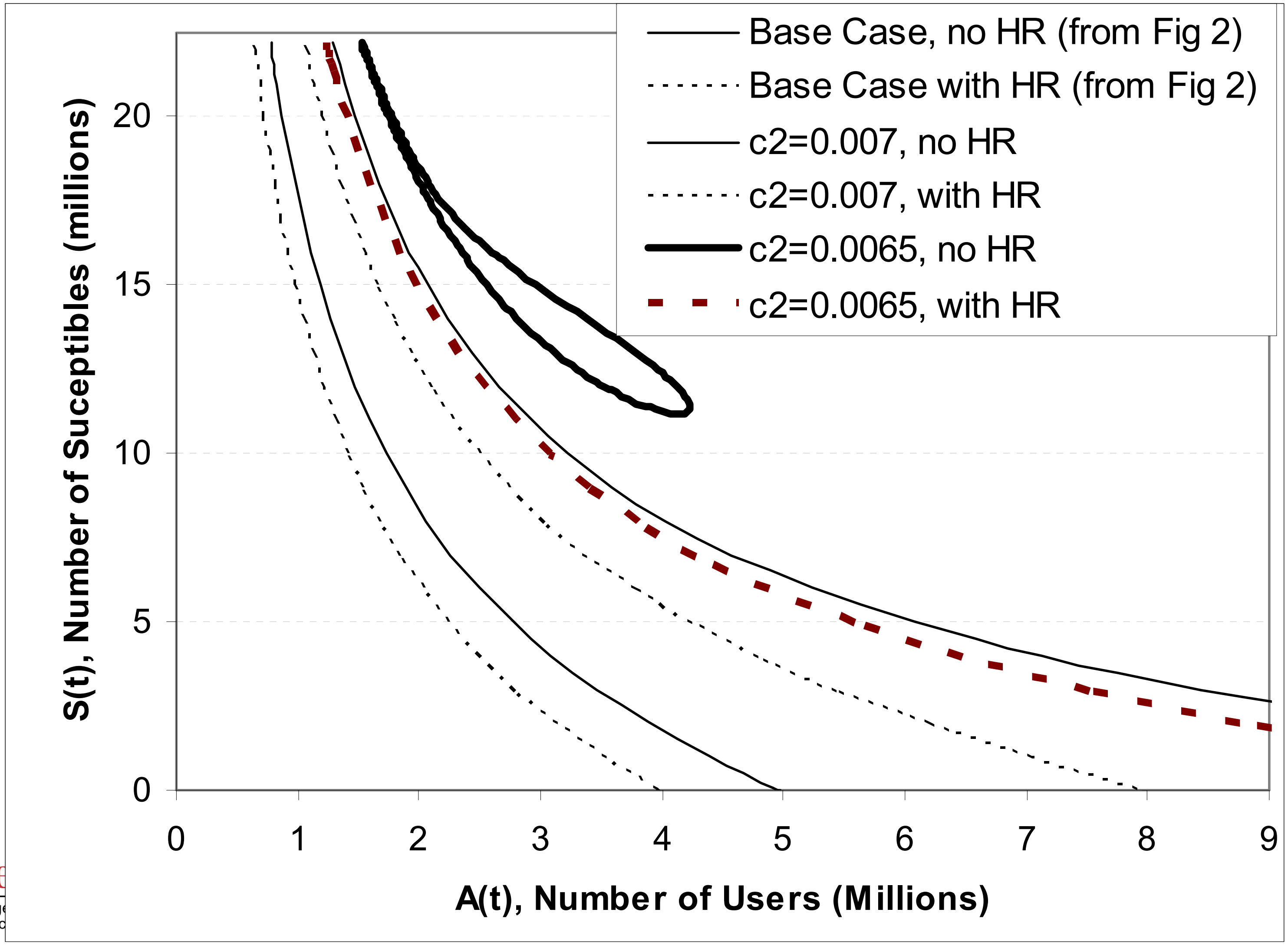
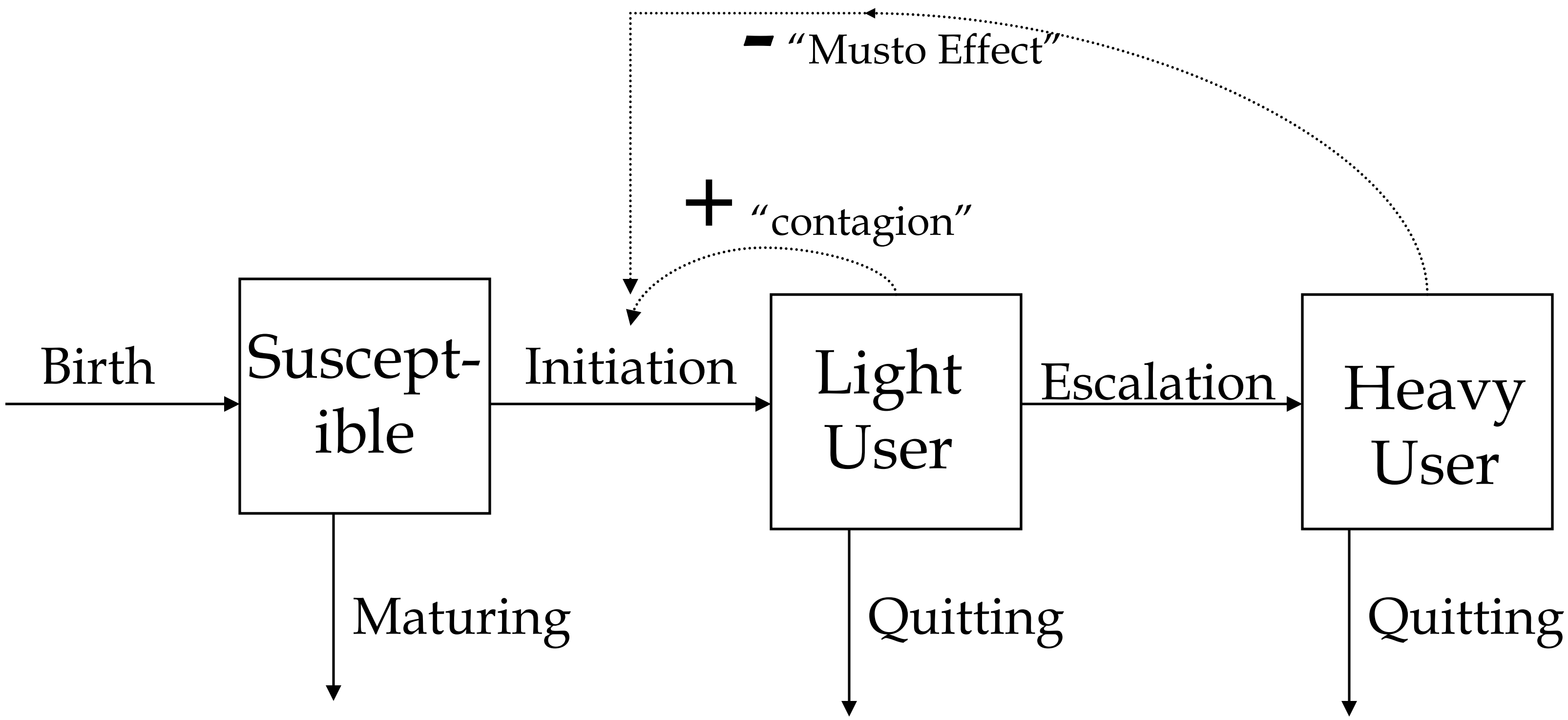
Unfortunately Hard to Know Whether Those Circumstances Pertain



