A Structural Analysis of Opioid Misuse: Labor, Health, Policy, and Misperception of Opioid Misuse Risk

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Motivation

- Opioid misuse is defined as "using opioids not as directed by a doctor."
  - Today's pain relief and reward vs. tomorrow's negative labor and health outcomes
- Three kinds of opioid misuse result in different probabilities of death:
  - Misuse his own prescribed (Rx) opioids
  - Use illegally traded opioids
  - Use both Rx and illegally traded opioids

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- During 2015-2019, opioid misuse has decreased, but deaths have increased.
  - Opioid misuse was decreasing in all kinds of misuse.
  - Illegally traded opioids have driven the increase in deaths by opioids.

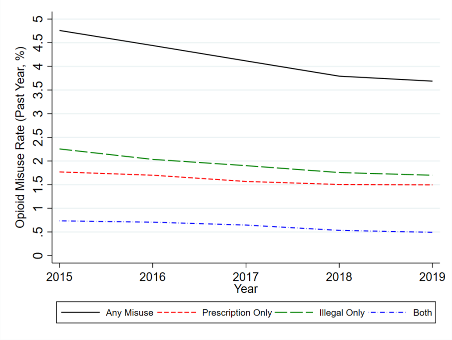

Figure: Opioid Misuse Rates by Type

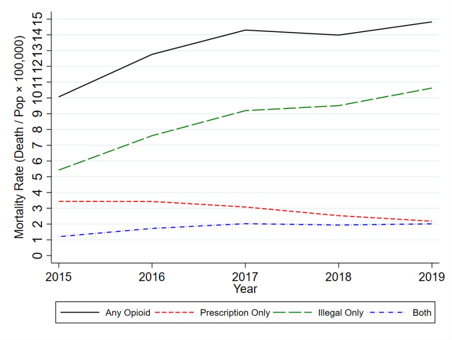

Figure: Opioid Mortality Rates by Type

Research Question

- How have aggregate changes affected opioid misuse during 2015-2019?
  - The probability of death from opioid misuse
  - Policies in prescribing opioids
  - Prices for illegally traded opioids
- To what extent do labor and health factors contribute to opioid misuse?
  - Who is most likely to respond by increasing illegal opioid use following policy changes?
- How large is the misperception of opioid misuse risk playing a role in opioid misuse?
- This paper highlights:
  - Heterogeneous responses to opioid policies driven by health and labor.
  - The role of misperceived opioid misuse risk in amplifying these responses.

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What I do in this paper

- Show novel data facts on opioid misuse and the perception of opioid misuse risk.
- Develop a dynamic model of work and opioid misuse with stochastic perception bias.
  - People with perception bias discount the probability of dying from opioid misuse by 70%.
- Conduct counterfactual analysis on opioid misuse.
  - Shutting down the perception bias would decrease the opioid misuse rate by 20%.
  - Opioid misuse would drop by 44% if 2015's population faced 2019 environment.
    - Policies do not decrease the aggregate opioid misuse rate, but change **who** misuse opioids.
    - The probability of death from opioid misuse decreases opioid misuse by 42%.
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- This paper evaluates the heterogeneous effect of health policies via labor and health conditions with novel data.
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Data

- **NSDUH**: Restricted National Survey of Drug Use and Health, 2015-2019
  - Unique **repeated cross-section** data set on drug use of the US population
  - SES, Received Rx Opioids, Opioid Misuse, and perception of opioid misuse risk
- Marginal Transitions on Health, Labor, Opioid Prescription
  - **SIPP**: Public Survey of Income and Program Participation, 2014 and 2019 panel
  - **MEPS**: Public Medical Expenditure Panel Survey, 2015-2019
- **NVSS**: Restricted National Vital Statistics System, 2000-2019
  - Mortality data in the US with causes of deaths
  - Opioid overdose (Rx, illegal, both), Other Causes of Death
- **StreetRx**: Restricted data on illegally traded opioid prices, 2013-2019
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Motivation

- During 2015-2019, we have three aggregate trends:
  1. The probability of death from opioid misuse has increased.
  2. State-level policies on opioid prescribing have spread out.
  3. Prices of illegally traded opioids have fluctuated.

	2015	2016	2017	2018	2019
Opioid Overdose					
Prescription opioids only	0.19	0.20	0.19	0.17	0.15
Illegal opioids only	0.25	0.38	0.50	0.57	0.64
Both	0.68	0.91	1.10	1.25	1.33
Other Causes of Death	1.13	1.12	1.14	1.14	1.14

Table: Statistical Probabilities of Death from Other Causes of Death and Opioid Overdose (in percent), PUF NSDUH & Restricted NVSS, 2015-2019

Motivation

- During 2015-2019, we have three aggregate trends:
  1. The probability of death from opioid misuse has increased.
  2. States imposed policies on opioid prescribing to decrease opioid overdose deaths.
  3. Prices of illegally traded opioids have fluctuated.

- Must-access PDMP requires doctors to check a patient's prescription history.
- State-level laws limit the number of days supplied for each prescription.

	2015	2016	2017	2018	2019
Must-access PDMP	8	9	18	22	22
State-level Laws	5	9	22	33	36

Table: Number of States with Policies on Opioid Prescribing

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- Rationale #1: Opioids are extensively prescribed, facilitating misuse.
- Rationale #2: People are over-confident about the risk of opioid misuse.

	2015	2016	2017	2018	2019	All
Great Risk	85.62	86.11	86.81	86.93	85.79	86.25
Not a Great Risk	14.38	13.89	13.19	13.07	14.21	13.75
Total	100	100	100	100	100	100

Table: Perception of Opioid Misuse Risk, PUF NSDUH, 2015-2019

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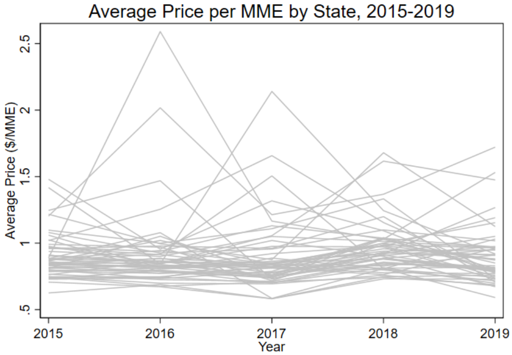


Data Patterns: Health

- Fact 1: People with poorer health are more likely to misuse opioids.

	Nonuser	Rx User	*Opioid Misuse* Rx Only	Illegal Only	Both	Total
Excellent	76.37	21.17	0.95	1.20	0.31	100
Very Good	68.31	28.00	1.35	1.84	0.50	100
Good	60.82	34.51	1.71	2.22	0.75	100
Fair/Poor	48.08	46.08	2.79	2.05	1.00	100
All	64.78	31.18	1.58	1.85	0.61	100

Table: Row Percentages of Opioid Use by Health Measure (4-levels), RUF NSDUH, 2015-2019

colpct

Data Patterns: Labor

- Fact 2: People in worse labor status are more likely to misuse opioids.

	Nonuser	Rx User	*Opioid Misuse* Rx Only	Illegal Only	Both	Total
Out of labor	66.60	28.97	1.84	1.88	0.72	100
Employed	67.31	28.48	1.57	2.02	0.61	100
Unemployed	63.65	27.83	2.64	4.08	1.80	100
Unable to Work	35.61	57.88	3.42	2.06	1.03	100
Retired	63.79	34.71	0.71	0.67	0.12	100
Total	66.88	28.96	1.61	1.93	0.62	100

Table: Row Percentages of Opioid Use by Work Status, RUF NSDUH, 2015-2019

colpct

Other Data Patterns

- State-level policies on opioid prescribing are. . .
  - Negatively associated with decrease in prescription rates. ▸ TWFE ▸ Transition
  - Not associated with illegally traded opioid prices. ▸ TWFE
- People with worse health and labor status perceive misusing opioids does not have a great risk. ▸ AME ▸ Questionnaire
- In the model . . .
  - The transitions for opioid prescription are estimated with state-level policies.
  - Policies do not affect the prices of illegally traded opioids.
  - Individuals expect that policies and prices will remain constant forever in each period.
  - Perception on opioid misuse risk is stochastically determined by SES.

Dynamic Model of Work and Opioid Use

Overview

- Infinite horizon model with endogenous death risk and stochastic perception bias.
- A representative individual lives in location s with education e.
- He faces a risk of dying every period, and it increases if he misuses opioids.

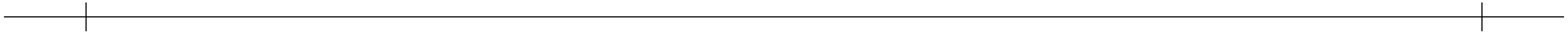


Figure: State Realization and Decision in Each Period

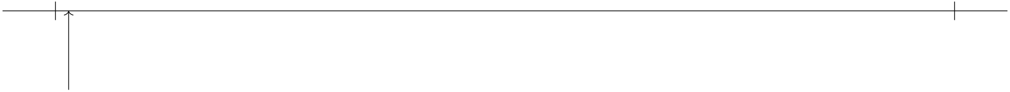
$$\Omega_s = (s, r_{s,t}, m_{s,t}, p^{il}_{s,t}), x = (e, \mathrm{xp}, h, \mathrm{cw}, \mathrm{rx}), b, \varepsilon$$

State Space

Dynamic Model of Work and Opioid Use

Overview

- The individual observes his location's policies on prescribing opioids $r_{s,t}$, $m_{s,t}$, and illegal opioid price $p^{il}_{s,t}$.
- He knows his past year's work experience $\mathrm{xp} \in \{0, 1\}$.



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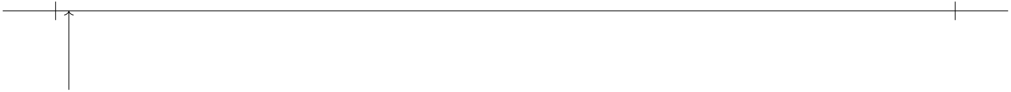

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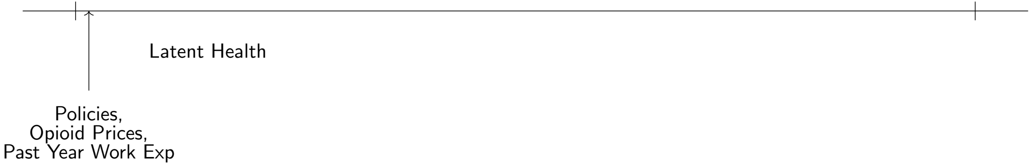
Overview

- Two-dimensional latent health state (h_1, h_2), $h_k \in \{G, B\}$ for $k = 1, 2$ is realized.
- h_1 and h_2 represent physical and mental health, respectively.
- Denote $h = \mathbf{1}\{h_2 = B\} + 2 \times \mathbf{1}\{h_1 = B\}$.



