The Downward Spiral

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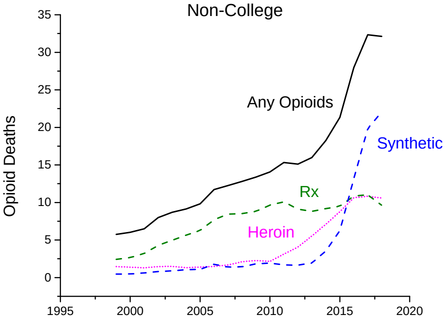
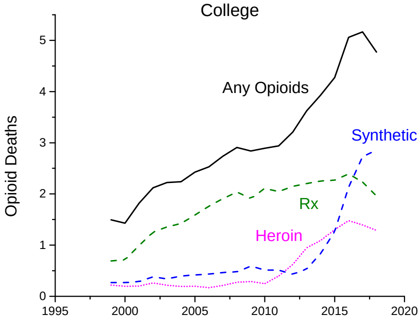
*The views expressed do not necessarily reflect the position of the Federal Reserve Bank of Cleveland or the Federal Reserve System.

- Since 2000, more than 500,000 opioid overdose deaths.
- Leading cause of accidental death since 2017.

Opioid Deaths per 100,000 population by education





- Death rate and rise in synthetic opioids death rate particularly high for non-college.

Question

- What accounts for the dramatic rise in opioid overdose deaths?

Analysis

- Model recreational opioid usage, addiction, and death
- Calibrate to 2015–18 cross-sectional medical/economic data
  - Separate calibrations for college and non-college
  - Perform a cross-state validation check
- Assess various causal factors for the opioid crisis
  - Changes from 2000 to 2015–18 in
    - Prices (Rx and street)
    - Medical practices (Rx dosage levels and Rx durations)
    - Risk of death conditional on addiction
    - Misinformation about addiction risk

related lit

Main Findings

- All factors together account for:
  - 73% of the ↑ in non-college deaths
  - 49% of the ↑ in college deaths
- Most important factors: ↓ in prices, ↑ in death risk, ↓ in misinformation
- Consumers value recreational opioids
  - non-college: 0.52% of their consumption
  - college: 0.23%
- Consumers value medical interventions that reduce addiction or death risk
  - even though these could increase opioid consumption and deaths

In the 1990s physicians rethought the need to manage pain

- 1995: Dr. James Campbell addresses the American Pain Society: treat pain as the "fifth vital sign" (American Pain Society, 1999)

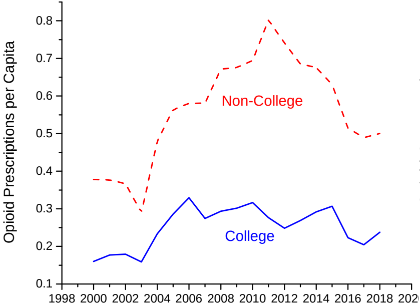
Drug companies entered the scene

- 1996: Purdue Pharma introduces OxyContin with aggressive marketing campaign claiming:
  - "(d)elayed absorption, as provided by OxyContin tablets, is believed to reduce the abuse liability of a drug"
  - rate of addiction: $< 1\%$
- Pills were open to abuse by crushing then snorting or injecting.

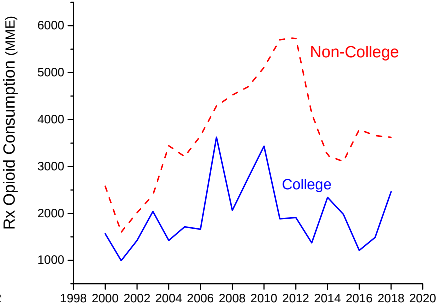
Detailed timeline

Starting in early 2000's, large increase in Rx opioid use.

Opioid prescriptions per capita

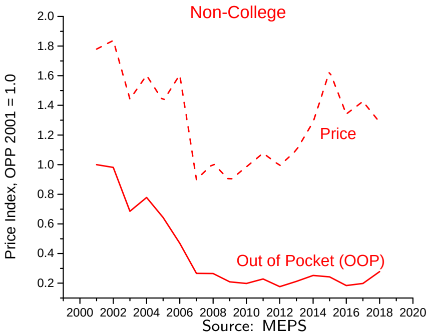


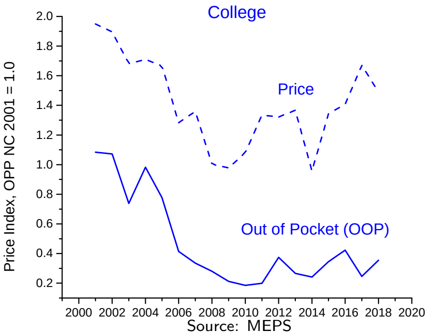
Avg Rx opioid consumption cond on a prescription



Source: Medical Expenditure Panel Survey (MEPS), sample: non-students ages 18–64

And dramatic fall in prescription opioid prices.



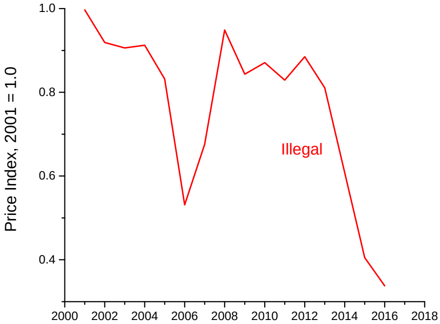


Drivers:

- advent of generic prescription opioids in 2004
- 2001–2010: % of Rx opioids funded by govt ↑ from 17% to 60% due to Medicare Part D Rx drug coverage (2006) and ↑ in SSDI recepiency.

Details

As well as fall in illegal opioid prices.



Source: 2020 Economic Report of the President

Drivers:

- diversion of opioids from legal sources onto the black market
- illegal imports of inexpensive powerful and more deadly synthetic opioids, fentanyl

US Population Ages 18-64 by Opioid Use, 2015/18

	Nonuser	Prescription	Misuser	Addict	Dead
Non-College	0.80688	0.13477	0.04479	0.01328	0.00028
College	0.87342	0.09182	0.03040	0.00432	0.00005

Source: NSDUH, MEPS, and CDC Vital Statistics

- **Misuser:** use any opioids w/o a prescription, use for reasons other than directed by a physician, use more than prescribed
- **Addict:** misuser who has an opioids dependence according to criteria in the American Psychiatric Association *Diagnostic and Statistical Manual of Mental Disorders* (DSM-5)
- Calibrated model will match this distribution

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College	0.87342	0.09182	0.03040	0.00432	0.00005
NC/CL		1.47	1.47	3.07	5.60

Source: NSDUH, MEPS, and CDC Vital Statistics

- Non-college:
  - 3 times more likely to be an addict
  - 5.6 times more likely to die from opioid overdose
  - About twice as likely to die conditional on addiction

Non-college account for **86%** of addicts and **93%** of deaths.

shares demo

Goods

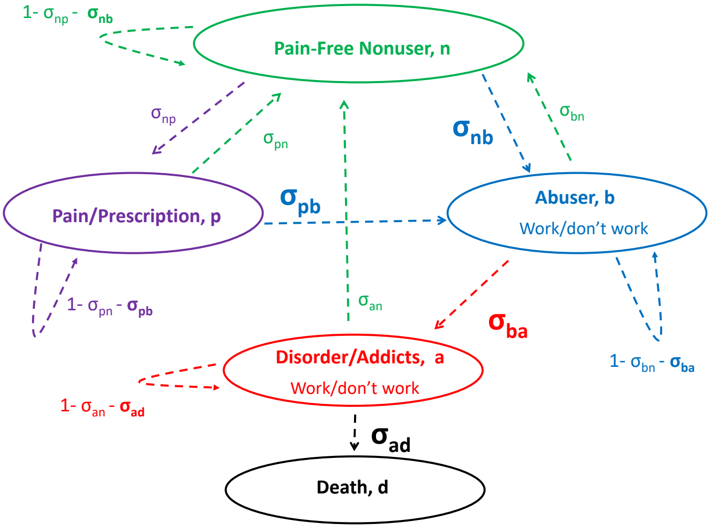
- Three goods: consumption, c, leisure, l, and opioids, o
  - price of prescription opioids, p
  - prescription level of opioids, $\underline{o}$
  - price of black market opioids, q