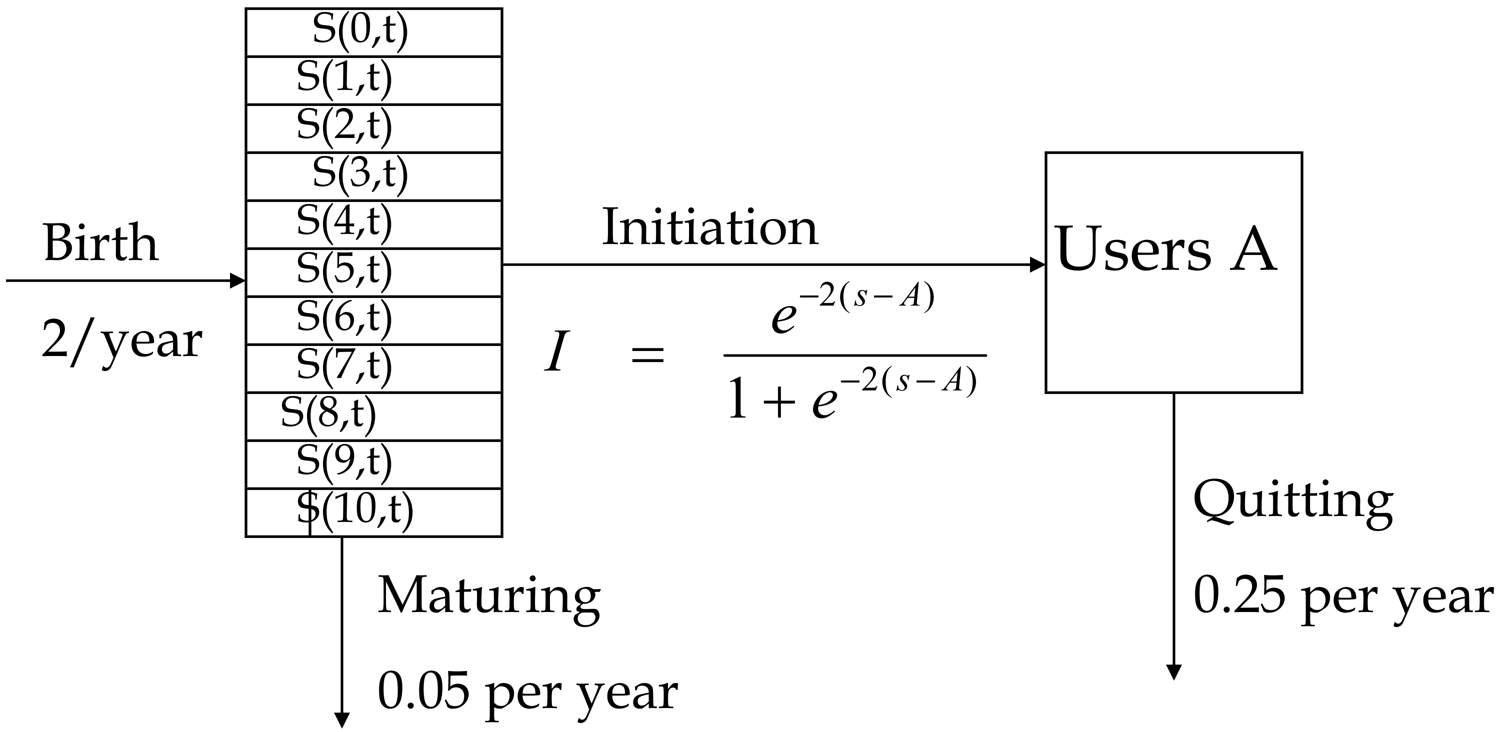
Integrated SLH Model



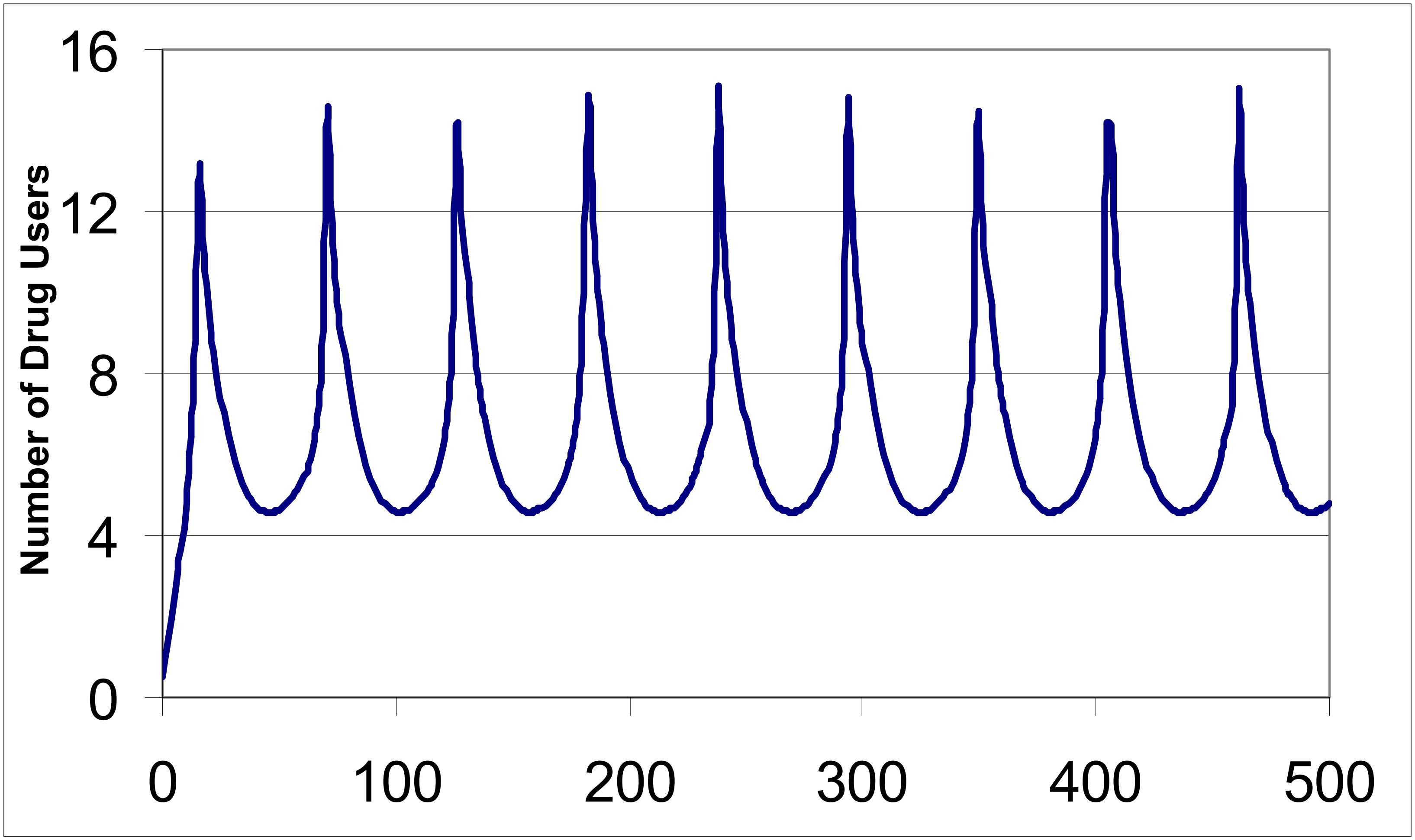
Another View of Susceptibility

- Let S(s,t) be the number of people at time t whose susceptibility to deviant behavior is s
- Correlates of high susceptibility might include genetic predisposition to be a risk seeker, having only one parent, etc.