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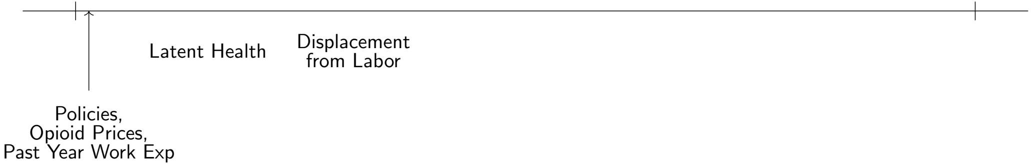
Dynamic Model of Work and Opioid Use

Overview

- Then, his status in the labor market cw $\in \{0, 1, 2, 3\}$ is realized.
- 0 : No separation, 1 : Unemployed, 2 : Unable to work due to health, 3 : Retired



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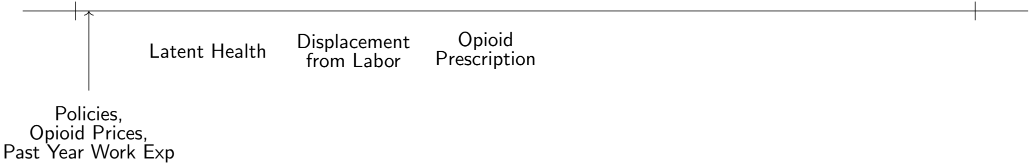
- Next, he is prescribed opioids rx $\in \{0, 1\}$ conditional on his SES and policies.



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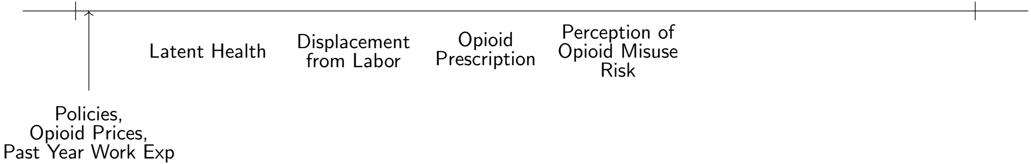
Dynamic Model of Work and Opioid Use

Overview

- Perception of opioid misuse risk b is realized based on his SES.
- $b \in \{H, L\}$, H: High opioid misuse risk, L: Low opioid misuse risk



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Dynamic Model of Work and Opioid Use

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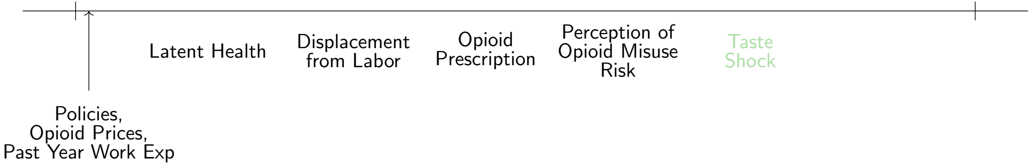
- A vector of idiosyncratic shocks for choices ε is realized.
- The individual decides on working d_w, misusing prescribed opioids d_o^{rx}, and using illegally traded opioids d_o^{il}.



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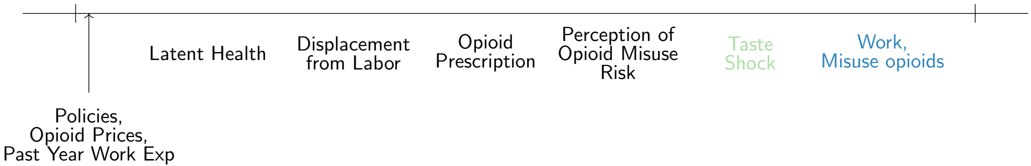

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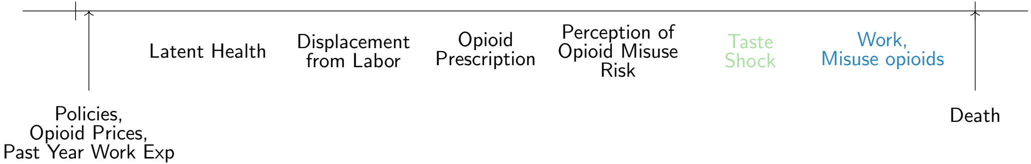
- Death is realized conditional on his health state and opioid misuse.



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State Space

Dynamic Model of Work and Opioid Use

Choice Set

- The individual can work and misuse opioids each period:

$$
\begin{aligned}
d_w &= \mathbf{1}\{\text{work}\} \\
d_o^{rx} &= \mathbf{1}\{\text{misuse prescribed opioids}\} \\
d_o^{il} &= \mathbf{1}\{\text{use illegal opioids}\}
\end{aligned}
$$

- Choices are indexed by $j = 1 + d_o^{il} + 2d_o^{rx} + 4d_w$ and $d_j = \mathbf{1}\{\text{Chooses } j\}$.
- The choice set is affected by i) separation from labor cw and ii) being prescribed opioids rx.
  - He cannot work in this period if he is separated from labor ($\text{cw} \neq 0$).
  - He can misuse prescription opioids only if he is prescribed ($\text{rx} = 1$).
  - Using illegal opioids is always an option.
  - If prescribed opioids, he must misuse them before using illegal opioids.

Formal Table

Dynamic Model of Work and Opioid Use

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  - He cannot work in this period if he is separated from labor ($cw \neq 0$).
  - He can misuse prescription opioids only if he is prescribed ($rx = 1$).
  - Using illegal opioids is always an option.
  - If prescribed opioids, he must misuse them before using illegal opioids.

Formal Table

Dynamic Model of Work and Opioid Use

Choice Set

- The individual can work and misuse opioids each period:

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Dynamic Model of Work and Opioid Use

Flow Utility

- Denote x the vector of state variables except for perception bias b.
- The flow utility flexibly captures preferences for working and misusing opioids.

$$u(x, j; \boldsymbol{\theta}^y, \boldsymbol{\theta}^u) = \underbrace{u_0}_{\text{Baseline}} + \underbrace{d_w u_w(e, \mathrm{xp}, h, \mathrm{rx}; \boldsymbol{\theta}^u)}_{\text{Working}}$$

$$+ \alpha \underbrace{d_w y(h, \mathrm{rx}, e, \mathrm{xp}, j; \boldsymbol{\theta}^y) + (1 - d_w)(\theta_1^y \mathbf{1}_{e=0} + \theta_2^y \mathbf{1}_{e=1})}_{\text{log Income}}$$

$$+ \mathrm{rx} d_o^{rx} \left(\underbrace{(1 - d_o^{il}) u_{rx}(h, cw, d_w; \boldsymbol{\theta}^u)}_{\text{Rx Opioid Only}} + \underbrace{d_o^{il} u_{bth}(h, cw, d_w; \boldsymbol{\theta}^u)}_{\text{Both Rx and Illegal}} \right)$$

$$+ d_o^{il} \left(\underbrace{(1 - \mathrm{rx})(1 - d_o^{rx}) u_{il}(h, cw, d_w; \boldsymbol{\theta}^u)}_{\text{Illegal Opioid Only}} + \underbrace{u_p(h, cw, rx; \boldsymbol{\theta}^u)}_{\text{Illegal Opioid Price}} \right)$$

▸ Detail ▸ Observational Equivalence

Dynamic Model of Work and Opioid Misuse

Probability of Death and the Role of the Perception of Opioid Misuse Risk

- The individual stochastically perceives the risk of misusing opioids. Result
  - High ($b = H$): expects the actual probability of death from opioid misuse.
  - Low ($b = L$): discounts the probability of death from opioid misuse by δ.

$$f_d(h, b, j; \boldsymbol{\theta}^d, \delta) = \underbrace{f_d(ocd|h; \boldsymbol{\theta}^d)}_{\text{Other Causes of Death}} + (1 - \delta \mathbf{1}\{b = L\}) \sum_{\text{OD}} \underbrace{f_d(\text{OD}|d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^d)}_{\text{Opioid Overdose Death}}$$

where $\text{OD} \in \{\text{Rx Only}, \text{Illegal Only}, \text{Both}\}$. Equation MDE Estimation Steps Questionnaire

Other Causes of Death		*Opioid Overdose*	2015	2016	2017	2018	2019
Baseline	0.59	Rx only	0.19	0.20	0.19	0.17	0.15
Bad Physical Health	+2.35	Illegal only	0.25	0.38	0.50	0.57	0.64
Bad Mental Health	+1.28	Both	0.68	0.91	1.10	1.25	1.33

Table: Probability of Death: Other Causes of Death and Opioid Overdose Deaths (in percent)

Other Components

- Income process captures variation in productivity across SES and opioid misuse.
- Transition probabilities capture the dynamics of health, labor, and prescription.
  - Health captures the effect of opioid misuse on health.
  - Labor captures the effect of health transitions and labor dynamics by education.
  - Prescription captures the effect of health, labor status, and state policies.

Income Health Labor Rx

Dynamic Model of Work and Opioid Use

Value Function Representation

- The value function of a living individual $V(x, b, \varepsilon; \Omega_s)$ is

$$V(x,b,\varepsilon;\Omega_s) = \max_{j\in\mathcal{J}(\mathbf{1}\{\text{cw}\neq 0\},\text{rx})} u(x,h,j;\boldsymbol{\theta}^y,\boldsymbol{\theta}^u) + \varepsilon_j + \beta \underbrace{f_d(h,b,j;\boldsymbol{\theta}^d,\delta)}_{\text{Death}} W$$
$$+ \beta \sum_{x',b'} \mathbb{E}_{\varepsilon'}\left[V(x',b',\varepsilon')\right] \underbrace{f(x',b'|x,j,\Omega_s;\boldsymbol{\theta}^h,\boldsymbol{\theta}^{cw},\boldsymbol{\theta}^{rx})}_{\text{Transition conditional on survival}} \underbrace{(1-f_d(h,b,j;\boldsymbol{\theta}^d,\delta))}_{\text{Survival}}$$

- The individual expects that the probability of death, policy, and prices will stay the same.
- When the individual dies, he receives $W = 0$ and the optimization problem ends.