Addiction

- Five stages of potential addiction, $s = n, p, b, a, d$
- n, nonuser—everyone starts here
- p, prescription user
  - $\rightarrow$ b, abuser—either nonuser or prescription user
  - $\rightarrow$ a, addict
  - $\rightarrow$ d, death

Transition Probabilities

- Transition probability from stage i to j, σ_{ij}
  - some endogenous, some exogenous


1- σnp - σnb
Pain-Free Nonuser, n
σnp
σpn
σnb
σbn
Pain/Prescription, p
σpb
Abuser, b
Work/don't work
1- σpn - σpb
σan
σba
1- σbn - σba
Disorder/Addicts, a
Work/don't work
1- σan - σad
σad
Death, d

Labor

- Hours worked are indivisible, $h \in \{0, \mathfrak{h}\}$
- Productivity in stage s, π_s
  - $\pi_a < \pi_b < \pi_p = \pi_n$
- Non-employment transfer, t
- Employment decision made after opioid decision
- Nonusers and prescription users always work

Budget Constraint

$$c = \begin{cases} \pi_s \mathfrak{h}, & \text{works}/{\sim}\text{use, } s = n; \\ \pi_s \mathfrak{h} - qo, & \text{works/uses, } s = n, b, a; \\ \pi_s \mathfrak{h} - p\underline{o} - q(o - \underline{o}), & \text{works/uses, } s = p; \\ t - qo, & {\sim}\text{work/uses, } s = b, a. \end{cases}$$

Opioid utility function – state contingent

$$O(o-\underline{o}) = \begin{cases} O_s(o-\underline{o}) + \varepsilon_s = \mu_s[(o-\underline{o})^{1-\psi} - 1]/(1-\psi) + \varepsilon_s, & \text{user in } s = n, p; \\ O_s(o-\underline{o}) = \mu_b[(o-\underline{o})^{1-\psi} - 1]/(1-\psi), & \text{user in } s = b; \\ O_s(o-\underline{o}) = \mu_a[(o-\underline{o})^{1-\psi} - 1]/(1-\psi) - \omega_a, & \text{user in } s = a; \\ 0, & \text{nonabuser in } s = n, p. \end{cases}$$

with state contingent weights

$$\mu_a \geq \mu_b \geq \mu_p \geq \mu_n;$$

Gumbel euphoria shocks

$$\Pr[\varepsilon_s \leq \tilde{\varepsilon_s}] = \Gamma(\tilde{\varepsilon_s}) = \exp\left(-\exp[-(\tilde{\varepsilon_s} - \nu_s)/\zeta_s]\right), \text{ for } s = n, p;$$

and addiction utility cost $\omega_a \geq 0$.

Leisure utility function – state contingent

$$L(l) = \begin{cases} L_s(1-\mathfrak{h}) = (1-\mu_s)\eta \ln(1-\mathfrak{h}), & \text{work, } s = n, p, b, a; \\ L_s(1) + \lambda_s = \lambda_s & \sim\text{work, } s = b, a. \end{cases}$$

with Gumbel leisure shocks

$$\Pr[\lambda_s \leq \tilde{\lambda_s}] = \Lambda(\tilde{\lambda}_s) = \exp\left(-\exp[-(\tilde{\lambda_s} - \iota_s)/\xi_s]\right), \text{ for } s = b, a.$$

Goods utility function – state contingent

$$U(c) = (1-\mu_s)(1-\eta)(c^{1-\rho}-1)/(1-\rho).$$

Objective probabilities of addiction and death – endogenous

$$\sigma_{ij} = S_{ij}(o) = \kappa_j \sqrt{o}, \text{ for } (i \to j) = (b \to a), (a \to d)$$

- function of opioid use, o

Subjective probability of addiction – early stage of crisis

$$\widetilde{\sigma}_{ba} = \alpha S_{ba}(o), \text{ with } 0 \leq \alpha \leq 1$$

- degree of misperception, α

Expected Lifetime Utilities

- N, nonuser
  - before ecstasy shock, ε_n
- P, prescription user
  - before ecstasy shock, ε_p
- B, abuser
  - before leisure shock, λ_b
- A, addict
  - before leisure shock, λ_a
- δ, value of death
- β, discount factor

Prescription User

- *Threshold rule for opioid use*

$$o = \begin{cases} \underline{o}, & \text{abide by Rx, if } \varepsilon_p < \varepsilon_p^*; \\ o > \underline{o}, & \text{don't abide, if } \varepsilon_p > \varepsilon_p^*. \end{cases}$$

- *Odds abide by prescription*

$$\Pr(\text{abide}) = \underbrace{\Gamma(\varepsilon_p^*)}_{\text{Gumbel}}$$

$$\Pr(\text{don't abide}) = 1 - \Gamma(\varepsilon_p^*)$$

Nonuser

Prescription User's Bellman equation

$$P = \underbrace{\Gamma(\varepsilon_p^*)}_{\text{abide}}\Big\{U(\pi_p\mathfrak{h} - \boldsymbol{p}\underline{\boldsymbol{o}}) + L_p(1-\mathfrak{h}) + \beta\big[(1-\boldsymbol{\sigma_{pn}})P + \boldsymbol{\sigma_{pn}}N\big]\Big\}$$

$$+\underbrace{[1-\Gamma(\varepsilon_p^*)]}_{\text{don't abide}}\Big\{\max_{o>\underline{o}} U\big(\pi_p\mathfrak{h} - \boldsymbol{p}\underline{\boldsymbol{o}} - \boldsymbol{q}(o-\underline{\boldsymbol{o}})\big) + O_p(o-\underline{o})$$

$$+\mathbf{E}[\varepsilon_p|\varepsilon_p \geq \varepsilon_p^*] + L_p(1-\mathfrak{h}) + \beta\big[(1-\sigma_{bn})B + \sigma_{bn}N\big]\Big\}.$$

Abusers

- *Threshold rule for working*

$$h = \begin{cases} 1, & \text{work, if } \lambda_b < \lambda_b^*; \\ 0, & \text{don't work, if } \lambda_b > \lambda_b^*. \end{cases}$$

- *Odds of work and no work*

$$\Pr(\text{work}) = \Lambda(\lambda_b^*) \text{ and } \Pr(\text{don't work}) = 1 - \Lambda(\lambda_b^*)$$

- *Odds of addiction*
  - Actual: $S_{ba}(o)$
  - Perceived: $\boldsymbol{\alpha} S_{ba}(o)$
    - functions of opioid use, o

Abuser's Bellman equation

$$B = \max_{o > \underline{o}} \Bigg\{ \underbrace{\Lambda(\lambda_b^*)}_{\text{work}} \Big\{ U\big(\pi_b \mathfrak{h} - \boldsymbol{q} o\big) + O_b(o - \underline{o}) + L_b(1 - \mathfrak{h})$$

$$+ [1 - \boldsymbol{\alpha} S_{ba}(o)]\beta\big[(1 - \sigma_{bn})B + \sigma_{bn}N\big] + \boldsymbol{\alpha} S_{ba}(o)\beta A \Big\}$$

$$+$$

$$\underbrace{[1 - \Lambda(\lambda_b^*)]}_{\text{don't work}} \Big\{ U\big(t - \boldsymbol{q} o\big) + O_b(o - \underline{o}) + L_b(1) + \mathbf{E}[\lambda_b | \lambda_b \geq \lambda_b^*]$$