- State transitions depend on individual susceptibility (s) and population level aggregates such as the number of light or heavy users
- Highly susceptible people initiate, escalate, etc. when population aggregates are "less favorable" toward drug use than do less susceptible people
- Use does not necessarily affect susceptibility

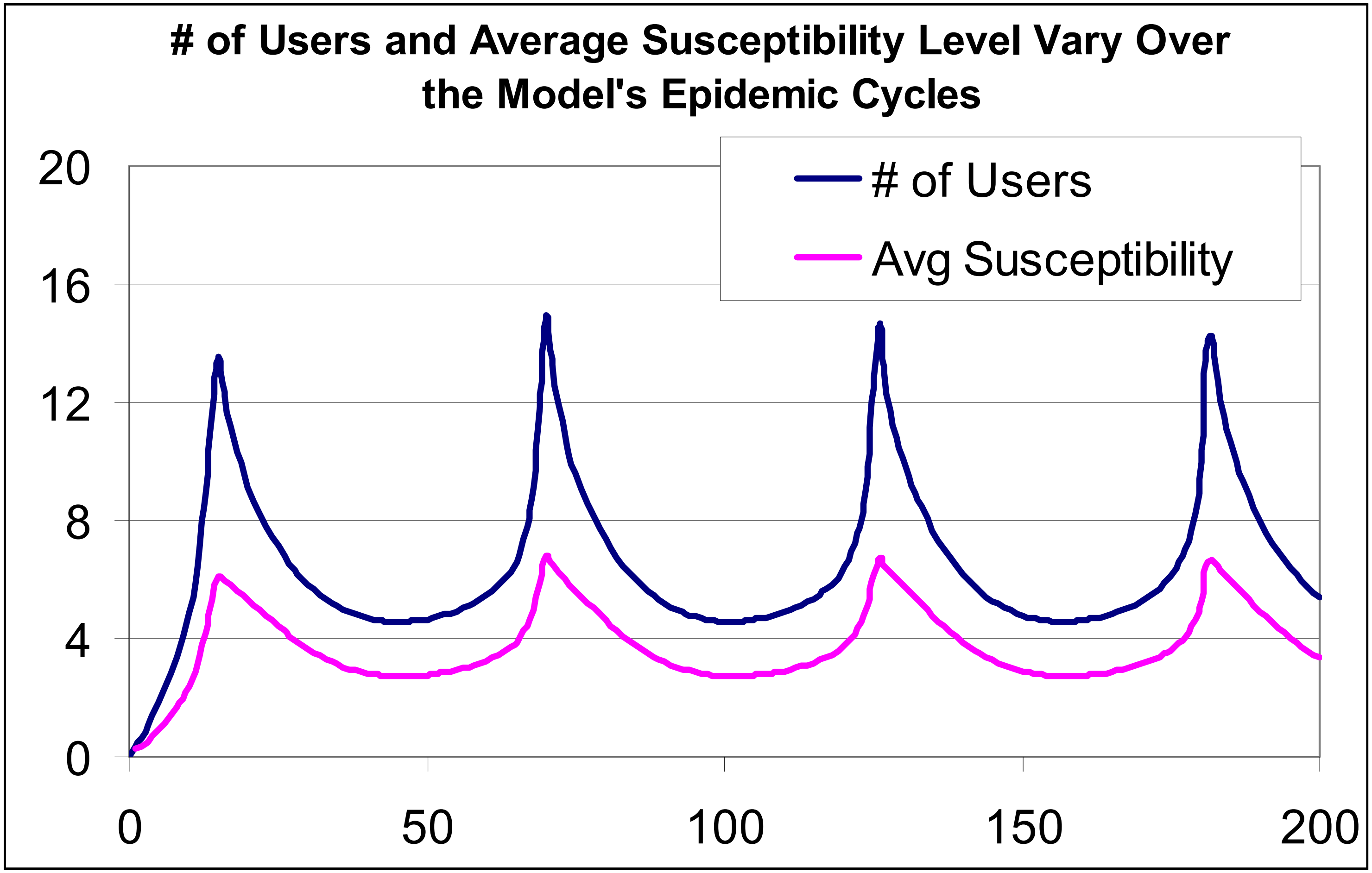
Simple Discrete-Time Example of Such a Model