Why $W = 0$? Observational Equivalence

Identification

The parameters to identify are:

- Health type probability $\bar{q}(h|e;\boldsymbol{\theta}^q,\boldsymbol{\theta}^{pxy})$
- Per-period utility
  - Income process $\boldsymbol{\theta}^y$, σ_y
  - Flow utility $\boldsymbol{\theta}^u$
- Transition probabilities
  - Death $\boldsymbol{\theta}^d$
  - Health $\boldsymbol{\theta}^h$
  - Displacement from work $\boldsymbol{\theta}^{cw}$
  - Prescription to opioids $\boldsymbol{\theta}^{rx}$, α_s^{rx}
  - Perception of the risk of misusing opioids $\boldsymbol{\theta}^b$
- Perception bias δ
- Discount factor $\beta = 0.98$
- Distribution of ε: T1EV

Identification

Latent Health, Transition Probabilities, Utilities, and Perception Bias

- The distribution of latent health $\bar{q}(h|e;\theta^q,\theta^{pxy})$ is identified by using health and disability as proxies. (Hwang [2020]) ▸ Proxies
- The transition probabilities are identified by state-level variations in the data.
  - The distribution of opioid misuse and the marginal transition probabilities for health, labor, and Rx vary between states.
  - I attribute the state-level variation in transition probabilities to opioid misuse.
- Utility from misusing opioids θ^u, Perception bias δ
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Estimation

A modified 'two-step' CCP estimation (Arcidiacono and Miller 2011, 2019):

Stage 1: Estimate CCPs and the transition probabilities.

1. EM Algorithm: θ^q, θ^{pxy}, θ^b, and $P_j(x, h, b)$ Details
2. Interval Regression: θ^y Details
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Stage 2: Estimate θ^u and δ.

1. Construct a set of conditional value function (CVF) differences.
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Perception Process

- Bad mental health and unemployment are the main drivers of the misperception.

	Opioid Misuse: Not Great Risk
Latent Health	
(Good,Bad)	0.336 (0.041)
(Bad,Good)	-0.087 (0.198)
(Bad,Bad)	0.260 (0.042)
Labor Status	
Unemployed	0.334 (0.045)
Unable to Work	-0.061 (0.040)
Retired	-0.172 (0.033)
Other	
College	0.346 (0.021)
Work Exp	-0.256 (0.020)
Rx'd Opioids	-0.131 (0.021)
Constant	-1.763 (0.027)

* The standard errors are in parentheses and are computed by bootstrapping 30 times.

Perception and Death

Utility Parameters and Perception Bias Estimates

- Preference for opioid misuse is higher for people with ...
  - Bad health but untreated with Rx opioids.
  - Unfavorable labor conditions (unemployed, unable to work).

	Opioid Misuse								
	Rx Only	Both	Illegal Only		Price		Work		Work
Health				*Health*		*Health*		*Rx Misuse*	
(Good, Bad)	-0.32	-0.30	1.02	(Good, Bad)	0.17	(Good, Bad)	-0.62	Constant	1.25
(Bad, Good)	-1.16	-2.12	0.10	(Bad, Good)	0.12	(Bad, Good)	-3.36	× Bad Health	2.03
(Bad, Bad)	-0.47	-0.55	1.69	(Bad, Bad)	-0.14	(Bad, Bad)	-3.01	× Work Exp	-0.20
No College ×				*Labor*		*Edu × Exp*		*Illegal Use*	
Unemployed	1.43	0.39	1.37	Unemployed	0.44	College	0.67	Constant	1.29
Unable to Work	0.84	1.78	1.45	Unable to Work	-1.33	Work Exp	-5.97	× Bad Health	0.37
Retired	-0.77	-0.73	0.62	Retired	-0.21	College × Exp	-0.16	× Work Exp	0.31
College ×				*Other*		*Bad Health ×*			
Unemployed	0.39	1.95	1.35	Rx'd Opioids	-0.15	Rx'd Opioids	-0.69		
Unable to Work	0.22	2.20	2.32	Constant	-0.03	Work Exp	2.24		
Retired	-0.18	-0.68	0.67						
Other								Baseline Utility u_0	0.58
Work Exp	0.21	0.73	-0.42					Labor Income α	2.27
Constant	-3.00	-3.30	-3.70					Perception Bias δ	0.71

Baseline: Opioid Misuse in 2015

- People with bad mental health misuse opioids more.

Latent Health	Rx Only	Both	Illegal Only	Total
(Good, Good)	0.85	0.78	1.05	3.53
(Good, Bad)	2.42	3.57	9.22	15.22
(Bad, Good)	0.90	1.28	6.47	8.65
(Bad, Bad)	0.77	3.50	27.07	31.34
Labor	Rx Only	Both	Illegal Only	Total
No Separation	1.70	2.71	3.63	8.05
Unemployed	0.76	0.28	5.67	6.72
Unable to Work	0.42	1.03	8.73	10.46
Retired	0.18	0.19	4.90	5.27
All	1.32	2.07	4.24	7.63

Table: Predicted Opioid Misuse Rate in 2015 (in Percent)

Counterfactual: Correcting the Perception Bias ($\delta = 0$)

- Correcting the perception bias would reduce opioid misuse rate by 20%.

Latent Health	Rx Only	Both	Illegal Only	Total
(Good, Good)	-12.94	-62.82	-19.33	-28.12
(Good, Bad)	0.00	-40.90	-15.08	-18.73
(Bad, Good)	-3.33	-39.06	-11.75	-14.91
(Bad, Bad)	3.90	-25.43	-8.27	-9.89
Labor	Rx Only	Both	Illegal Only	Total
No Separation	-4.71	-40.59	-15.15	-21.61
Unemployed	-13.16	-68.45	-14.81	-16.96
Unable to Work	-9.52	-49.23	-8.71	-13.86
Retired	-11.11	-50.67	-10.82	-12.33
All	-5.30	-41.55	-13.44	-19.53

Table: Predicted Opioid Misuse Rate in 2015 given $\delta = 0$ (in Percent)

2019 Aggregate Changes: Net Effect on Opioid Misuse

- The opioid misuse rate in 2015 decreases by 44% if given the environment in 2019.

Latent Health	Rx Only	Both	Illegal Only	Total
(Good, Good)	32.94	-64.10	-66.67	-39.30
(Good, Bad)	40.50	-60.50	-60.74	-44.61
(Bad, Good)	35.56	-67.19	-64.14	-54.34
(Bad, Bad)	63.64	-63.43	-54.75	-52.84
Labor	Rx Only	Both	Illegal Only	Total
No Separation	32.94	-64.94	-59.78	-41.99
Unemployed	18.42	-64.29	-54.85	-46.88
Unable to Work	21.43	-64.62	-53.04	-51.53
Retired	16.67	-65.21	-55.31	-53.32
All	31.06	-64.73	-57.78	-44.30

Table: Predicted Opioid Misuse Rate given 2019's Environment (in Percent)

2019 Aggregate Changes: Policies on Rx Opioids

- Expansion of state policies does not decrease aggregate opioid misuse rate.
  - Opioid misuse rate for people with unfavorable labor conditions increases
  - Opioid misuse rate for people with good health decreases

Latent Health	Rx Only	Both	Illegal Only	Total
(Good, Good)	-2.35	-2.56	0.67	-0.96
(Good, Bad)	-1.24	-1.68	0.22	-0.46
(Bad, Good)	-2.22	-3.13	0.46	-0.23
(Bad, Bad)	-1.30	-2.29	0.44	0.10
Labor	Rx Only	Both	Illegal Only	Total
No Separation	-7.06	-7.38	4.41	-2.11
Unemployed	-6.58	-7.14	4.76	2.83
Unable to Work	-4.76	-4.62	9.62	7.17
Retired	-11.11	-5.26	5.92	4.93
All	-7.58	-7.25	5.42	-0.26

Table: Predicted Opioid Misuse Rate given 2019's Policies on Opioid Prescribing (in Percent)

2019 Aggregate Changes: Probability of Death on Opioid Misuse

- The increase in the probability of death from illegal opioid use decreases the opioid misuse rate by 42% by decreasing illegal opioid use.

Latent Health	Rx Only	Both	Illegal Only	Total
(Good, Good)	35.29	-62.82	-66.67	-38.34
(Good, Bad)	42.15	-59.94	-60.74	-44.22
(Bad, Good)	38.89	-66.41	-64.14	-53.76
(Bad, Bad)	66.23	-62.57	-54.05	-52.01
Labor	Rx Only	Both	Illegal Only	Total
No Separation	42.94	-61.99	-61.43	-39.63
Unemployed	27.63	-60.71	-57.67	-48.07
Unable to Work	26.19	-60.00	-55.10	-52.49
Retired	22.22	-61.49	-57.35	-54.84
All	40.91	-61.84	-59.67	-42.73

Table: Predicted Opioid Misuse Rate given 2019's Probability of Death by Opioid Misuse (in Percent)

2019 Aggregate Changes: Illegal Opioids Price

- Changes in prices for illegally traded opioids are ineffective.

Latent Health	Rx Only	Both	Illegal Only	Total
(Good, Good)	0.00	-1.28	-0.67	-0.58
(Good, Bad)	0.00	0.00	0.22	0.00
(Bad, Good)	0.00	-0.78	-0.46	-0.35
(Bad, Bad)	0.00	-1.14	-1.44	-1.37
Labor	Rx Only	Both	Illegal Only	Total
No Separation	0.59	-0.37	0.28	-0.12
Unemployed	0.00	3.57	1.94	1.64
Unable to Work	0.00	-5.38	-3.89	-4.02
Retired	0.00	0.00	-0.82	-0.76
All	0.00	-2.90	-0.47	-0.39

Table: Predicted Opioid Misuse Rate given 2019's Illegal Opioid Price (in Percent)

Conclusion

- This paper evaluates state policy interventions on opioid prescribing and highlights the role of misperception of opioid misuse risk.
  - Focuses on the role of health and labor for state policy's heterogeneous effects.
  - Quantifies the size of perception bias on the probability of dying from opioid misuse.
- Counterfactual analysis indicates that:
  - Stricter policies on opioid prescribing are ineffective in decreasing opioid misuse rate.
  - Correcting perception bias would reduce opioid misuse by at most 20%.

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  - Stricter policies on opioid prescribing are ineffective in decreasing opioid misuse rate.
  - Correcting perception bias would reduce opioid misuse by at most 20%.

Data Patterns: Perception

- Fact 3: The perception of the risk of opioid misuse is associated with SES.