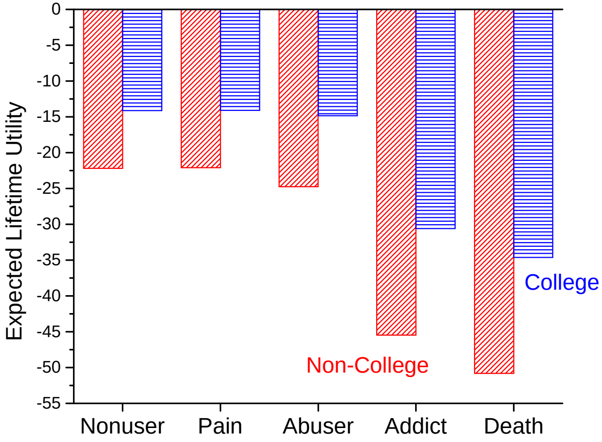
$$+ [1 - \boldsymbol{\alpha} S_{ba}(o)]\beta\big[(1 - \sigma_{bn})B + \sigma_{bn}N\big] + \overbrace{\boldsymbol{\alpha}}^{\text{misinformation}} \underbrace{S_{ba}(o)}_{\text{addiction}} \beta A \Big\} \Bigg\}.$$

Addicts

- Between 2000 and 2018:
  - $\downarrow$ opioid prices ($\boldsymbol{p}$ and $\boldsymbol{q}$)
  - $\uparrow$ prescription dosage level ($\underline{\boldsymbol{o}}$)
  - $\uparrow$ prescription duration ($\downarrow \boldsymbol{\sigma_{pn}}$)
  - $\uparrow$ death risk conditional on addiction ($\boldsymbol{\kappa_d}$)
    - due to shift in opioid consumption towards more deadly fentanyl
  - $\downarrow$ misinformation about addiction risk ($\uparrow \boldsymbol{\alpha}$)
- Assess impact of these changes on usage and deaths

- Model period is one year.
- Calibrate model to 2015–2018 cross-sectional data assuming no misinformation ($\alpha = 1$).
- Some parameters are set directly others are chosen by targeting moments such as
  - opioid consumption levels and transition rates by stage of usage, opioid price elasticity, VSL.
- To determine α in 2000:
  - assume beliefs about addiction risk in 2000 are same as in 2010 (peak of Rx distribution).
  - target 2010–2018 change in deaths given observed changes in prices, Rx's, and death risk.
- Separate calibrations for college and non-college.

details



Expected Lifetime Utility
0
-5
-10
-15
-20
-25
-30
-35
-40
-45
-50
-55
Nonuser
Pain
Abuser
Addict
Death
College
Non-College

Cross-State Validation Check

Triplicate Prescription Programs

- When OxyContin was introduced in 1996, some states had drug monitoring programs called Triplicate Prescription Programs.
  - California, Idaho, Illinois, NY, Texas

- Triplicate states:
  - OxyContin distribution was $\approx$ 50% $\downarrow$
  - Less marketing of OxyContin
  - Opioid deaths were 45% $\downarrow$
  - Number of people misusing opioids was 50% $\downarrow$

  (Alpert, Evans, Lieber and Powell, 2019)

- Is the model-implied relationship between distribution and marketing of Rx opioids and opioid misuse/deaths consistent with this evidence?

Exercise: Compare misuse/deaths in

- 2000 steady state and
- 2000 steady state with Triplicate Prescription Programs:
  - Rx opioid distribution 50% lower:
    1. $\downarrow$ # Rx users (σ_{np})
    2. $\downarrow$ Rx strength ($\underline{o}$ in budget constraint only)
    3. Equal share decline in both
  - Less OxyContin marketing:
    - Eliminated misinformation

Deaths in 2000: Effect of Triplicate Prescription Programs

	Deaths	Misusers (%)
2000 steady state	17,449	3.0
Rx opioid distribution 50%↓		
↓ *# Rx users*	7,124 (59.2%↓)	1.3 (56.1%↓)
↓ *Rx strength*	10,608 (39.2%↓)	2.0 (33.3%↓)
↓ *Both*	8,632 (50.5%↓)	1.6 (46.3%↓)

- Alpert et al (2022): 45% lower deaths in triplicate states.

Deaths in 2000: Effect of Triplicate Prescription Programs

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- Alpert et al (2022): 50% less misusers in triplicate states.

- Between 2000 and 2018
  1. prices declined
  2. prescriptions became more powerful
  3. prescription lengths got longer
  4. risk of death conditional on addiction increased
  5. misinformation about addiction risk declined
- Use model to assess the contribution of each factor to the rise in opioid usage and death.

Experiment: Higher prices

Increase opioid prices: street 155%, prescription 350%

Non-college

	Baseline 2018	$\uparrow$ p and q 2000	% Change 2018 to 2000
Opioid Consumption			
Average	*365.6*	119.7	67% $\downarrow$
Misusers	*3,967.8*	3,877.7	
Addicts	*14,372.3*	8,865.2	
Demographics			
Misusers	*0.0444*	0.0179	
Addicts	*0.0132*	0.0057	
Deaths	*37,596*	12,662	
Deaths, explained		83%	

- Higher prices $\Rightarrow$ 67% decline in opioid consumption for non-college.

employment

Experiment: Higher prices

Increase opioid prices: street 155%, prescription 350%

Non-college

	Baseline 2018	$\uparrow$ p and q 2000	% Change 2018 to 2000
Opioid Consumption			
Average	*365.6*	119.7	
Misusers	*3,967.8*	3,877.7	2% $\downarrow$
Addicts	*14,372.3*	8,865.2	38% $\downarrow$
Demographics			
Misusers	*0.0444*	0.0179	60% $\downarrow$
Addicts	*0.0132*	0.0057	57% $\downarrow$
Deaths	*37,596*	12,662	
Deaths, explained		83%	

- Both consumption conditional on misuse/addiction and the number of misusers/addicts decline.

employment

Experiment: Higher prices

Increase opioid prices: street 155%, prescription 350%

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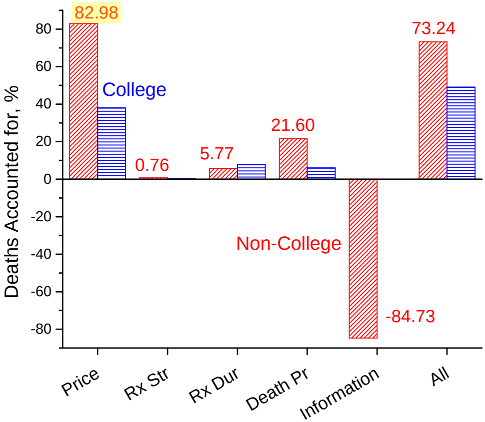
Deaths, explained		83%	

- Non-college: ≈7,549 deaths in 2000
- Change in prices generates ≈83% of change in deaths

employment

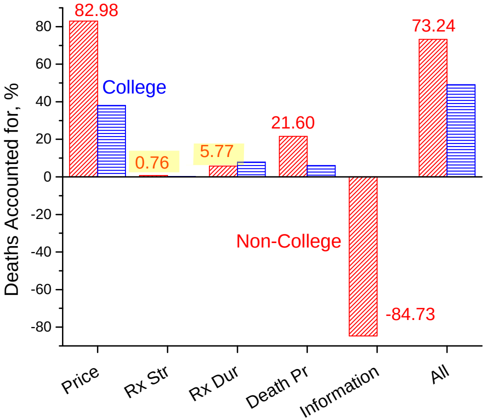
Results Summary

Accounting for the increase in opioid deaths 2000 to 2018



- Decline in prices had the largest effect accounting for 83% of the rise in non-college deaths.

