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

Jonathan P. Caulkins

Carnegie Mellon University Heinz School and Qatar Campus
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

Ways Drug Programs Work

- Displace Problem
- Reduce Consumption
- Reduce Cost per Unit Consumption

Reduce Demand
- Prevention (w/ enforcement)
- Treatment (w/ enforcement)

Insert Wedge: Non-Dollar Costs
- "Search Time" Health Effects
- Social Approbation
- User Sanctions

Reduce Supply
- Short-Term Effects: Physical Shortages
- Price Spikes
- Long-Run Effects: Destroy Market or Drive Up Prices

Reduce Cost per Unit Consumption

Health Effects
- Physical Shortages
- Price Spikes

Social Approbation
- User Sanctions

User Sanctions

Non-Dollar Costs

Search Time Health Effects

Physical Shortages

Price Spikes

Destroy Market or Drive Up Prices

Prevention (w/ enforcement)

Treatment (w/ enforcement)
Horse Race Results of Cost-Effectiveness Studies

Cost-effectiveness at reducing cocaine consumption

- Prevention (low estimate)
- Source country control
- Longer sentences, typical dealers
- Interdiction
- Prevention (middle estimate)
- Domestic enforcement, typical dealers
- Longer sentences, federal defendants
- Federal enforcement
- Prevention (high estimate)
- Treating heavy users
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

% reduction (from no-prevention scenario) in past-year cocaine users recorded by NHSDA

- Prevention, low estimate of effect
- Prevention, middle estimate of effect
- Prevention, high estimate of effect
## Prevention’s Cost-Effectiveness

<table>
<thead>
<tr>
<th>Units of Use</th>
<th>Cocaine</th>
<th>Marijuana</th>
<th>Cigarettes</th>
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</tr>
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<tbody>
<tr>
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<td>grams</td>
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<td>SRD</td>
</tr>
<tr>
<td>F1: Baseline Use per Initiate</td>
<td>350</td>
<td>560</td>
<td>8900</td>
<td>640</td>
</tr>
<tr>
<td>F2: Proportion Initiating</td>
<td>18%</td>
<td>62%</td>
<td>78%</td>
<td>58%</td>
</tr>
<tr>
<td>F3: Discount Factor</td>
<td>0.53</td>
<td>0.58</td>
<td>0.42</td>
<td>0.49</td>
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<tr>
<td>F4: Short-term Effectiveness</td>
<td>10.9%</td>
<td>16.0%</td>
<td>16.8%</td>
<td>12.8%</td>
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<tr>
<td>F5: Reduction in Lifetime</td>
<td>27.6%</td>
<td>19.4%</td>
<td>14.0%</td>
<td>17.3%</td>
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<tr>
<td>Use per Unit of F4</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>F6: Correl.-Causation Ratio</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
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<tr>
<td>F7: Scale-Up Factor</td>
<td>0.6</td>
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<tr>
<td>F8: Social Multiplier</td>
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<tr>
<td>F9: Market Multiplier</td>
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<td>F10: Social Cost per Unit of Use</td>
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<td>Total</td>
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Benefits Not Just from Illicits

- Cigarettes: 39%
- Alcohol: 28%
- Cocaine: 20%
- Marijuana: 3%
- Opiates: 8%
- All Other Illicit: 2%
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Perfect SB Prevention Starting in 1985 Could Cut Household Cocaine Prevalence

Proportion of Past-Month Days of Self-Reported Cocaine Use Attributable to People Born Before 1962, 1972, and 1982

Survey Year
But Would Have Only Modest Effect on Problematic Use

Cocaine Treatment Clients Over Time, by Birth Cohort

- Millenials: After 1982
- Late Gen X: 1973-1981
- Early Gen X: 1964-1972
- Late Boomers: 1955-1963
- Early Boomers: 1946-1954
- Silent Generation: Before 1946
And Even Household Crack Use

Proportion of Past-Month Days of Self-Reported Cocaine Use Attributable to People Born Before 1962, 1972, and 1982

Survey Year


100% 80% 60% 40% 20% 0%
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Focusing on Program Participants Overlooks Most Benefits of Prevention

Sources of prevention’s reduction in cocaine use

- Friends & associates: 45%
- People in program: 38%
- Others in market: 17%
Focusing on Program Participants Overlooks Most Benefits of Prevention

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Prevention of initiation accounts for one-fourth of total effect
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School-Based Prevention’s Cost per Participant Is Modest

<table>
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<th>Cost Category</th>
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<tr>
<td>Curriculum and training</td>
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**Cost-effectiveness at reducing cocaine consumption**