Result: Number of Users Cycles



Result: Both Number and “Character” of Users Varies Over Cycle



Some Policy Conclusions of the Vienna Models

- Interventions' effectiveness varies over epidemic so mix of interventions should too
- Intervening early is very valuable
- Early in the epidemic
  - decide whether to eradicate or accommodate
  - eradicate by constraining supply and removing individual users
  - treatment can be counter-productive if heavy users suppress initiation via reputation effect
- Later in the epidemic
  - reduce enforcement intensity (but not level)
  - rely more on treatment

Some Policy Conclusions of the Vienna Models

- In "end game" may want to cut level of enforcement, not just intensity
- Can be optimal to have prices collapse
- Prevention most valuable if it affects contagious spread
  - Cheap insurance later in epidemic
- Nature as well as level of elasticity of demand matters
- Initial reputation of drug matters
- Rate of "innovators" vs. "imitators" among initiates drives long-run level of use

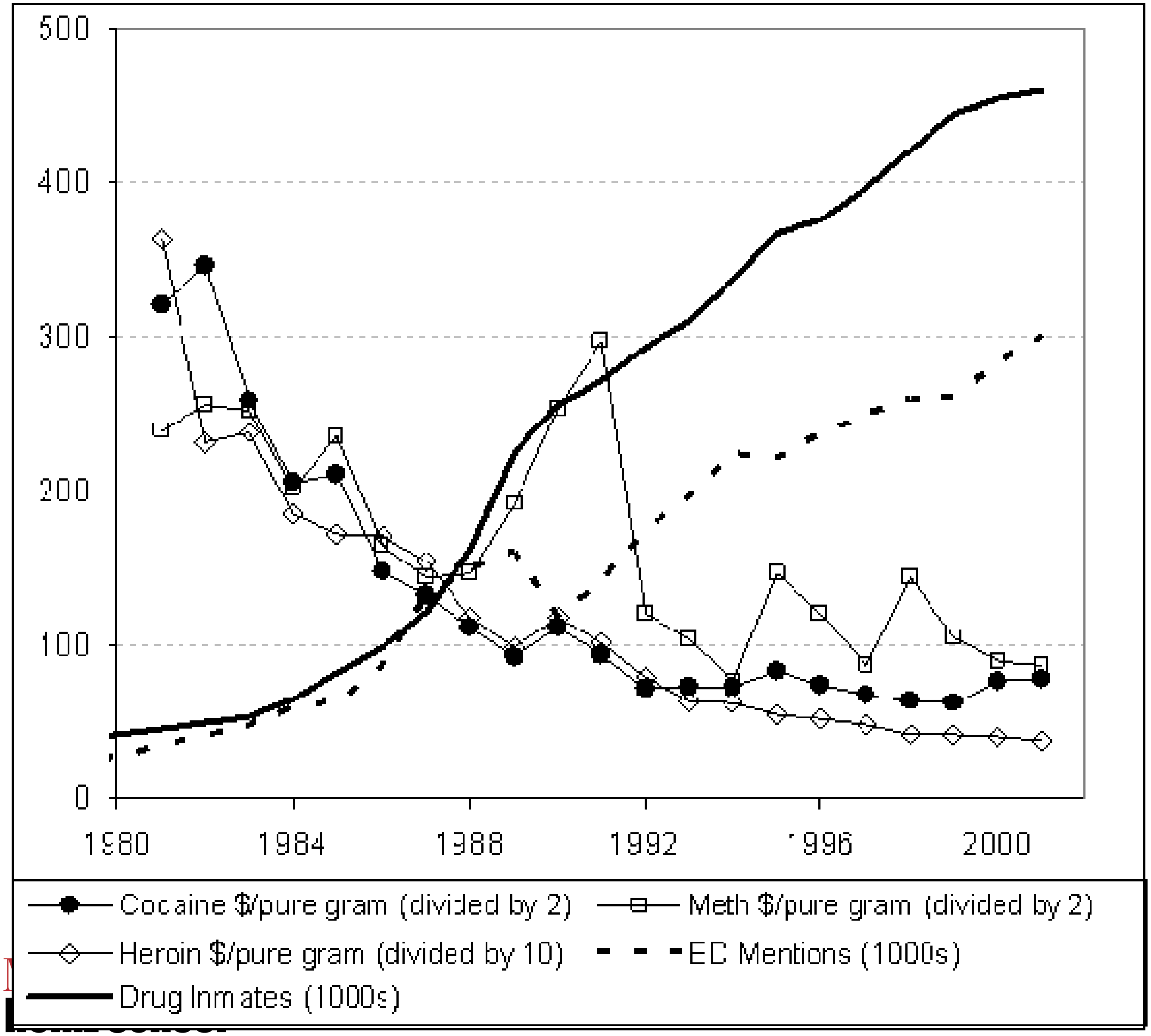
Conclusion

- Modeling drug epidemic dynamics
  - Intellectually interesting
  - Policy relevant
  - Intersects with many disciplines

Drug Markets

- ***Not*** monopolistic
- Highly competitive
  - About 1,000,000 Americans sold cocaine in the last 12 months
  - Average organizational size is very small
    - Only 5% of imprisoned retail sellers and 20% of imprisoned wholesale sellers reported being part of an organization
  - There are few barriers to entry
    - Processing drugs is trivial
    - (Surprisingly) easy credit and few capital constraints
- But not competitive in the usual sense
  - Inefficiently managed drug firms are never driven out of business
    - (Except when sellers become addicts who can't hold inventory)
  - Labor is essentially the only factor of production