details

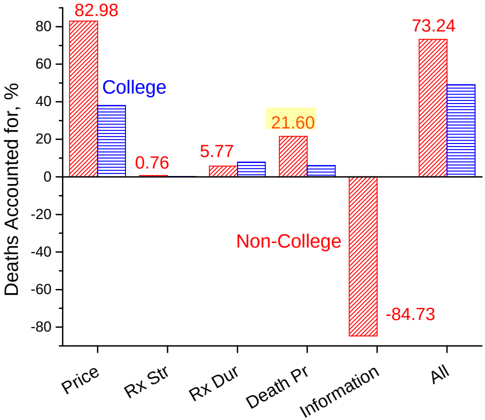


- Changes in Rx dosages and durations had little effect.

details

Results Summary

Accounting for the increase in opioid deaths 2000 to 2018

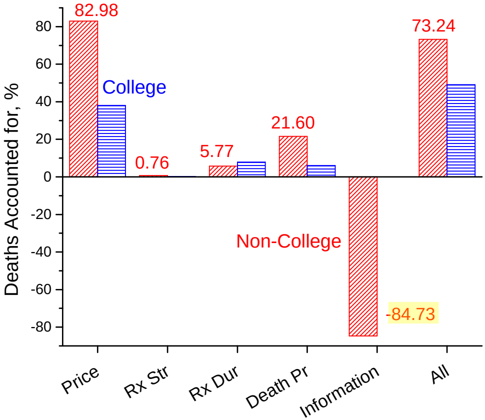


- Increases in the risk of death accounts for 22% of the rise.

details

Results Summary

Accounting for the increase in opioid deaths 2000 to 2018

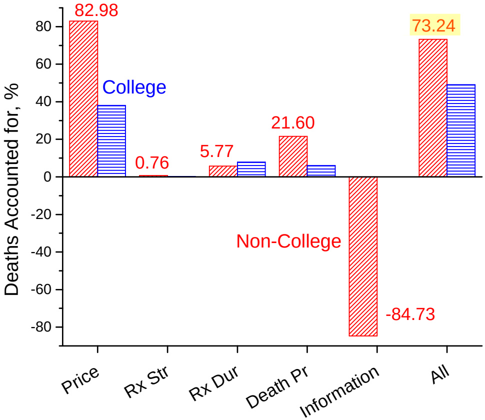


- Decline in misinformation reduced deaths by 85% of the rise.

details

Results Summary

Accounting for the increase in opioid deaths 2000 to 2018



- All factors together account for 73% of the rise in deaths for non-college and 49% for college.

details

- A model of the opioid crisis is developed and calibrated.
- Find:
  - drop in Rx and street prices of opioids
  - increases in Rx strength and duration
  - increase in addicts' death risk and
  - decline in misinformation

  can account for more than 70% of rise in non-college deaths.
- Drop in prices and increase in death risk had the largest impact.

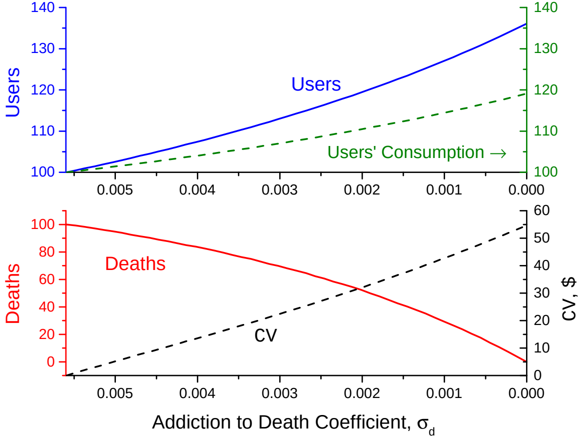
- Consider two medical advances:
  1. A reduction in the probability of death for a given level of opioid usage

     Example: improvements in drugs like Naloxone
  2. A reduction in the probability of addiction for a given level of opioid usage

     Example: development of less addictive opioids
- What are the implications for usage and deaths?

Results: Medical Advances

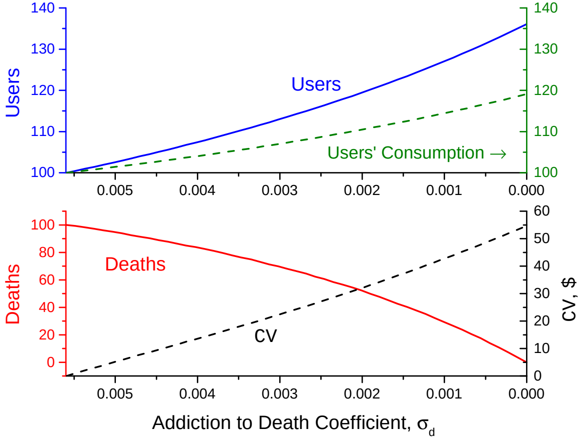
Reducing the probability of dying by lowering σ_d



- Number of users and their usage levels ↑.
- Consistent with Doleac and Mukherjee (2021) who find ↑ access to naloxone ⇒ ↑ usage using cross-state variation.

Results: Medical Advances

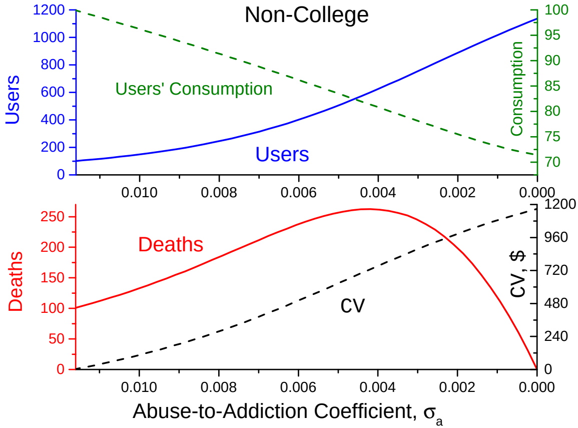
Reducing the probability of dying by lowering σ_d



- On net, deaths ↓.
- Avg. WTP ≈ $24 for 50% ↓ in cond. death prob.

Results: Medical Advances

Reducing the probability of addiction by lowering σ_a



- Number of users ↑ substantially but usage levels ↓ (less addicts). Deaths ↑ and then ↓.
- Avg. WTP ≈ \$522 for 50% ↓ in cond. addiction prob.

- What is the willingness to pay to move from a world without illegal opioids to their availability at the 2015–2018 prices?

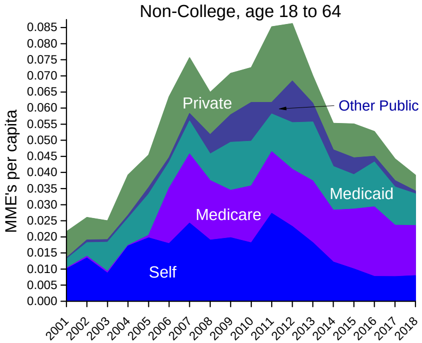
WTP to reduce illicit price of opioids from ∞ to baseline value

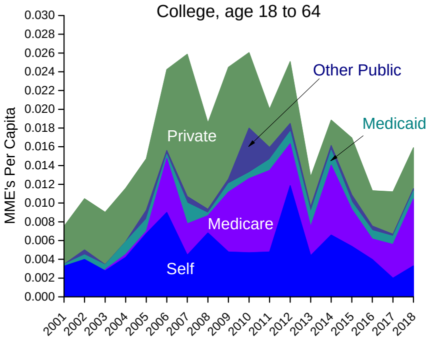
	Non-College	College
Non-user	\$198.64	\$146.40
Prescription-user	\$363.80	\$272.05
Average	\$225.85	\$159.99

- Non-college average WTP = 0.52% of non-opioid consumption.
- College is 0.23%.