	No College		College	
Labor				
Unemployed	0.0325	(0.0068)	0.0127	(0.0132)
Unable to Work	-0.0306	(0.0063)	-0.0584	(0.0168)
Retired	-0.0452	(0.0044)	-0.0265	(0.0075)
Past Year Work Experience	-0.0426	(0.0039)	-0.0255	(0.0076)
Health				
Very Good	0.0059	(0.0046)	0.0176	(0.0040)
Good	0.0176	(0.0038)	0.0211	(0.0067)
Fair/Poor	0.0149	(0.0045)	0.0225	(0.0116)
Opioids				
Prescribed Opioids	-0.0170	(0.0033)	-0.0186	(0.0055)

Table: Average Marginal Effects of Covariates on the Perception of Opioid Misuse Risk, RUF NSDUH 2015-2019. Controls include disability measures.

Reg 1 Reg 2 Reg 2 AME Questionnaire

Data Patterns: Policy

- Fact 4: State-level policies decrease prescription rates.

	log(MME)	log(#Rx/100 pop)
State Law Only	0.0324 (0.0275)	-0.0142 (0.0123)
MA-PDMP Only	-0.0007 (0.0265)	-0.0263 (0.0118)
Both	-0.0453 (0.0271)	-0.0840 (0.0121)
Year FE	Y	Y
State FE	Y	Y
Controls	Y	Y
N	500	500

Table: TWFE Regression Result: Opioid Prescription Rate and Policies, 2010-2019.

Back

Data Patterns: State Policies and Prices for Illegally Traded Opioids

- Fact 5: Illegally traded opioid prices are **not** associated with state policies.

	log($/MME)
State Law Only	-0.0420
	(0.0374)
Must-Access PDMP Only	-0.0725
	(0.0402)
Both	-0.0612
	(0.0414)
Year FE	Y
State FE	Y
Controls	Y
N	300

Table: TWFE Regression Result: Illegally Traded Opioid Prices and Policies

Rx Rates
Mortality Rates

Data Patterns: State Policies on Opioid Prescription

- Fact 4: State-level policies are negatively associated with opioid prescription rates.
- Combining both state-level restrictions and PDMP seems to be the most effective.

	Estimate		Estimate
State-level Law Only	-0.185	*Health*	
×(Good,Bad)	-0.004	(Good,Bad)	0.297
×(Bad,Good)	-0.041	(Bad,Good)	0.722
×(Bad,Bad)	-0.050	(Bad,Bad)	0.918
MA-PDMP Only	-0.140	*Labor*	
×(Good,Bad)	0.074	Unemployed	0.002
×(Bad,Good)	0.048	Unable to Work	0.823
×(Bad,Bad)	-0.046	Retired	0.056
Laws & PDMP	-0.228	Constant	-0.686
×(Good,Bad)	0.099		
×(Bad,Good)	0.042		
×(Bad,Bad)	-0.124		

Table: Transition Probability Estimates: Opioid Prescription

Functional Form
MDE

Dynamic Model of Work and Opioid Use

Per-period Income

- Let $y(h, \text{rx}, e, \text{xp}, j; \boldsymbol{\theta}^y)$ be the log income given state x and choice j.

$$
\begin{aligned}
y(x, j, \boldsymbol{\theta}^y) = \; & \underbrace{\theta_3^y d_w}_{\text{Baseline}} + \underbrace{(\theta_4^y e + \theta_5^y \text{xp} + \theta_6^y e \times \text{xp}) d_w}_{\text{Education \& Work Exp}} + \\
& + \underbrace{\sum_{k=1}^{3} \theta_{k+6}^y \mathbf{1}_{h=k} d_w}_{\text{Bad Health}} + \underbrace{\theta_{10} \text{rx} \mathbf{1}_{h \neq 0}}_{\text{Rx \& Bad Health}} + \underbrace{\theta_{11} \text{xp} \mathbf{1}_{h \neq 0}}_{\text{Work Exp \& Bad Health}} \\
& + \underbrace{(\theta_{12}^y d_o^{rx} \text{rx} + \theta_{13}^y d_o^{il}) d_w}_{\text{Opioid Misuse}} + \underbrace{(\theta_{14}^y d_o^{rx} \text{rx} + \theta_{15}^y d_o^{il}) d_w \times \mathbf{1}_{h \neq 0}}_{\text{Opioid Misuse \& Bad Health}} + \underbrace{(\theta_{16}^y d_o^{rx} \text{rx} + \theta_{17}^y d_o^{il}) d_w \times \text{xp}}_{\text{Opioid Misuse \& Work Exp}}
\end{aligned}
$$

Result Estimation Estimation Steps

Questions on the Perception of Opioid Misuse Risk-NSDUH

RK01f How much do people risk harming themselves physically and in other ways when they try **heroin once or twice**?

1 No risk
2 Slight risk
3 Moderate risk
4 Great risk
DK/REF

RK01g How much do people risk harming themselves physically and in other ways when they use **heroin once or twice a week**?

1 No risk
2 Slight risk
3 Moderate risk
4 Great risk
DK/REF

Figure: Questionnaire: Perception of Opioid Misuse Risk

Back

Questions on Health and Disability-NSDUH

QD12 This question is about your overall health. Would you say your health in general is excellent, very good, good, fair, or poor?

1 EXCELLENT
2 VERY GOOD
3 GOOD
4 FAIR
5 POOR

QD56 Are you deaf or do you have serious difficulty hearing?
1 Yes
2 No

QD57 Are you blind or do you have serious difficulty seeing, even when wearing glasses?
1 Yes
2 No

QD58 Because of a physical, mental or emotional condition, do you have serious difficulty concentrating, remembering, or making decisions?
1 Yes
2 No

QD59 Do you have serious difficulty walking or climbing stairs?
1 Yes
2 No

QD60 Do you have difficulty dressing or bathing?
1 Yes
2 No

QD61 [IF CURNTAGE >14] Because of a physical, mental or emotional condition, do you have difficulty doing errands alone such as visiting a doctors' office or shopping?
1 Yes
2 No

Figure: Questionnaire: Overall Health and Disability Measures

Back

Data Patterns

Fact 1: People with worse health misuse opioids more

	Nonuser	Prescription User	Misuse: Prescription Only	Misuse: Illegal Only	Misuse:
Excellent	23.8779	13.7511	12.1984	13.1305	10.3
Very Good	37.4552	31.9005	30.2520	35.2284	29.2
Good	27.8849	32.8748	31.9718	35.5521	36.5
Fair/Poor	10.7820	21.4737	25.5778	16.0890	23.8
Total	100	100	100	100	10

Table: Column Percentages of Opioid Use by Health Measure (4-levels), RUF NSDUH, 2015-2019

rowpct

Data Patterns

Fact 2: Opioid Misuse is Serious in the Working Age Group

	Nonuser	Rx User	*Opioid Misuse* Rx Only	Illegal Only	Both	All
Out of Labor	10.49	11.41	11.28	10.24	11.15	10.77
Working	53.38	51.78	52.02	56.23	53.31	52.95
Layoff	3.64	3.64	6.08	8.15	10.95	3.81
Unable to Work	2.34	8.70	9.40	4.95	7.58	4.38
Retired	12.15	15.03	4.92	3.05	1.44	12.63
18-21	6.82	4.60	8.36	10.62	10.54	6.30
12-17	11.18	4.84	7.93	6.76	5.03	9.17
Total	100	100	100	100	100	100

Table: Percentages of Opioid Use by Work Status in Columns, PUF NSDUH 2015-2019

rowpct

Data Patterns: Labor

- Fact 4: Opioid misuse and overdose deaths are prevalent among working age.

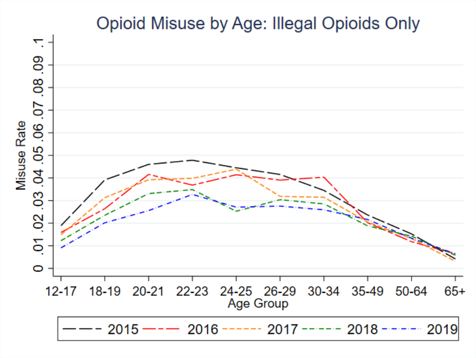

Figure: Opioid misuse: Illegal Only

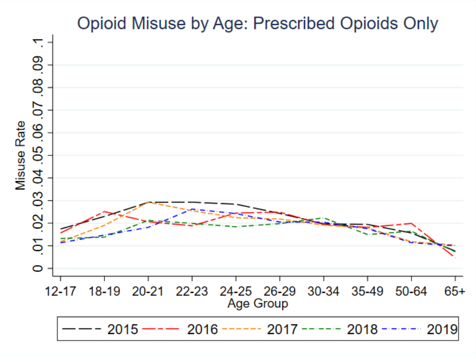

Figure: Opioid misuse: Rx Only

OD Back

Data Patterns: Labor

- Fact 4: Opioid misuse and overdose deaths are prevalent among working age.

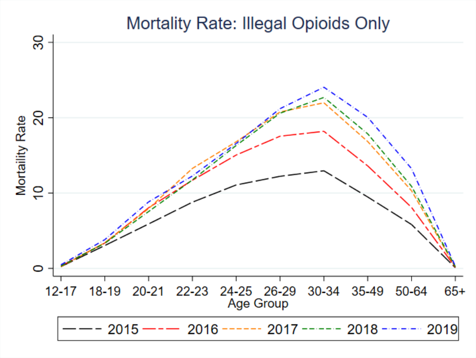

Figure: Opioid Death Rate: Illegal Only

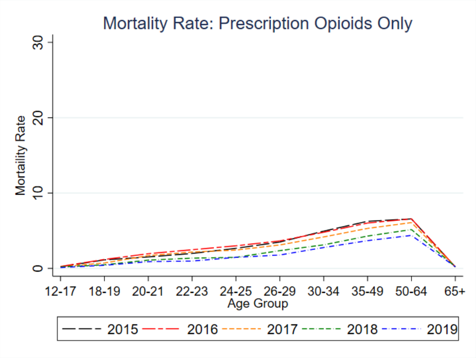

Figure: Opioid Death Rate: Rx Only

Misuse
Back

Data Patterns: Policy

- Fact 5: State-level policies have negative associations with prescription rates.

	log(MME)	log(#Rx/100 pop)
State Law Only	0.0324 (0.0275)	-0.0142 (0.0123)
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Both	-0.0453 (0.0271)	-0.0840 (0.0121)
Year FE	Y	Y
State FE	Y	Y
Controls	Y	Y
N	500	500

Table: TWFE Regression Result: Opioid Prescription Rate and Policies, 2010-2019.

Misuse Price Policies Back

Data Patterns: Policy

Fact 5: State-level Policies Are Associated with Opioid Prescription Rate ↓, Mortality Rate ↑

- Policies have negative associations with Rx opioid overdose deaths.
- Policies have positive associations with illegal opioid overdose deaths.