    - Factor mobility utterly dominated by individual judgmental trade-offs of high cash income vs. risk of arrest, sanction, injury, death, and social approval/approbation

Punishment Risk Up; Price Down!?!



Drivers of Price

- In 1992 it was possible to “justify” the price of cocaine by pricing out all industry-wide costs of doing business
- Prices before then were “too high”
- Could argue today that the prices are “too low”
- Why do sellers sell?
  - Boring reasons (high discount rate, etc.)
  - Maybe interesting reasons

Treatment's Cost-Effectiveness

- For $1800 get
  - 80% off for 0.3 years while in program
  - 13% off long-term (avg 10 yrs, net of relapse)
  - 0.80 * 0.3 + 0.13 * 10 = 1.54 yrs of use averted
- If heavy users consume 120 grams/yr.
- 120 grams * 1.54 years / $1.8 thousand = 103 kilograms/million dollars
- Treatment has even bigger edge over price-raising enforcement at
  - reducing crime
  - reducing use of other drugs

Example: E&R's CE Analysis of Cocaine Treatment

- For $1800 get
  - 80% off for 0.3 years while in program
  - 13% off long-term (PV avg 10 yrs, net of relapse)
  - 0.80 * 0.3 + 0.13 * 10 = 1.5 yrs of use averted
- If heavy users consume 120 grams/yr.
- 120 grams * 1.5 years / $1.8 thousand = 100 kilograms/million dollars
- Multiply by $215 average social cost per gram consumed
  - BC ratio > 20:1

When Margin Starts at 22:1, Lots of Robustness

- "All people in treatment still use drugs, so treatment is not a good investment!"
  - Plug in 0% for 80% and get BC > 18.6
- "You're wrong. Treatment costs $10,000 per admission, not $1,800
  - So BC = 4
- "You're wrong. Treatment's not CE because relapse rates are 100%"
  - Plug in 0% for 13% and get a BC = 3.4
  - "Incapacitation" effect along gets BC > 1

Spreadsheet Calculations

CE and BC of Treatment (SS to Implement Slide's Calculations)