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![Bar chart showing cost-effectiveness at reducing cocaine consumption]
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

Growth in ER Mentions for Cocaine and Incidence of AIDS

- **Cocaine ER Mentions**
- **Incidence of AIDS (X2)**

![Graph showing the growth in ER mentions for cocaine and the incidence of AIDS from 1978 to 1998.](image-url)
Convex Growth

US Cocaine Initiation (Millions)

- Series 1A
- Series 1B
- Series 2A
- Series 2B
- Series 3A
- Series 3B
Overshoot

Millions of US Cocaine Users

- Heavy
- Light

Years:
- 1972
- 1976
- 1980
- 1984
- 1988
- 1992
- 1996
- 2000
Sometimes Peak Leads to a Plateau (& Slow Decline?)
Sometimes Peak is Followed by Significant Decline

Past-Year Prevalence of Marijuana Use in the US Household Population
Sometimes Use Drops As Fast As It Rose

Persons Arrested for Paregoric in Detroit

[Graph showing the number of persons arrested for Paregoric in Detroit from 1955 to 1965.]
Evidence of Undershoot (or Perhaps Even Cycles?)

Past-Year Use by High School Seniors

- Marijuana/Hashish
- Cocaine
- Stimulants
More Evidence of Cycles?

Unintentional OD Deaths in Italy

- Marotta data
- Preti et al. CHD
- Preti et al. MOI Estimate
Linear Adjustment Dynamics
Can’t Explain This

• Suppose
  – \( \dot{\hat{Y}} = f(X; u) \)
  – \( \ddot{Y} = A(\dot{\hat{Y}} - Y) = A (f(X;u) - Y) \)

• 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

<table>
<thead>
<tr>
<th></th>
<th>Endogenous Dynamics</th>
<th>Control's Effect on Drug Use</th>
</tr>
</thead>
<tbody>
<tr>
<td>Symptom of root causes</td>
<td>ignored</td>
<td>minimal</td>
</tr>
<tr>
<td>Random walk</td>
<td>ignored</td>
<td>all determinative</td>
</tr>
<tr>
<td>&quot;Unbounded growth&quot; absent control</td>
<td>logistic, but high equilibrium is effectively &quot;out of bounds&quot;</td>
<td>our only salvation</td>
</tr>
<tr>
<td>Unstoppable, but bounded growth</td>
<td>logistic once triggered</td>
<td>none</td>
</tr>
<tr>
<td>Tipping models</td>
<td>logistic above threshold</td>
<td>can keep Pandora's box closed, but not close an open box</td>
</tr>
<tr>
<td>All infected, few addicted</td>
<td>SIR structure</td>
<td>minimal</td>
</tr>
<tr>
<td>Musto models</td>
<td>immediate positive feedback + lagged negative feedback</td>
<td>depends on timing</td>
</tr>
</tbody>
</table>
“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 ($A(t) = \# \text{ of “addicts”}$)
- 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

\[ \text{Min } J = \int_{0}^{\infty} e^{-rt} \left( \kappa \theta A(t) p(A(t), v(t))^{-\omega} + u(t) + v(t) \right) dt \]

\[ u(t), v(t) \geq 0 \]

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

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

\[ p(A(t), v(t)) = d + e \frac{v(t)}{A(t) + \varepsilon}, \]
It Can Be Optimal for Prices to Collapse As Epidemic Grows
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

Initiation → Light Users → Escalation → Heavy Users

- “reputation”
+ “contagion”

Quitting → Heavy Users

Quitting
Knowledge Base Concerning Cocaine Really Did Change

Changing Composition of Current Cocaine Users: Number of Years Since Starting Cocaine Use, by NHSDA Survey Year
Parallel Graph for Ever Users

Changing Composition of Ever Cocaine Users: Years Since Trying Cocaine, by NHSDA Survey Year
Some Measures of Cocaine’s “Reputation Effect” Over Time

![Graph showing measures of cocaine's reputation effect over time. The x-axis represents years from 1970 to 2000, and the y-axis represents a measure ranging from 0.00 to 0.40. The graph includes three lines: blue for initiates/user, pink for initiates/light user, and purple for 1-HS Seniors Rating. The lines show fluctuations over time, with peaks and troughs at different points.](image-url)
Basic Two-State LH Model

\[ J = \int_{0}^{\infty} e^{-r t} \left( \kappa Q(t) + u(t) + w(t) \right) dt \]

\[ \dot{L} = I(L, H) - (a + b)L, \quad L(0) = L_0 \]

\[ \dot{H} = bL - gH, \quad H(0) = H_0 \]

\[ Q(t) = 16.42 L(t) + 118.93 H(t) \]