- 1990s: pain management movement
- 1995: American Pain Society argues pain is the fifth vital sign
- 1996: Purdue Pharma introduces OxyContin with an aggressive marketing campaign targeted at physicians.
- 2002–2005: Hospital Consumer Assessment of Healthcare Providers and Systems Survey (HCAHPS) and 2005 Deficit Reduction Act links Medicare/Medicaid payments to hospitals to pain management survey results.
- 2004: generic opioids enter the Rx market
- 2006: a Mexican lab dramatically ↑ US fentanyl supply, was quickly shut down through cooperative action of US and Mexico.
- 2001–2010: % of Rx opioids funded by govt ↑ 17% to 60%
- 2006: Medicare part D prescription drug coverage
- 2007–2010: SSDI rolls expand
- 2010: tamper-resistant OxyContin formulation released, heroin usage ↑
- 2013: fentanyl enters the US black market primarily from China/Mexico

back





- 2001–2010: % of Rx opioids funded by govt ↑ 17% to 60%

back

- *Threshold rule for opioid use*

$$o = \begin{cases} 0, & \text{don't use, if } \varepsilon_n < \varepsilon_n^*; \\ o > \underline{o}, & \text{use, if } \varepsilon_n > \varepsilon_n^*. \end{cases}$$

–odds don't use and use, $\Gamma(\varepsilon_n^*)$ and $1 - \Gamma(\varepsilon_n^*)$

- *Nonuser's Bellman equation*

$$N = \underbrace{\Gamma(\varepsilon_n^*)}_{\text{don't use}} \left\{ U(\pi_n \mathfrak{h}) + L_n(1-\mathfrak{h}) + \beta\left[(1-\sigma_{np})N + \sigma_{np}P\right] \right\}$$

$$+ \underbrace{\left[1 - \Gamma(\varepsilon_n^*)\right]}_{\text{use}} \left\{ \max_{o > \underline{o}} U\left(\pi_n \mathfrak{h} - \boldsymbol{q} o\right) + O_n(o - \underline{o}) \right.$$

$$\left. + \mathbf{E}[\varepsilon_n | \varepsilon_n \geq \varepsilon_n^*] + L_n(1-\mathfrak{h}) + \beta\left[(1-\sigma_{bn})B + \sigma_{bn}N\right] \right\}$$

Back

Nonuser's threshold equation

$$\varepsilon_n^* = \underbrace{U(\pi_n \mathfrak{h}) + L_n(1-\mathfrak{h}) + \beta\left[(1-\sigma_{np})N + \sigma_{np}P\right]}_{\text{expected utility if don't use}}$$

$$\underbrace{- \max_{o>\underline{o}} \Big\{ U\big(\pi_n \mathfrak{h} - qo\big) + L_n(1-\mathfrak{h}) + O_n(o - \underline{o}) + \beta\left[(1-\sigma_{bn})B + \sigma_{bn}N\right]\Big\}}_{\text{expected utility if use net of euphoria shock}}.$$

Back

Addicts

- *Threshold rule for working*

$$h = \begin{cases} 1, & \text{work, if } \lambda_a < \lambda_a^*; \\ 0, & \text{don't work, if } \lambda_a > \lambda_a^*. \end{cases}$$

- *Odds of work and no work*

$$\Pr(\text{work}) = \Lambda(\lambda_a^*) \text{ and } \Pr(\text{don't work}) = 1 - \Lambda(\lambda_a^*)$$

- *Odds of death*, $S_{ad}(o)$

Addict's Bellman equation

$$A = \max_{o > \underline{o}} \left\{ \underbrace{\Lambda(\lambda_a^*)}_{\text{work}} \left\{ U\left(\pi_a \mathfrak{h} - \boldsymbol{q} o\right) + O_a(o - \underline{o}) + L_a(1 - \mathfrak{h}) \right. \right.$$

$$\left. + [1 - S_{ad}(o)]\beta\left[(1 - \sigma_{an})A + \sigma_{an}N\right] + S_{ad}(o)\beta\delta \right\}$$

$$+$$

$$\underbrace{[1 - \Lambda(\lambda_a^*)]}_{\text{don't work}} \left\{ U\left(t - \boldsymbol{q} o\right) + O_a(o - \underline{o}) + L_a(1) + \mathbf{E}[\lambda_a | \lambda_a \geq \lambda_a^*] \right.$$

$$\left. \left. + [1 - S_{ad}(o)]\beta\left[(1 - \sigma_{an})A + \sigma_{an}N\right] + \underbrace{S_{ad}(o)}_{\text{death}}\beta\delta \right\} \right\}.$$

Back

- In the estimated Markov chains:
  - stages are different
    - misusers: include abusers and first-time misusers
  - some transition matrix elements picked directly from the data
  - rest are estimated
    - use data on (unconditional) fractions of population in each stage details
    - and imposing model-implied restrictions on elements details
- Using estimation results:
  - solve nonlinear system to obtain some model parameters.

Back

Parameter	Explanation	Non-College	College
σ_{np}	Prob[$n \rightarrow p$]	0.0347	0.0449
σ_{pn}	Prob[$p \rightarrow n$]	0.1759	0.3703
σ_{bn}	Prob[$b \rightarrow n$]	0.1419	0.1854
σ_{an}	Prob[$a \rightarrow n$]	0.0455	0.0290
$\Gamma(\varepsilon_n^*)$	Non-misusers $\div$ Nonusers	0.9966	0.9989
$\Gamma(\varepsilon_p^*)$	Non-misusers $\div$ Prescription users	0.9689	0.9510
$S_{ba}(o)$	Prob[$b \rightarrow a$]	0.0232	0.0069
$S_{ad}(o)$	Prob[$a \rightarrow d$]	0.0212	0.0106

- Estimation gives us 4 exogenous transition probabilities and 4 target moments.

Back

US Population Ages 18-64 by Opioid Use, Fractions

	Nonuser	Prescription	Misuser	Addict	Dead
	$\mathtt{t}_{\mathtt{n}}$	$\mathtt{t}_{\mathtt{p}}$	$\mathtt{t}_{\mathtt{m}}$	$\mathtt{t}_{\mathtt{a}}$	$\mathtt{t}_{\mathtt{d}}$
Non-College	0.80688	0.13477	0.04479	0.01328	0.00028
College	0.87342	0.09182	0.03040	0.00432	0.00005

Source: 2015–2018 NSDUH, MEPS, and CDC Vital Statistics

- **Misuser:** use any opioids w/o a prescription, use them for reasons other than directed by a physician, use more than prescribed
- **Addict:** misuser who has an opioids dependence according to criteria in the American Psychiatric Association *Diagnostic and Statistical Manual of Mental Disorders* (DSM-5).

Back

Transition Matrix for the Model

$$T = [i \to j]$$

Cells have endogenous components

$$
\begin{array}{cc}
i/j & \begin{array}{ccccc} \to n & \to p & \to b & \to a & \to d \end{array} \\
\begin{array}{c} n \\ p \\ b \\ a \\ d \end{array} &
\begin{bmatrix}
\Gamma(\varepsilon_n^*)(1-\sigma_{np}) + [1-\Gamma(\varepsilon_n^*)]\sigma_{bn} & \Gamma(\varepsilon_n^*)\sigma_{np} & [1-\Gamma(\varepsilon_n^*)](1-\sigma_{bn}) & 0 & 0 \\
\Gamma(\varepsilon_p^*)\sigma_{pn} + [1-\Gamma(\varepsilon_p^*)]\sigma_{bn} & \Gamma(\varepsilon_p^*)(1-\sigma_{pn}) & [1-\Gamma(\varepsilon_p^*)](1-\sigma_{bn}) & 0 & 0 \\
[1-S_{ba}(o)]\sigma_{bn} & 0 & [1-S_{ba}(o)](1-\sigma_{bn}) & S_{ba}(o) & 0 \\
[1-S_{ad}(o)]\sigma_{an} & 0 & 0 & [1-S_{ad}(o)](1-\sigma_{an}) & S_{ad}(o) \\
1 & 0 & 0 & 0 & 0
\end{bmatrix}
\end{array}
$$