$1,800	Average cost per admission
0.30	Average duration of treatment
80%	% Abstinent During Treatment
0.24	Years of use averted during treatment (per admission)
13%	% Exiting Treatment in Some Reduced State
10.0	PV avg years of averted use per person whose long-term use w
1.3	Years of use averted post treatment (per admission)
1.54	PV Total years of use averted per admission
120	Average consumption (gms) per year of use
184.8	PV grams averted per participant
102.7	CE: PV Kilograms averted per million program dollars
$215	Average social cost per gram of use
22.1	BC

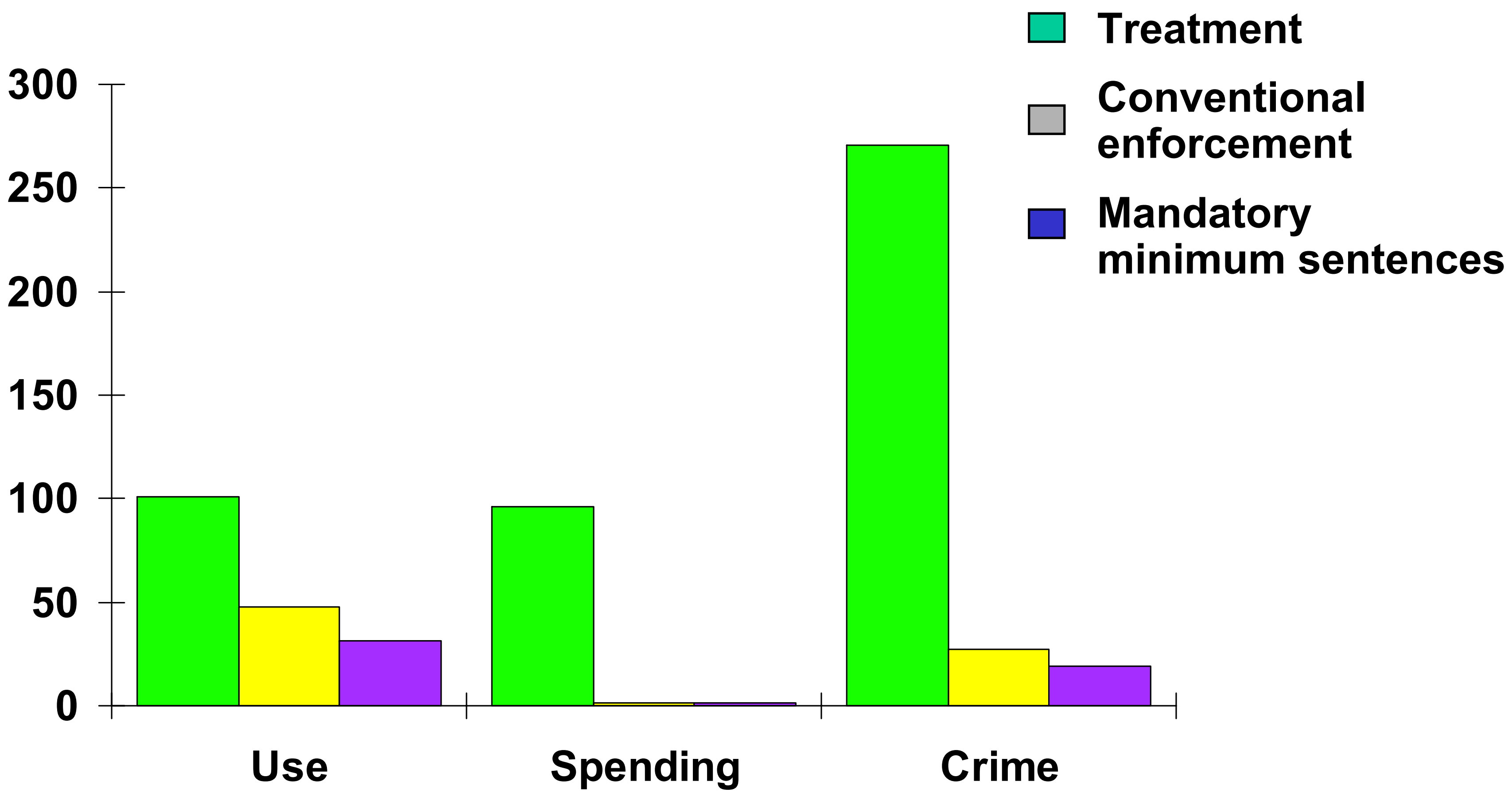
Breakeven Analysis

- NRC rightly pointed out that there is no strong scientific basis for the treatment effectiveness numbers
- They overlooked ability to "run model in reverse", e.g.,
  - Assume zero reduction in drug use during treatment
  - Goal seek BC bottom-line to 1:1 by varying proportion whose use is reduced long-term
  - Result: Treatment breaks even if 0.7% (one in 140) people entering treatment do not relapse immediately

Focus on Structural Insights, Not Just Point-Estimates

- Most important findings are structural, not the CE estimates
  - Treatment's performance relative to enforcement is stronger when focusing on crime than drug use
  - Treatment performance relative to enforcement depends strongly on the "planning horizon"
  - Etc.