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

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

\[ \beta(H, u) = c \left( u/(H + \delta) \right)^d \]
Early Intervention is Valuable

![Graph showing uncontrolled and controlled modeled epidemics with labeled years 1967, 1975, 1979, and 1996. The controlled model is optimally allocated budget.]
Transition Quickly from All Prevention to All Treatment
Dramatic Result
Treat and Prevent -- But Not at the Same Time

Control spending in billion dollars

Year

prevention
treatment
LHY or LHE Versions of Models with “Musto” Dynamics

Initiation → Light Users → Escalation → Heavy Users

Memory of Ill Effects

“reputation” → Light Users

“contagion” → Heavy Users

“bad experiences” → Heavy Users

Quitting → Light Users

Quitting → Heavy Users
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 prespecified reduction in future discounted demand).
Characterize Types of Drugs that are Prone to Epidemics
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???

![Australian Heroin Initiation and Quitting Rates](chart.png)

- **Australian Heroin Initiation and Quitting Rates**
- *(Kaya, based on Household Survey)*

- **Initiation**
- **Quitting**


Initiation and quitting rates are shown from 1970 to 2000. The graph indicates a correlation between quitting and initiation rates, with significant short-term cycles evident in the data.
LMHQ Model

- "Musto Effect"
- "contagion"
- "contagion"

Initiation ➔ Light Users (L) ➔ Progression (b) ➔ Moderate Users (M) ➔ Escalation (h) ➔ Heavy Users (H)

- "adverse reactions"

Quitting (a) ➔ Recent Quitters (Q) ➔ Irrelevance (µ)

Quitting (g-h) ➔ Quitting (δ)
LMHQ Model: Implemented in Discrete Time

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

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Can Get “Cycles of Cycles”

Scaled Plots of L, H, I over Time

Very Long Term View of Cycles of Cycles
Continuous Time Model Has Similar “Toroidal” Behavior
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

prevention programs (age-specific)

- (decreasing effects)

initiation rate (age-specific)

reputation (age-specific)

users

influences the number of users

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

Birth → Susceptible

Initiation

Susceptible + "contagion" → Users

Maturing

Escalation

Quitting
Implementing HR with Modest Effect on Initiation Might “Tip” Epidemic – only in Certain Circumstances
Unfortunately Hard to Know Whether Those Circumstances Pertain
Integrated SLH Model

- Birth
- Susceptible
  - Maturing
- Initiation
- Light User
  - Escalation
  - Quitting
- Heavy User
  - Quitting

- "Musto Effect"
- "contagion"
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

Birth 2/year

<table>
<thead>
<tr>
<th>S(0,t)</th>
<th>S(1,t)</th>
<th>S(2,t)</th>
<th>S(3,t)</th>
<th>S(4,t)</th>
<th>S(5,t)</th>
<th>S(6,t)</th>
<th>S(7,t)</th>
<th>S(8,t)</th>
<th>S(9,t)</th>
<th>S(10,t)</th>
</tr>
</thead>
</table>

Initiation

\[ I = \frac{e^{-2(s-A)}}{1 + e^{-2(s-A)}} \]

Users A

Maturing 0.05 per year

Quitting 0.25 per year
Result: Number of Users Cycles
Result: Both Number and “Character” of Users Varies Over Cycle

# of Users and Average Susceptibility Level Vary Over the Model's Epidemic Cycles

- Blue line: # of Users
- Pink line: Avg Susceptibility
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)
  – $0.80 \times 0.3 + 0.13 \times 10 = 1.54$ yrs of use averted

• If heavy users consume 120 grams/yr.
• $120 \text{ grams} \times 1.54 \text{ years} / $1.8 \text{ thousand} = 103$ 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)
  - \(0.80 \times 0.3 + 0.13 \times 10 = 1.5\) yrs of use averted
- If heavy users consume 120 grams/yr.
- \(120\) grams \(\times 1.5\) 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)

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

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Carnegie Mellon Heinz School
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

<table>
<thead>
<tr>
<th>Program characteristic</th>
<th>Treatment of users</th>
<th>Long sentences for dealers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Program cost</td>
<td>Early</td>
<td>Late</td>
</tr>
<tr>
<td>Consumption reduction</td>
<td>Late</td>
<td>Early</td>
</tr>
</tbody>
</table>
Effect of Evaluation Horizon on Program Performance

Kilos of consumption prevented (per $ million)

- Treatment
- Conventional enforcement
- Mandatory minimum sentences

Evaluation horizon (years)