	Rx Opioid Only		Illegal Opioid Only		Both	
	Rate	log	Rate	log	Rate	log
State Restriction Only	-0.0654	-0.0370	1.0196	0.0945	0.2293	0.2234
	(0.1305)	(0.0618)	(0.3252)	(0.0795)	(0.0805)	(0.1111)
Must-Access PDMP Only	-0.3414	-0.0924	1.6370	0.1274	0.2581	-0.0179
	(0.1288)	(0.0610)	(0.3235)	(0.0791)	(0.0801)	(0.1103)
Both	-0.6685	-0.1801	3.2704	0.3976	0.2701	0.1252
	(0.1316)	(0.0623)	(0.3299)	(0.0806)	(0.0817)	(0.1129)
Year FE	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
N	556	556	556	556	556	553

Table: TWFE Regression Result: Mortality Rate by Opioid Overdose Type and Policies

▸ Misuse ▸ Price ▸ Policies ▸ Back

Estimation Result

Table: Probability Distribution of Physical Health by Proxies

Table: Probability Distribution of Mental Health by Proxy

Back

State-Level Policies on Opioid Prescribing

- State laws on all opioid prescriptions to adults
  - Set the maximum number of days filled e.g., “fewest days,” “7-14 days”, etc.
  - 2015: 5 states, 2019: 26 states including D.C.
- Must-Access Prescription Drug Monitoring Program (MA-PDMP)
  - Requires doctors to check patient’s prescription history
  - 2015: 16 states, 2019: 34 states including D.C.
- In this paper, policies affect prescription rates on the extensive margin.

Rx Rate
OD Rate

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Rx Rate OD Rate

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- In this paper, policies affect prescription rates on the extensive margin.

▸ Rx Rate ▸ OD Rate

State-level Restrictions and Rx Opioids

- I use aggregate data to proxy for opioid Rx rate ($y_{i,t}$):
  - Rx/100: Opioid Rx per 100 population in state g in year t
  - MME[1]: The amount of opioids dispensed in state g in year-**quarter** t
- Two-way fixed effects (TWFE) regression with 2000-2019 data:

$$\log(y_{g,t}) = \beta_0 r_{g,t} + \sum_{k=1}^{3} \beta_j f\{cw = k\}_{g,t} + \beta_4 f\{bh\}_{g,t} + \alpha_g + \delta_t + \varepsilon_{g,t}$$

- The coefficient β are negative for both regressions.

Back

State-level Restrictions and Illegal Opioids

Prices for illegally traded opioids: 2014-2019

- Are street prices correlated with the state-level restrictions on prescription opioids?
- Average of the reported price per MME in state g and year t during 2013-2019

$$\bar{p}_{s,t} = \beta_0 r_{s,t} + \sum_{k=1}^{3} \beta_j f\{cw = k\}_{s,t} + \beta_4 f\{bh\}_{s,t} + \alpha_s + \delta_t + \varepsilon_{s,t}$$

- The coefficient β is statistically insignificant.

Back

State-level Restrictions and Mortality Rates

Mortality rates by types of opioid

- Mortality Rate = Number of Deaths / Population * 100,000
- Two-way fixed effect regression:

$$\text{Mortality Rate}_{s,t} = \beta_0 r_{s,t} + \sum_{k=1}^{3} \beta_j f\{cw = k\}_{s,t} + \beta_4 f\{bh\}_{S,t} + \alpha_s + \delta_t + \varepsilon_{s,t}$$

- The coefficients β are positive for synthetic opioids, negative for heroin, and (insignificant) positive for Rx opioids.

Back

Choice Set

- An individual can choose to work or misuse opioids each period:

$$d_w = \mathbf{1}\{\text{work}\}$$
$$d_o^{rx} = \mathbf{1}\{\text{misuse Rx opioids}\}$$
$$d_o^{il} = \mathbf{1}\{\text{use illegal opioids}\}$$

- An action is indexed by $j = 1 + d_o^{rx} + 2d_o^{il} + 4d_w$ and $d_j = \mathbf{1}\{\text{Chooses } j\}$.
- The choice set $\mathcal{J}(rx, k)$ is defined by i) being prescribed opioids rx and ii) displacement from labor market $k = \mathbf{1}\{cw \neq 0\}$:

$$\mathcal{J}(0,0) = \{1,3,5,7\}$$
$$\mathcal{J}(1,0) = \{1,2,4,5,6,8\}$$
$$\mathcal{J}(0,1) = \{1,3\}$$
$$\mathcal{J}(1,1) = \{1,2,4\}$$

Back Table State Space

Choice Set

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$$
\begin{aligned}
d_w &= \mathbf{1}\{\text{work}\} \\
d_o^{rx} &= \mathbf{1}\{\text{misuse Rx opioids}\} \\
d_o^{il} &= \mathbf{1}\{\text{use illegal opioids}\}
\end{aligned}
$$

- Denote $\tilde{d}_j$ as a negation of action d_j.

(cw, rx)	d_w	$d_o^{rx}, \tilde{d}_o^{il}$	$\tilde{d}_o^{rx}, d_o^{il}$	d_o^{rx}, d_o^{il}
(0,0)	✓	✗	✓	✗
(0,1)	✓	✓	✗	✓
(1,0)	✗	✗	✓	✗
(1,1)	✗	✓	✗	✓

Table: Choice Set

Back Formal State Space

Dynamic Model of Work and Opioid Use

State Variables

- State location s, Education e
- State-level restrictions $r_{s,t} \in \{0, 1\}$, Must-Access PDMP $m_{s,t} \in \{0, 1\}$
- Illegal opioid price $p^{il}_{s,t}$
- Work experience $\mathrm{xp} \in \{0, 1\}$
- Health $h = 1 + \mathbf{1}(h_2 = B) + 2\mathbf{1}(h_1 = B)$, $h_1 \in \{G, B\}$, $h_2 \in \{G, B\}$
- Displacement from work: $\mathrm{cw} \in \{0, 1, 2, 3\}$
  - 1: Laid off/No job available, 2: Unable to work due to health conditions, 3: Retired.
  - $k := \mathbf{1}\{cw \neq 0\}$
- Prescribed opioids: $rx \in \{0, 1\}$
- Perception of the risk of misusing opioids $b \in \{0, 1\}$
- Idiosyncratic shocks to preference $\boldsymbol{\varepsilon} := \left(\varepsilon_1, \ldots, \varepsilon_{J(rx,k)}\right)$

Choice Set

Dynamic Model of Work and Opioid Use

Flow Utility

- Denote x the vector of state variables except for perception bias b.
- The flow utility $u(x, j; \boldsymbol{\theta}^y, \boldsymbol{\theta}^u)$ preference to opioid misuse and work:

$$
\begin{aligned}
u(x, h, j; \boldsymbol{\theta}^u) &= u_0 + \alpha d_w y(e, h, rx, j; \boldsymbol{\theta}^y) + (1 - d_w)(\theta^y_1 \mathbf{1}_{e=0} + \theta^y_2 \mathbf{1}_{e=1}) \\
&+ \left(\theta^u_1 \mathbf{1}_{e=1} + \theta^u_2 \mathbf{1}_{\mathrm{xp}=1} + \theta^u_3 \mathbf{1}_{e=1 \ \&\ \mathrm{xp}=1} + \sum_{m=1}^{3} \theta^u_{m+3} \mathbf{1}_{h=m} + \sum_{m=1}^{3} \theta^u_{m+6} \mathbf{1}_{h=m} \mathrm{rx} \right) d_w \mathbf{1}_{cw=0} \\
&+ \left(\theta^u_{10} + \theta^u_{11} d_w \mathbf{1}_{cw=0} + \sum_{m=1}^{3} \theta^u_{m+11} \mathbf{1}_{h=m} + \sum_{m=1}^{3} \theta^u_{m+14} \mathbf{1}_{cw=m} \right) \mathrm{rx} d^{rx}_o (1 - d^{il}_o) \\
&+ \left(\theta^u_{18} + \theta^u_{19} d_w \mathbf{1}_{cw=0} + \sum_{m=1}^{3} \theta^u_{m+19} \mathbf{1}_{h=m} + \sum_{m=1}^{3} \theta^u_{m+22} \mathbf{1}_{cw=m} \right) \mathrm{rx} d^{rx}_o d^{il}_o \\
&+ \left(\theta^u_{26} + \theta^u_{27} d_w \mathbf{1}_{cw=0} + \sum_{m=1}^{3} \theta^u_{m+27} \mathbf{1}_{h=m} + \sum_{m=1}^{3} \theta^u_{m+30} \mathbf{1}_{cw=m} \right) (1 - \mathrm{rx})(1 - d^{rx}_o) d^{il}_o \\
&+ \left(\theta^u_{34} + \theta^u_{35} \mathrm{rx} + \sum_{m=1}^{3} \theta^u_{m+35} \mathbf{1}_{h=m} + \sum_{m=1}^{3} \theta^u_{m+38} \mathbf{1}_{cw=m} \mathbf{1}_{d_w=0} \right) p^{il}_{s,t} d^{il}_o
\end{aligned}
$$

Back

Observational Equivalence

- At a high level, this model is a DDCM with a terminal state W.
- Arcidiacono and Miller [2020]: we must know a true utility value for one of the choices for each (x, t) given (T, β, f, g) for identification.
- Terminal state is also a state; we must know its true value for identification.
- Parametrizing $W = 0$ is not an innocuous assumption. (next slide)

▸ Flow Utility

Observational Equivalence

Define the transition probability of arriving at x in period $\tau+1$ conditional on survival by $\kappa^*_\tau(x|x_t, j)$ and the transition probability of dying at $\tau+1$ by $\kappa^W_\tau(x|x_t, j)$:

$$\kappa^*_\tau(x_{\tau+1}|x_t, j) = \begin{cases} (1 - f_W(x_t, j))f_\tau(x_{\tau+1}|x_t, j) & \text{if } \tau = t \\ \sum_{x=1}^{X} \kappa^*_{\tau-1}(x|x_t, j)(1 - f_W(x_\tau, I(x,\tau)))f_\tau(x_{\tau+1}|x, I(x,\tau)) & \text{if } \tau > t \end{cases} \quad (1)$$

$$\kappa^W_\tau(x_t, j) = \begin{cases} f_W(x_t, j) & \text{if } \tau = t \\ \kappa^*_{\tau-1}(x|x_t, j)f_W(x, I(x,\tau)) & \text{if } \tau > t \end{cases} \quad (2)$$

where $I(x, t)$ is the choice at (x, t) that we know its true flow utility value. ▸ Flow Utility