Back

Transition Matrix for the Model Mapped to the Data

$$T = [i \to j]$$

Cells have endogenous components

$$\begin{array}{cc} i/j & \begin{array}{ccccc} \to n & \to p & \to m & \to a & \to d \end{array} \\ \begin{array}{c} n \\ p \\ m \\ a \\ d \end{array} & \begin{bmatrix} \Gamma(\varepsilon_n^*)(1-\sigma_{np}) & \Gamma(\varepsilon_p^*)\sigma_{np} & [1-\Gamma(\varepsilon_n^*)](1-\sigma_{np}) + [1-\Gamma(\varepsilon_p^*)]\sigma_{np} & 0 & 0 \\ \Gamma(\varepsilon_n^*)\sigma_{pn} & \Gamma(\varepsilon_p^*)(1-\sigma_{pn}) & [1-\Gamma(\varepsilon_n^*)]\sigma_{pn} + [1-\Gamma(\varepsilon_p^*)](1-\sigma_{pn}) & 0 & 0 \\ \{\tilde{e}_b[1-S_{ba}(o)] + \tilde{e}_n + \tilde{e}_p\}\Gamma(\varepsilon_n^*)\sigma_{bn} & 0 & T_{\text{mm}} & \tilde{e}_b S_{ba}(o) & 0 \\ [1-S_{ad}(o)]\sigma_{an}\Gamma(\varepsilon_n^*) & 0 & [1-S_{ad}(o)]\sigma_{an}[1-\Gamma(\varepsilon_n^*)] & [1-S_{ad}(o)](1-\sigma_{an}) & S_{ad}(o) \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

Back

Estimated Transition Matrix–Data

2 cross-cell restrictions–implied by model

$$
\begin{array}{cc}
i/j & \begin{array}{ccccc} \to n & \to p & \to m & \to a & \to d \end{array} \\
\begin{array}{c} n \\ p \\ m \\ a \\ d \end{array} &
\begin{bmatrix}
1 - T_{np} - T_{nm} & T_{np} & T_{nm} & 0 & 0 \\
T_{pn} & 1 - T_{pn} - T_{pm} & T_{pm} & 0 & 0 \\
T_{mn} & 0 & 1 - T_{mn} - T_{ma} & T_{ma} & 0 \\
T_{an} & 0 & T_{an}(1 - T_{dn})/T_{dn} & 1 - T_{an} - T_{ad} & T_{ad} \\
(T_{nn}T_{pp} - T_{np}T_{pn})/(T_{pp} - T_{np}) & 0 & 1 - T_{dn} & 0 & 0
\end{bmatrix}
\end{array},
$$

Back

Non-College	
Prescription	
avg annual usage, $\underline{o}$	3,544 MME
avg OOP expenses	\$48.38
price, p (avg OOP exp/avg usage)	\$0.014/MME
Street	

Source: MEPS
MME - morphine milligram equivalents

- avg annual usage $\approx$ 10 MME a day
- Typical doses:
  - Starting: 15 MME every 12 hours
  - Standard: less than 60 MME every 12 hours

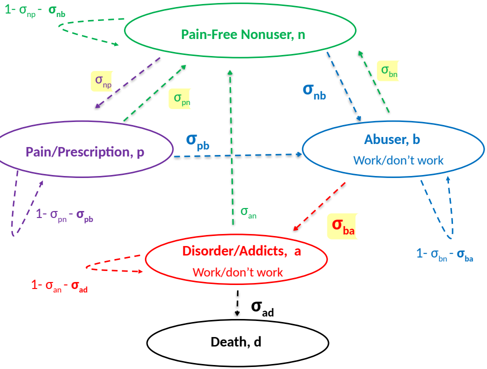
Non-College

Prescription	
avg annual usage, $\underline{o}$	3,544 MME
avg OOP expenses	\$48.38
price, p (avg OOP exp/avg usage)	\$0.014/MME
Street	
oxycodone street price	\$0.67/MME
given by friends/relatives or stolen	65%
price, q (0.35$\times$ street price)	\$0.24/MME

Source: MEPS
MME - morphine milligram equivalents

- street price: $q = \$0.67 \times 0.35 = \$0.24$ per MME

details



- Data: Some transitions taken directly from data and some estimated by targeting usage demographics.
- Calibration: Set exogenous transitions to observed/estimated values and use endogenous ones as targets.

details exog params

Opioid usage:

- weights on opioid utility, euphoria shock variances, addiction and death probabilities
- **Targets:** abusers and addicts opioid consumption; transition rates: nonuser (Rx user) to abuser, abuser to addict, addict to dead

Employment:

- variances of leisure shocks and labor productivities of abusers and addicts
- **Targets:** abusers and addicts relative employment rates and income

Rest:

- death and addiction disutility, extent of misperception in 2000
- **Targets:** statistical value of life, opioid price elasticity, 2010-18 Δdeaths

details back

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details back

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details back

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- **Targets:** abusers and addicts relative employment rates and income

Rest:

- death and addiction disutility, extent of misperception in 2000
- **Targets:** statistical value of life, opioid price elasticity, 2010-18 Δdeaths

details back

Source of Opioids for Misusers and Addicts

Source	Misusers	Addicts	Total
Non-College			
Prescribed by one or more doctor	31.92	34.42	32.40
Given from friends/relatives	44.49	23.31	40.43
Bought from friends/relatives	10.06	17.43	11.47
Stolen (hospitals, friends/relatives)	3.57	2.82	3.43
Bought from dealer	5.29	18.47	7.82
Other	4.67	3.54	4.45
College			
Prescribed by one or more doctor	43.09	57.24	44.60
Given from friends/relatives	44.89	15.55	41.75
Bought from friends/relatives	4.56	17.79	5.97
Stolen (hospitals, friends/relatives)	3.50	1.93	3.33
Bought from dealer	0.88	6.04	1.43
Other	3.09	1.46	2.91

back

$ Street Price per mg

Opioid	*Street Rx*	*DDS*	*Silk Road*	*MME*
Hydromorphone	3.29	4.47	3.55	4
Oxymorphone	1.57	1.65	1.58	3
Methadone	0.96	1.16	0.93	3
Oxycodone	0.97	0.86	0.99	1.5
Hydrocodone	0.81	0.9	0.97	1

Source: Dasgupta et al. (2013)
MME - morphine milligram equivalents

- Oxycodone street price $\approx$ \$1 per mg = \$0.67 per MME
- StreetRx: website of anonymously submitted street prices for drugs
- Drug Diversion Survey (DDS): data from an illegal drug surveillance group run by Denver Health
- Silk Road: anonymous online drug marketplace

back

		Non-College	College
Average yearly prescribed opioid usage	$\underline{o}$	3,544 MME (≈10 MME a day)	1,785 MME (≈5 MME a day)
Avg OOP expenses on prescribed opioids in 2015		\$48.38	\$37.10
Prescription price (avg OOP exp/avg usage)	p	\$0.014 per MME	\$0.021 per MME

Source: MEPS
MME - morphine milligram equivalents

Parameters Set Directly

Parameter	Explanation	Non-College	College	Comment
		From the Literature		
ρ	Relative risk aversion	2		Standard
η	Weight on leisure	0.64		C.&P. (1995)
β	Discount factors, nonaddicts	0.96		Standard
		From the US Data		
Transitions				
σ_{np}	Prob[$n \rightarrow p$]	0.0347	0.0449	PTM estimation
σ_{pn}	Prob[$p \rightarrow n$]	0.1759	0.3703	PTM estimation
σ_{bn}	Prob[$b \rightarrow n$]	0.1419	0.1854	PTM estimation
σ_{an}	Prob[$a \rightarrow n$]	0.0455	0.0290	PTM estimation
Employment				
$\mathfrak{h}$	Hours worked	0.38	0.41	CPS
π_n	Productivity, nonusers	1	1.49	normalization
t	Income, non-employed	0.079	0.129	CPS
Opioids				
$\underline{o}$	Rx usage, MME	3,543.75	1,785.00	MEPS
p	Rx price/1,000 MME	0.000137	0.000208	MEPS
q	Street price/1,000 MME	0.00235	0.00125	MEPS and NSDUH

back

- **Parameters:**
  - weights on opioid utility, euphoria shock variances, addiction and death probabilities
- **Target moments:**