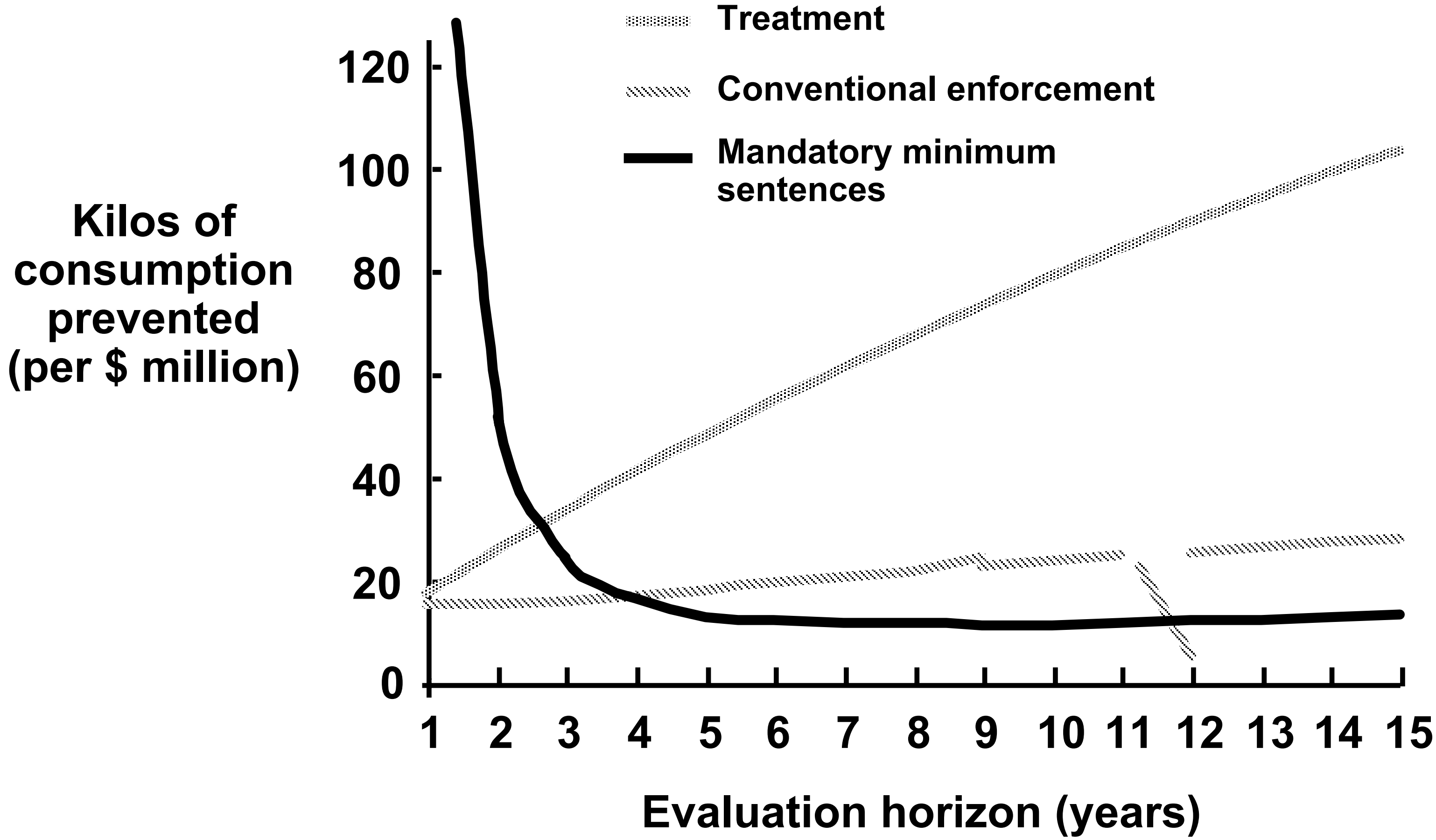
Reductions in Drug Use (kgs), Spending ($100K), and Serious Crime per Million Program Dollars



Timing of Costs and Benefits

Program characteristic	Treatment of users	Long sentences for dealers
Program cost	Early	Late
Consumption reduction	Late	Early

Effect of Evaluation Horizon on Program Performance



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