Observational Equivalence

By applying the representation theorem from Arcidiacono and Miller [2011], the choice-specific conditional value function is represented by

$$
\begin{aligned}
v_{j,t}(x_t) = u_{j,t}(x_t) + \psi_j(\mathbf{p}_\tau(x_t)) &+ \sum_{\tau=t+1}^{T} \sum_{x=1}^{X} \beta^{\tau-t} W \kappa^{W}_{\tau-1}(x|x_t, j) \\
&+ \sum_{\tau=t+1}^{T} \sum_{x=1}^{X} \beta^{\tau-t} \Big(u_{l(x,\tau),\tau}(x) + \psi_{l(x,\tau)}(\mathbf{p}_\tau(x)) \Big) \kappa^{*}_{\tau-1}(x|x_t, j).
\end{aligned}
$$

Flow Utility

Observational Equivalence

Corollary

Denote the payoff of the normalizing action at a state x at time t by $u^*_{l(x,t)}(x_t)$. For each $R = 1, 2, \ldots,$ define an alternative payoff function for all $x \in \mathcal{X}$, $j \in \mathcal{J}$ and $t = 1, 2, \ldots, R$:

$$
\begin{aligned}
u^*_{j,R}(x) &:= u_{j,R}(x) + u^*_{l(x,t),R}(x) - u_{l(x,R),R}(x) \\
u^*_{j,t}(x) &:= u_{j,t}(x) + u^*_{l(x,t),t}(x) - u_{l(x,t),t}(x) \\
&+ \lim_{R \to T} \left\{ \sum_{\tau=t+1}^{T} \sum_{x'=1}^{X} \beta^{\tau-t} W \left(\kappa^W(x|x_t, j) - \kappa^W(x|x_t, l(x,t)) \right) \right. \\
&\quad \left. + \sum_{\tau=t+1}^{T} \sum_{x'=1}^{X} \beta^{\tau-t} \left(u^*_{l(x,\tau),\tau}(x') - u_{l(x,\tau),\tau}(x') \right) \left(\kappa^*_{\tau-1}(x|x_t, l(x,t)) - \kappa^*_{\tau-1}(x|x_t, j) \right) \right\}
\end{aligned}
$$

The model defined by a tuple (T, β, f, g, u^*, W) is observationally equivalent to the model defined by a tuple (T, β, f, g, u, W). Conversely, suppose the two models are equivalent. By choosing a normalizing action function $l(x,t) : \mathcal{X} \times \mathcal{T} \to \mathcal{J}$ and its corresponding payoff $u^*_{l(x,t),t}(x) : \mathcal{X} \times \mathcal{J} \times \mathcal{T} \to \mathbb{R}$, the relationship above holds for all (x, j, t).

▸ Flow Utility

Estimating the Income Process

Interval Regression

- I only observe the income bin $(y^l_{k,n}, y^u_{k,n})$ for observation n.
- $y^l_{k,n} \leq y(x, j, \boldsymbol{\theta}^y) + \varepsilon \leq y^l_{k,n}$ where $\varepsilon \sim \mathcal{N}(0, \sigma_y)$.
- The likelihood of observing $(y^l_{k,n}, y^u_{k,n})$ conditional on (x_n, j_n) is:

$$\mathcal{L}((y^l_k, y^u_k)_n | x_n, j_n; \boldsymbol{\theta}^y) = \Phi\left(\frac{y^u_{k,n} - y(x_n, j_n, \boldsymbol{\theta}^y)}{\sigma_y}\right) - \Phi\left(\frac{y^l_{k,n} - y(x_n, d_{w,n}, \boldsymbol{\theta}^y)}{\sigma_y}\right)$$

▸ Functional Form ▸ Result ▸ Estimation Steps

Estimation Result: log Income

	Estimate
Constant	9.252 (0.033)
Education and Work Exp	
College	0.476 (0.064)
Experience	1.040 (0.033)
College × Experience	0.267 (0.025)
Health (Physical, Mental)	
(Good, Bad)	-0.012 (0.005)
(Bad, Good)	-0.020 (0.005)
(Bad, Bad)	-0.026 (0.005)
Bad Health	
× Received Rx Opioids	0.027 (0.010)
× Work Experience	-0.006 (0.004)
Opioid Misuse	
Rx Opioids	-0.008 (0.119)
× Bad Health	-0.028 (0.018)
× Work Experience	-0.026 (0.116)
Illegal Opioids	-0.131 (0.115)
× Bad Health	0.000 (0.009)
× Work Experience	-0.068 (0.117)
Not Working	
No College	9.174 (0.009)
College	9.642 (0.022)
SD of Measurement Error σ_y	1.264 (0.004)

* The standard errors are in parentheses and are computed by bootstrapping 30 times.

Table: Coefficients for Perception of Opioid Misuse Risk Process

Likelihood
Estimation Steps

Perception Process

- The realization process for the perception of opioid misuse risk has a logit form:

$$\log \frac{f_b(b = L|x)}{f_b(b = H|x)} = \theta_1^b + \theta_2^b \mathrm{e} + \theta_3^b \mathrm{xp} + \sum_{k=2}^{4} \theta_{k+2}^b \mathbf{1}_{h_k = B} + \sum_{k=1}^{3} \theta_{k+6}^b \mathbf{1}_{\mathrm{cw} = k} + \theta_{10}^b \mathrm{rx}.$$

Result

Proxies in Common

- Proxies for physical and mental health status:
  - Proxy 1: Overall Health (ordered, 4 levels)
  - Proxy 2: Difficult to do errands & difficult to dress (partially ordered, 4 values)
- Proxy for physical health only:
  - Proxy 1: Difficult to walk (binary)
  - Proxy 2: Difficult to see (binary)
  - Proxy 3: Difficult to hear (binary)
- Proxy for mental health only: Difficult to think (binary)

Back

Proxies in Common

Item	NSDUH	SIPP	MEPS	Scale
Overall Health	health2	ehltstat	rthlth	4
Difficult to Do Errands	differand	eerrands	dfernd	2
Difficult to Dress	diffdress	eselfcare	dfdrsb	2
Difficult to Walk	diffwalk	eambulat	dfwlkc	2
Difficult to See	diffsee	eseeing	dfsee	2
Difficult to Hear	diffhear	ehearing	dfhear	2
Difficult to Think	diffthink	ecognit	dfcog	2

Table: Proxy Variables

Back

Transition Probability: Health

	Next Period's Health (h'_1, h'_2) (Good,Bad)	(Bad,Good)	(Bad,Bad)
Constant	$(-)$	$(-)$	$(-)$
College	$(-)$	$(-)$	$(-)$
Health (h_1, h_2)			
(Good,Bad)	$(++)$	$(+)$	$(+)$
(Bad,Bad)	$(+)$	$(++)$	$(+)$
(Bad,Bad)	$(+)$	$(+)$	$(++)$
Labor			
Laid Off	$(+)$	$(+)$	$(+)$
Unable to Work	$(+)$	$(++)$	$(+)$
Retired	$(.)$	$(.)$	$(.)$
Opioid & Work			
Work Exp	$(+)$	$(+)$	$(+)$
Work	$(-)$	$(++)$	$(+)$
Rx'd, No Misuse	$(+)$	$(+)$	$(+)$
Rx'd, Rx Misuse	$(+)$	$(+)$	$(+)$
Use Illegal Opioids	$(+)$	$(--)$	$(-)$

Table: Transition Probability Estimates: Health

Functional Form MDE

Transition Probability: Labor

- Both policies decrease Opioid Rx rates with different effects across health.
- Combining both state-level restrictions and PDMP to be most effective.

	Next Period's Labor Status		
	Unemployed	Unable to Work	Retired
Labor: No College			
Constant	(−)	(−)	(−)
Laid Off	(+)	(+)	(+)
Unable to Work	(−)	(+)	(.)
Retired	(+)	(+)	(+)
Labor: College			
Constant	(−)	(−)	(−)
Laid Off	(−)	(+)	(.)
Unable to Work	(−)	(+)	(+)
Retired	(−)	(+)	(++)
Health: Next Period			
(Good,Bad)	(+)	(−)	(+)
(Bad,Good)	(−)	(++)	(+)
(Bad,Bad)	(+)	(+)	(+)
Opioids & Work			
Work Exp	(−)	(−)	(−)
Work	(−)	(−)	(−)
Received Rx	(−)	(+)	(+)
Any Opioid Misuse	(+)	(+)	(−)

Table: Transition Probability Estimates: Labor

Stage 1: CCP-EM Algorithm

- The likelihood of observing $(\{\text{pxy}_{k,n}\}_{k=1}^{6}, b_n, d_{j,n})$ given (x_n, e_n) is

$$\sum_{h=1}^{4} \bar{q}(h|e_n; \boldsymbol{\theta}^q) \prod_{k=1}^{6} f_{\text{pxy},k}(\text{pxy}_{k,n}|h; \boldsymbol{\theta}^{\text{pxy}}) f_b(x_n, e_n, h; \boldsymbol{\theta}^b) P(d_{j,n}|x_n, h, b_n)$$

- In the EM Algorithm, I use the following log-likelihood:

$$\sum_{n=1}^{N} \sum_{h=1}^{4} \bar{q}(h|e_n; \boldsymbol{\theta}^q) \log \left[\prod_{k=1}^{6} f_{\text{pxy},k}(\text{pxy}_{k,n}|h; \boldsymbol{\theta}^{\text{pxy}}) \right] f_b(x_n, e_n, h; \boldsymbol{\theta}^b) P(d_{j,n}|x_n, h, b_n)$$

- At k-th iteration,
  - M-Step: Maximize the log-likelihood wrt $\boldsymbol{\theta}^{\text{pxy}}$, $\boldsymbol{\theta}^b$, and CCP's given $\boldsymbol{\theta}^q_{(k)}$.
  - E-Step: Update $\boldsymbol{\theta}^u$ given $\boldsymbol{\theta}^{\text{pxy}}_{(k+1)}$, $\boldsymbol{\theta}^b_{(k+1)}$, and $\text{CCP}_{(k+1)}$ using the Bayes rule.