Non-College

	Data	Model
Opioid Consumption		
Misusers	3,967.8	3,967.8
Addicts	14,372.5	14,372.3
Transition Probabilities		
Nonuser $\rightarrow$ Abuser	0.0029	0.0029
Prescription User $\rightarrow$ Abuser	0.0267	0.0267
Abuser $\rightarrow$ Addict	0.0232	0.0232
Addict $\rightarrow$ Death	0.0212	0.0212

weights euphoria add/dth

- **Parameters:**
  - variances of leisure shocks and relative labor productivities of abusers and addicts
- **Target moments:**

Non-College

	Data	Model
Employment		
Misuser/Nonuser	0.94	0.94
Addict/Nonuser	0.73	0.73
Income		
Misuser/Nonuser	0.90	0.90
Addict/Nonuser	0.67	0.67

parameters

- **Parameters:**
  - death utility, addiction disutility, misinformation in 2000
- **Target moments:**

Non-College

	Data	Model
Value of Statistical Life	\$9ml	\$8.9ml
Opioid price elasticity	-0.95	-0.88
Change in deaths 2018 to 2010	50%↓	50%↓

- In 2000, non-college underestimate addiction risk by 17.5% ($\alpha = 0.825$).

parameters back

Gumbel leisure shocks

$$\Pr[\lambda_s \leq \tilde{\lambda}_s] = \Lambda(\tilde{\lambda}_s) = \exp\left(-\exp[-(\tilde{\lambda}_s - \iota_s)/\xi_s]\right), \text{ for } s = b, a.$$

$E[\lambda_s]$ is normalized to zero.

Parameter Values

		Non-College	**College**
ξ_b,ι_b	leisure shock, abusers	1.760, -1.0159	0.471, -0.2719
ξ_a,ι_a	leisure shock, addicts	1.360, -0.7850	1.200, -0.6927
π_b	relative productivity, abusers	0.934	0.895
π_a	relative productivity, addicts	0.841	0.986

Targets

	Model	**Data**	**Model**	**Data**
	Non-College		*College*	
Employment (fraction)				
All misusers/Nonusers	0.94	0.94	0.99	0.99
Addicts/Nonusers	0.73	0.73	0.85	0.85
Income				
All misusers/Nonusers	0.90	0.90	0.91	0.91
Addicts/Nonusers	0.67	0.67	0.87	0.87

back

Gumbel euphoria shocks

$$\Pr[\varepsilon_s \leq \tilde{\varepsilon_s}] = \Gamma(\tilde{\varepsilon_s}) = \exp\left(-\exp[-(\tilde{\varepsilon_s} - \nu_s)/\zeta_s]\right), \text{ for } s = n, p;$$

$E[\varepsilon_s]$ is normalized to zero.

Parameter Values

		Non-College	College
ζ_n,ν_n	euphoria shock, nonusers	0.4160, -0.2401	0.0910, -0.0525
ζ_p,ν_p	euphoria shock, Rx users	0.7560, -0.4364	0.2406, -0.1389

Targets

	Model	Data	Model	Data
	Non-College		*College*	
Nonuser $\rightarrow$ Abuser	0.0029	0.0029		
Prescription User $\rightarrow$ Abuser	0.0267	0.0267		

back

Odds of Addiction and Death

$$\sigma_{ij} = S_{ij}(o) = \sigma_j \sqrt{o}, \text{ for } (i \rightarrow j) = (b \rightarrow a), (a \rightarrow d).$$

Parameter Values

		Non-College	**College**
σ_a	Prob$[b \rightarrow a]$	0.01165	0.00406
σ_d	Prob$[a \rightarrow d]$	0.00559	0.00286

Targets

	Model	**Data**	**Model**	**Data**
	Non-College		*College*	
Prob$[b \rightarrow \mathtt{a}]$	0.0232	0.0232	0.0069	0.0069
Prob$[\mathtt{a} \rightarrow \mathtt{d}]$	0.0212	0.0212	0.0106	0.0106

back

Targets

	Model	Data	Model	Data
		Non-College		*College*
Opioid Consumption				
Usage, first-time misusers, MME		3,967.8		2,893.2
Usage, abusers, MME		3,967.8		2,893.2
Usage, addicts, MME		14,372.5		13,772.0

Non-college

$$3,967.8 = (50 \text{ MME per day}) \times (22\% \text{ of days per year})$$
$$14,372.5 = (90 \text{ MME per day}) \times (43\% \text{ of days per year})$$

College

$$2,893.2 = (50 \text{ MME per day}) \times (16\% \text{ of days per year})$$
$$13,772.0 = (90 \text{ MME per day}) \times (42\% \text{ of days per year})$$

Sources: Dowell et al. (2016) and Glanz et al. (2019), NSDUH (days per year)

back

Targets

	Model	Data	Model	Data
	Non-College		*College*	
Opioid Consumption				
Usage, first-time misusers, MME	3,967.7	3,967.8	2,901.6	2,893.2
Usage, abusers, MME	3,967.8	3,967.8	2,900.7	2,893.2
Usage, addicts, MME	14,372.3	14,372.5	13,772.4	13,772.0

Parameter Values

		Non-College	College
ψ	elasticity of opioid use	1.652	
$\mu_n = \mu_p$,	utility weight on opioids	0.00131	
μ_b	utility weight on opioids	0.0182	0.0237
μ_a	utility weight on opioids	0.870	0.333

back

Targets

	Model	Data	Model	Data
	Non-College		*College*	
VSL (millions of 2018 dollars)		9.0		11.8
	All			
Opioid price elasticity		-0.95		

- VSL: value of statistical life based on willingness to pay to reduce risk of death
- Mean VSL of $10 million and income elasticity of 0.5 (Viscusi and Aldy, 2003)

back

Targets

	Model	Data	Model	Data
	Non-College		*College*	
VSL (millions of 2018 dollars)		9.0		11.8
	All			
Opioid price elasticity		-0.95		

- Opioid price elasticity: Estimates range from -1.5 to -0.4
- Target -0.95, midpoint of range

back

Targets

	Model	Data	Model	Data
	Non-College		*College*	
VSL (millions of 2018 dollars)	8.9	9.0	11.9	11.8
	All			
Opioid price elasticity	-0.88	-0.95		

Parameter Values

		Non-College	College
δ	utility associated with death	-50.80	-34.63
ω_a	utility cost of addiction	4.004	1.84

back

Experiment: Higher prices

Increase opioid prices: street 155%, prescription 350%

Non-college

	Baseline 2018	$\uparrow$ p and q 2000	% Change 2018 to 2000
Employment			
Misusers	*0.9439*	0.9680	3% $\uparrow$
Addicts	*0.7260*	0.8001	10% $\uparrow$
All	*0.9939*	0.9983	0.4% $\uparrow$

- Higher prices $\Rightarrow$ more misusers and addicts employed.
- $\uparrow$ employment due to less misusers/addicts and their higher employment rate.

back

Experiment: Less powerful prescriptions

Decrease Rx strength ($\underline{o}$) by 42%

Non-college

	Baseline 2018	$\downarrow \underline{o}$ 2000	% Change 2018 to 2000
Opioid Consumption			
Average	*365.6*	363.4	0.60% $\downarrow$
Misusers	*3,967.8*	3,967.2	0.02% $\downarrow$
Addicts	*14,372.3*	14,372.2	0.00% $\downarrow$
Demographics			
Misusers	*0.0444*	0.0441	0.68% $\downarrow$
Addicts	*0.0132*	0.0131	0.76% $\downarrow$
Deaths	*37,596*	37,367	0.61% $\downarrow$
Deaths, explained		0.76%	

- Lower Rx strength $\Rightarrow$ 0.6% decline in opioid consumption.
- Change in prices generates $\approx$0.76% of change in deaths