Estimation Steps

Probability of Death

The Set of Equations for Transition Probabilities for Death by Opioid Misuse

- The death probability increases when you have bad health or misuse opioids:

$$f_d(h, d_{rx}, d_{il}; \boldsymbol{\theta}^d) = f_d(\text{ocd}|h_1, h_2; \boldsymbol{\theta}^d) + \sum_{\text{OD}} f_d(\text{OD}|d_{rx}, d_{il}; \boldsymbol{\theta}^d)$$

where $\text{OD} \in \{\text{rx}, \text{il}, \text{bth}\}$.

$$\begin{aligned}
f_d(\text{ocd}|h_1, h_2; \boldsymbol{\theta}^d) &= \theta_1^d + \theta_2^d h_1 + \theta_3^d h_2 \\
f_d(\text{rx}|d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^d) &= \theta_4^d d_o^{rx} \\
f_d(\text{il}|d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^d) &= \theta_5^d d_o^{il} + \theta_6^d d_o^{rx} d_o^{il} \\
f_d(\text{bth}|d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^d) &= \theta_7^d d_o^{rx} d_o^{il}
\end{aligned}$$

MDE
Estimation Steps

Transition Probability: Health

- Transition probability of health has multinomial logit form:

$$\log \frac{P(h' = k|x, d_j; \boldsymbol{\theta}^h)}{P(h' = 0|x, d_j; \boldsymbol{\theta}^h)} = \theta^h_{1,k} + \theta^h_{2,k}\mathbf{1}\{e = 1\} + \sum_{m=1}^{3} \theta^h_{m+2}\mathbf{1}\{h = m\}$$
$$+ \sum_{m=1}^{3} \theta^h_{m+5}\mathbf{1}\{cw = m\} + \theta^h_{9,k}\mathrm{xp} + \theta^h_{10,k} d_w$$
$$+ \theta^h_{12,k}\mathrm{rx}(1 - d_o^{rx})\theta^h_{13,k} + \mathrm{rx} d_o^{rx} + \theta^h_{15,k} d_o^{il}$$

for $k = 1, 2, 3$. Note: $h = \mathbf{1}\{h_2 = B\} + 2 \times \mathbf{1}\{h_1 = B\}$ ▸ Result ▸ MDE ▸ Transition: Summary

Transition Probability: Labor

- Transition probability of labor status has multinomial logit form:

$$\log \frac{P(\mathrm{cw}' = k | x, d_j; \boldsymbol{\theta}^{cw})}{P(\mathrm{cw}' = 0 | x, d_j; \boldsymbol{\theta}^{cw})} = \sum_{m=0}^{3} \theta^{cw}_{m+1,k} \mathbf{1}\{cw = m\} \mathbf{1}\{e = 0\}$$
$$+ \sum_{m=0}^{3} \theta^{cw}_{m+5,k} \mathbf{1}\{cw = m\} \mathbf{1}\{e = 1\}$$
$$+ \sum_{m=1}^{3} \theta^{cw}_{m+8,k} \mathbf{1}\{h' = m\}$$
$$+ \theta^{cw}_{12,k} \mathrm{rx} + \theta^{cw}_{13,k} \mathrm{xp} + \theta^{cw}_{14} d_w + \theta_{15,k} \mathbf{1}\{d^{rx}_o = 1 \vee d^{il}_o = 1\}$$

for $k = 1, 2, 3$. Result MDE Transition: Summary

Transition Probability: Prescription

- Transition probability of prescription to opioids is in logit form:

$$
\begin{aligned}
\log \frac{P(\mathrm{rx}' = 1 | x, s; \boldsymbol{\theta}^{rx}, \boldsymbol{\alpha}_s)}{P(\mathrm{rx}' = 0 | x, s; \boldsymbol{\theta}^{rx}, \boldsymbol{\alpha}_s)} = {} & \theta_1^{rx} + \sum_{m=1}^{3} \theta_{m+1}^{rx} \mathbf{1}\{h' = m\} + \sum_{m=1}^{3} \theta_{m+4}^{rx} \mathbf{1}\{cw' = m\} \\
& + \left(\theta_8^{rx} + \sum_{m=1}^{3} \theta_{8+m}^{rx} \mathbf{1}\{h' = m\} \right) r_s'(1 - m_s') + \\
& + \left(\theta_{12}^{rx} + \sum_{m=1}^{3} \theta_{12+m}^{rx} \mathbf{1}\{h' = m\} \right) (1 - r_s') m_s' + \\
& + \left(\theta_{16}^{rx} + \sum_{m=1}^{3} \theta_{16}^{rx} \mathbf{1}\{h' = m\} \right) r_s' m_s' + \alpha_s
\end{aligned}
$$

▸ Result ▸ MDE ▸ Transition: Summary

Transition Probabilities

For each state s and year t, compute:

- NVSS: Fractions of population died from specific causes of death
- NSDUH: Posterior distribution of health and fractions of opioid misusers

$$P_d^{ocd}(s,t) = \sum_{h_1,h_2} f_d(ocd|h_1,h_2;\boldsymbol{\theta}_d)\hat{P}(h_1,h_2|s,t)$$

$$P_d^{rx}(s,t) = \sum_{d_o^{il}=0,1} f_d(\mathrm{rx}|d_o^{rx},d_o^{il};\boldsymbol{\theta}_d)\hat{P}(d_o^{rx}=1,d_o^{il}|s,t)$$

$$P_d^{il}(s,t) = \sum_{d_o^{rx}=0,1} f_d(\mathrm{il}|d_o^{rx},d_o^{il}=1;\boldsymbol{\theta}_d)\hat{P}(d_o^{rx},d_o^{il}=1|s,t)$$

$$P_d^{bth}(s,t) = f_d(\mathrm{bth}|d_o^{rx}=1,d_o^{il}=1;\boldsymbol{\theta}_d)\hat{P}(d_o^{rx}=1,d_o^{il}=1|s,t)$$

Equation Estimation Steps

Transition Probabilities

The Set of Equations for Transition Probabilities for Health

The following equations are constructed by combining SIPP, MEPS, and NSDUH:

$$
\begin{aligned}
P(h'|h, \text{cw}, \text{xp}, d_w, s, t, e) = \sum_{\text{rx}, d_o^{rx}, d_o^{il}} & f(h'|e, h, \text{cw}, \text{rx}, \text{xp}, d_w, d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^h) \times \\
& (1 - \hat{f}_d(h, d_o^{rx}, d_o^{il}, t; \hat{\boldsymbol{\theta}}_d)) \times \\
& \hat{P}(\text{rx}, d_o^{rx}, d_o^{il}|h, \text{cw}, \text{xp}, d_w, s, t, e) \\
P(h'|h, \text{cw}, \text{rx}, \text{xp}, d_w, t, e) = \sum_{\text{rx}, d_o^{rx}, d_o^{il}} & f(h'|e, h, \text{cw}, \text{rx}, \text{xp}, d_w, d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^h) \times \\
& (1 - \hat{f}_d(h, d_o^{rx}, d_o^{il}, t; \hat{\boldsymbol{\theta}}_d)) \times \\
& \hat{P}(\text{rx}, d_o^{rx}, d_o^{il}|h, \text{cw}, \text{rx}, \text{xp}, d_w, t, e)
\end{aligned}
$$

where $\tilde{f}_d$ is the fitted transition probability of surviving. Estimation Steps

Transition Probabilities

The Set of Equations for Transition Probabilities for Labor Market Displacement

The following equations are constructed by combining SIPP, MEPS, and NSDUH:

$$\hat{P}(\mathrm{cw}'|h', \mathrm{cw}, \mathrm{xp}, d_w, s, t, e) = \sum_{h,\mathrm{rx},d_o^{rx},d_o^{il}} f_{cw}(\mathrm{cw}'|e, h', \mathrm{cw}, \mathrm{rx}, \mathrm{xp}, d_w, d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^{cw}) \hat{f}_h \tilde{f}_d \hat{P}(\mathrm{rx}, d_o^{rx}, d_o^{il}|h, \mathrm{cw}, \mathrm{xp}, d_w, s, t, e)$$

$$\hat{P}(\mathrm{cw}'|e, h', \mathrm{cw}, \mathrm{rx}, \mathrm{xp}, d_w, t, e) = \sum_{h,\mathrm{rx},d_o^{rx},d_o^{il}} f_{cw}(\mathrm{cw}'|e, h', \mathrm{cw}, \mathrm{rx}, \mathrm{xp}, d_w, d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^{cw}) \hat{f}_h \tilde{f}_d \hat{P}(\mathrm{rx}, d_o^{rx}, d_o^{il}|h, \mathrm{cw}, \mathrm{rx}, \mathrm{xp}, d_w, t, e)$$

- $\tilde{f}_d$ is the fitted transition probability of surviving.
- $\hat{f}_h$ is the fitted transition probability for health.

Estimation Steps

Transition Probabilities

The Set of Equations for Transition Probabilities for Receiving Prescription Opioids

The following equations are constructed by combining MEPS and NSDUH:

$$\hat{P}(\mathrm{rx}', h', \mathrm{cw}' | \mathrm{rx}, d_w, t, e) = \sum_{h, \mathrm{rx}, d_o^{rx}, d_o^{il}} f_{rx}(\mathrm{rx}' | e, h', \mathrm{cw}', \mathrm{rx}, m_s', r_s'; \boldsymbol{\theta}^{rx}, \alpha_s) \hat{f}_{cw} \hat{f}_h \tilde{f}_d \hat{P}(h, \mathrm{cw}, d_o^{rx}, d_o^{il} | \mathrm{rx}, d_w, t, e)$$

$$\hat{P}(\mathrm{rx}', h', \mathrm{cw}' | s, t, e) = \sum_{h, \mathrm{rx}, d_o^{rx}, d_o^{il}} f_{rx}(\mathrm{rx}' | e, h', \mathrm{cw}', \mathrm{rx}, m_s', r_s'; \boldsymbol{\theta}^{rx}, \alpha_s) \hat{f}_{cw} \hat{f}_h \tilde{f}_d \hat{P}(h, \mathrm{cw}, \mathrm{rx}, d_w, d_o^{rx}, d_o^{il} | s, t, e)$$

- $\tilde{f}_d$ is the fitted transition probability of surviving.
- $\hat{f}_h$ is the fitted transition probability for health.
- $\hat{f}_{cw}$ is the fitted transition probability for labor market displacement.

Estimation Steps

Identification

Challenge

- I use proxies to identify latent health distribution $\bar{q}(h|e)$
  - Physical health only h_1: Walking, Seeing, Hearing
  - Mental health only h_2: Thinking
  - Health (h_1, h_2): Health (4-level), Doing errands alone and dressing
- Assumption on the proxy variables:
  - Each proxy is independent conditional on h.
  - $f(\text{Difficult to Walk}|h_1 = 1) > f(\text{Difficult to Walk}|h_1 = 0)$
  - $f(\text{Difficult to Think}|h_2 = 1) > f(\text{Difficult to Think}|h_2 = 0)$
- Then, $\bar{q}(h|e)$ and $\{f^{pxy}(\text{pxy}_k|h)\}_{k=1}^{6}$ are uniquely identified. (Hwang [2020])

Likelihood

Why Is W Zero?