Experiment: Less powerful prescriptions

Decrease Rx strength ($\underline{o}$) by 42%

Non-college

	Baseline	$\downarrow \underline{o}$	% Change
	2018	2000	2018 to 2000
Employment			
Misusers	*0.9439*	0.9439	0.00%
Addicts	*0.7260*	0.7260	0.00%

- No effect on misusers' and addicts' employment.

back

Experiment: Shorter prescription lengths

Increase $p \rightarrow n$ transitions (σ_{pn}) by 16%

Non-college

	Baseline 2018	$\uparrow \sigma_{pn}$ 2000	% Change 2018 to 2000
Opioid Consumption			
Average	*365.6*	348.7	5% $\downarrow$
Misusers	*3,967.8*	3,967.7	0% $\downarrow$
Addicts	*14,372.3*	14,372.3	0% $\downarrow$
Demographics			
Misusers	*0.0444*	0.0423	5% $\downarrow$
Addicts	*0.0132*	0.0126	5% $\downarrow$
Deaths	*37,596*	35,862	5% $\downarrow$
Deaths, explained		5.77%	

- Reducing Rx lengths has a small effect.
- Longer Rx lengths accounts for ≈6% of rise in deaths

Experiment: Shorter prescription lengths

Increase $p \rightarrow$n transitions (σ_{pn}) by 16%

Non-college

	Baseline 2018	$\uparrow \sigma_{pn}$ 2000	% Change 2018 to 2000
Employment			
Misusers	*0.9439*	0.9439	0.00%
Addicts	*0.7260*	0.7260	0.00%

- No effect on misusers' and addicts' employment.

back

Experiment: Lower death probability

Decrease Prob$[a \to d]$ by 41%

Non-college

	Baseline 2018	$\downarrow$ Prob$[a \to d]$ 2000	% Change 2018 to 2000
Opioid Consumption			
Average	*365.6*	410.0	12% $\uparrow$
Misusers	*3,967.8*	3,971.3	0% $\uparrow$
Addicts	*14,372.3*	14,736.6	3% $\uparrow$
Demographics			
Misusers	*0.0444*	0.0468	5% $\uparrow$
Addicts	*0.0132*	0.0152	15% $\uparrow$
Deaths	*37,596*	31,106	17% $\downarrow$
Deaths, explained		21.60%	

- Lowering death prob: opioid consumption $\uparrow$ but deaths $\downarrow$.
- Higher death prob accounts for $\approx$22% of rise in deaths

Non-college

	Baseline 2018	$\downarrow$ Prob$[a \to d]$ 2000	% Change 2018 to 2000
Employment			
Misusers	*0.9439*	0.9439	0%
Addicts	*0.7260*	0.7286	0.36%

back

Experiment: Misinformation about addiction risk

$\alpha = 0.825$

Non-college

	Baseline 2018	Misinformation 2000	% Change 2018 to 2000
Opioid Consumption			
Average	*365.6*	614.2	68% ↑
Misusers	*3,967.8*	4,004.8	1% ↑
Addicts	*14,372.3*	14,364.5	0% ↓
Demographics			
Misusers	*0.0444*	0.0741	67% ↑
Addicts	*0.0132*	0.0221	67% ↑
Deaths	*37,596*	63,054	68% ↑
Deaths, explained		-84.73%	

- With misinformation opioid consumption ↑.
- Eliminating misinformation reduced deaths by ≈-85%

Non-college

	Baseline 2018	$\alpha = 0.77$ 2000	% Change 2018 to 2000
Employment			
Misusers	*0.9439*	0.9440	0.00%
Addicts	*0.7260*	0.7260	0.00%

back

Experiment: All changes

prices, dosage, Rx length set to 2000 values

	Baseline 2018	All changes 2000	% Change 2018 to 2000
Opioid Consumption			
Average	*365.6*	199.3	45% ↓
Misusers	*3,967.8*	3,920.5	1% ↓
Addicts	*14,372.3*	8,900.1	38% ↓
Demographics			
Misusers	*0.0444*	0.0287	35% ↓
Addicts	*0.0132*	0.0098	26% ↓
Deaths	*37,596*	15,591	59%↓
Deaths, explained		73.24%	

- All 3 changes $\Rightarrow$ 45% decline in opioid consumption.
- Together accounts for $\approx$73% of rise in deaths

Non-college

	Baseline 2018	All changes 2000	% Change 2018 to 2000
Employment			
Misusers	*0.9439*	0.9682	2.57%
Addicts	*0.7260*	0.8012	10.36%

back

- Build on the models of rational addiction by Becker and Murphy (1988), Orphanides and Zervos (1995), and Strulik (2021).
- Habit-formation in Becker and Murphy (1988) is replaced by state-contingent preferences.
  - BM-type models can have multiple steady states and cycles.
- First quantitative model of opioid crisis where stages map naturally into the data.
- Captures three key features of addiction:
  - Reinforcement: current opioid consumption $\uparrow$ future consumption.
  - Tolerance: utility declines with opioid consumption.
  - Withdrawal: users crave opioids.
- Allows for: dynamics, misinformation, medical innovations, deaths and death risk.

emplit back

- Ruhm (2018): changes in unemployment, poverty, median household incomes, home prices, and exposure to import competition account for less than 10% of the increase in opioid deaths from 1999 to 2015.
- Pierce and Schott (2020): an increase from 25th to 75th percentile in a county's import competition from China (due to the permanent normal trade relations bill in 2000) accounts for less than 20% of the increase in the drug overdose death rate between 1999 and 2018.
- Ruhm (2019) and Case and Deaton (2017): changes in unemployment rates and median income have only a minor effect on opioid deaths.
- Charles, Hurst, and Schwartz (2019): decline in manufacturing share of employment from 2000 to 2015 could explain all of the increase in opioid deaths over that period (using state-level data).
- Cutler and Glaeser (2021): estimating CHS 2019 model at the commuting zone level and including basic demographic controls eliminates the relationship between manufacturing decline and opioid deaths.
- Cutler and Glaeser (2021): changes in demand-side factors alone, such as physical pain, depression, despair, and social isolation can only explain a small fraction of the increase in opioid use and deaths from 1996 to 2012.

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2015/18 US Population Ages 18-64, Education Shares by Opioid Use

	Population	Prescription	Misuser	Addict	Dead
Non-College	0.667	0.747	0.748	0.861	0.925
College	0.333	0.253	0.252	0.139	0.075

Source: NSDUH, MEPS, and CDC Vital Statistics

- Most addicts and opioid deaths are non-college.

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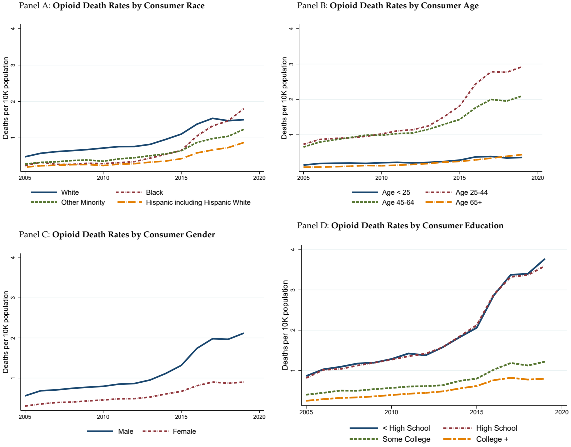
Opioid Death Rates by Demographics

From: Agarwal, Li, Roman, and Sorokina (2022)

Figure 3 **Opioid Death Rates by Consumer Demographics**

This figure plots opioid-related overall death rates per 10K population by consumer demographics (age groups, gender, race groups, and education groups) over time. Rates are constructed relative to their respective population. Data source: CDC/NCHS, National Center for Health Statistics, Mortality.



Source: Agarwal, Li, Roman, and Sorokina (2022)

- Death rates are higher and rose faster among 25–64 year-olds, males, and those with a high school degree or less education.

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