- The probability of death consists of two parts: OCD + Opioid Overdose.

$$\left(f_d(ocd|h_1, h_2; \boldsymbol{\theta}^d) + (1 - \delta \mathbf{1}\{b = L\}) \sum_{\text{OD}} f_d(\text{OD}|d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^d) \right) W$$

- Notice that the first term $f_d(ocd|h; \boldsymbol{\theta}^d)W$ identifies W.
- Health affects the probability of dying from OCD, which affects the flow utility by W.
- Thus, δ is identified relative to how much people (dis)like W.

Back

CVF Differences

- Hotz-Miller inversion implies:

$$
\begin{aligned}
&\log \frac{P(d_j|x,b)}{P(d_1|x,b)} = v_j(x,b) - v_1(x,b) \\
&= u(x,j;\boldsymbol{\theta}^u) - u(x,1;\boldsymbol{\theta}^u) \\
&+ \beta \left[\begin{array}{r} (1-\pi\delta) f_{s_1',j} \left(f_{d|s_1',j} W + \sum_{x'} \bar{V}(x',s_1') f_{x'|x,s_1',j}(\boldsymbol{\theta}^{ch},\boldsymbol{\theta}^{rx}) \right) \\ +[1-(1-\pi\delta) f_{s_1',j})] \left(f_{d|s_0',j} W + \sum_{x'} \bar{V}(x',s_0') f_{x'|x,s_0',j}(\boldsymbol{\theta}^{ch},\boldsymbol{\theta}^{rx}) \right) \end{array} \right] \\
&- \beta \left[\begin{array}{r} (1-\pi\delta) f_{s_1',1} \left(f_{d|s_1',1} W + \sum_{x'} \bar{V}(x',s_1') f_{x'|x,s_1',1}(\boldsymbol{\theta}^{ch},\boldsymbol{\theta}^{rx}) \right) \\ +[1-(1-\pi\delta) f_{s_1',1})] \left(f_{d|s_0',1} W + \sum_{x'} \bar{V}(x',s_0') f_{x'|x,s_0',1}(\boldsymbol{\theta}^{ch},\boldsymbol{\theta}^{rx}) \right) \end{array} \right]
\end{aligned}
$$

Estimation Steps

CVF Differences with Finite Dependence

Hotz-Miller inversion implies there is a unique mapping ψ such that:

$$\bar{V}(x,b) = v_j(x,b) + \psi_j(\mathbf{p}(x,b)) \text{ for all } j \in \mathcal{J}$$

where choice-specific conditional value function $v_j(x,b)$ is

$$\begin{aligned} u(x,j;\theta^u) &+ \beta W(f_d^{ocd}(x) + (1-\delta)\mathbf{1}_L^b f_d^{OD}(x,j)) \\ &+ \beta\left(1-(f_d^{ocd}(x)+(1-\delta)\mathbf{1}_L^b f_d^{OD}(x,j))\right)\sum_{x',b'}\bar{V}(x',b')f(x',b'|x,b,j) \end{aligned}$$

Back

Monte Carlo Simulation

Infinite Horizon DDCM with Terminal State

- State space: $x_1 = 0, 1, 2, 3,\ x_2 = 0, 1,\ b = 0, 1$
- Choices: $j = 1 + d_w + 2d_o$
- $\beta = 0.96,\ W = 0,\ \delta = 0.28$
- Transition probabilities:

$$\log \frac{f_d(x_1, x_2, d_o; \delta)}{1 - f_d(x_1, x_2, d_o; \delta)} = -3.5 + 0.25x_1 + (1-\delta)0.05d_o$$

$$f_d((x_1', x_2') = k | x_1, x_2, j; \text{alive}) = \frac{\exp(x'\theta_k)}{1 + \sum_{l=2}^{8}(\exp(x'\theta_l))} \text{ for } k = 2, \ldots, 8$$

$$\log \frac{f_b((x_1, x_2) = 1)}{f_b((x_1, x_2) = 0)} = -2.5 + 0.5x_1 + 0.3x_2$$

Estimation Strategy

Monte Carlo Simulation

Infinite Horizon DDCM with a Terminal State

- Flow utility is specified as:

$$
\begin{aligned}
u(x_1, x_2, j) = {} & 0.1\,\mathbf{1}\{x_1 = 0\}\,d_w + 0.25\,x_1 d_w \\
& + 0.15\,\mathbf{1}\{x_2 = 0\}\,d_w + 0.65\,x_2 d_w \\
& - 0.5\,\mathbf{1}\{x_1 = 0\}\,d_o + 0.75\,x_1 d_o \\
& - 0.25\,\mathbf{1}\{x_2 = 0\}\,d_o - 0.15\,x_2 d_o
\end{aligned}
$$

Estimation Strategy

Monte Carlo Simulation

Infinite Horizon DDCM with a Terminal State

Monte Carlo simulation shows that the iterative method works well.

- Case 1: Estimate utility parameters only.
- Case 2: Iterative Method: estimate utility parameters and δ.
- Case 3: Iterative Method: estimate utility parameters, δ, and W.

	DGP	Case 1	Case 2	Case 3
θ_1	0.1	0.1000 (0.0002)	0.1000 (0.0002)	0.1000 (0.0004)
θ_2	0.25	0.2500 (0.0000)	0.2500 (0.0000)	0.2500 (0.0001)
θ_3	0.15	0.1500 (0.0000)	0.1500 (0.0000)	0.1500 (0.0003)
θ_4	0.65	0.6500 (0.0000)	0.6500 (0.0000)	0.6500 (0.0001)
θ_5	-0.5	-0.5000 (-0.0000)	-0.5000 (-0.0000)	-0.5000 (-0.0001)
θ_6	0.75	0.7500 (0.0000)	0.7500 (0.0000)	0.7500 (0.0001)
θ_7	-0.25	-0.2500 (-0.0001)	-0.2500 (-0.0002)	-0.2500 (-0.0028)
θ_8	-0.15	-0.1500 (-0.0002)	-0.1500 (-0.0003)	-0.1500 (-0.0049)
δ	0.28	Set to 0.28	0.2800 (-0.0000)	0.2800 (-0.0032)
W	0	Set to 0	Set to 0	-0.0028

Table: Monte Carlo Simulation Result

Numbers in parentheses are percent (%) differences. ▸ Estimation Strategy

Monte Carlo Simulation

Infinite Horizon DDCM with a Terminal State

Setting $W = 0$ creates a bias in utility estimates and the predicted CCP's

- Case 1: Estimate utility parameters and δ while setting $W = 0$.
- Case 2: Estimate utility parameters, δ, and W altogether.

	DGP #1	Case 1	Case 2
θ_1	0.1	0.0994 (0.5088)	0.1000 (0.0004)
θ_2	0.25	0.2499 (0.0489)	0.2500 (0.0001)
θ_3	0.15	0.1502 (0.1760)	0.1500 (0.0005)
θ_4	0.65	0.6504 (0.0617)	0.6500 (0.0001)
θ_5	-0.5	-0.49951 (-0.0983)	-0.5000 (-0.0001)
θ_6	0.75	0.75031 (0.0415)	0.7500 (0.0000)
θ_7	-0.25	-0.2566 (-2.6464)	-0.2500 (-0.0004)
θ_8	-0.15	-0.1571 (-4.7180)	-0.1500 (-0.0070)
δ	0.28	0.2880 (2.8571)	0.2800 (0.0000)
W	-3	Set to 0	-3.0025 (0.0833)
CCP Differences			
L2	-	0.0248	2.3141e-05
L0	-	0.0058	5.4928e-06

Table: Monte Carlo Simulation Result: $W = -3$

Numbers in parentheses are percent (%) differences. Estimation Strategy

Monte Carlo Simulation

Infinite Horizon DDCM with a Terminal State

…and the bias gets larger as W gets farther away from 0.

	DGP #2	Case 1	Case 2
θ_1	0.1	0.0982 (1.7346)	0.1000 (0.0013)
θ_2	0.25	0.2460 (0.1644)	0.2500 (0.0002)
θ_3	0.15	0.1509 (0.6069)	0.1500 (0.0006)
θ_4	0.65	0.6514 (0.2093)	0.6500 (0.0002)
θ_5	-0.5	-0.4984 (-0.3243)	-0.5000 (-0.0002)
θ_6	0.75	0.7510 (0.1355)	0.7500 (0.0000)
θ_7	-0.25	-0.2720 (-8.7834)	-0.2500 (-0.0190)
θ_8	-0.15	-0.1735 (-15.6710)	-0.1500 (-0.0322)
δ	0.28	0.3060 (9.2889)	0.2800 (-0.0071)
W	-10	Set to 0	-10.0071(0.0711)
CCP Differences			
L2	-	0.0833	4.6562e-05
L0	-	0.0198	1.1242e-05

Table: Monte Carlo Simulation Result: $W = -10$

Numbers in parentheses are percent (%) differences. ▸ Estimation Strategy

Estimation: Stage 2

- Using the one-to-one mapping between CCPs and CVF differences:

$$
\begin{aligned}
&\psi_1(x,s) - \psi_j(x,s) = v_j(x,s) - v_1(x,s) \\
&= \left(\bar{y}_j(\theta^y) + u_{o,j}(\theta^o)\right) - \left(\bar{y}_1(\theta^y) - u_{o,1}(\theta^o)\right) && \text{Today's Utility} \\
&+ \beta W \begin{bmatrix} f_{d|s_0',j} + (1-\pi\delta) f_{s_1'|j}\left(f_{d|s_1',j} - f_{d|s_0',j}\right) \\ - f_{d|s_0',1} - (1-\pi\delta) f_{s_1'|1}\left(f_{d|s_1',1} - f_{d|s_0',1}\right) \end{bmatrix} && \text{Death} \\
&+ \beta(1-\pi\delta) \sum_{x'} \bar{V}(x', s_1') \begin{bmatrix} f_{x'|x,s_1',j}(1 - f_{d|s_1',j}) f_{s_1',j} \\ - f_{x'|x,s_1',1}(1 - f_{d|s_1',1}) f_{s_1',1} \end{bmatrix} && \text{Tomorrow's Life with OUD} \\
&+ \beta \sum_{x'} \bar{V}(x', s_0') \begin{bmatrix} f_{x'|x,s_0',j}(1 - f_{d|s_0',j})\left(1 - (1-\pi\delta) f_{s_1',j}\right) \\ f_{x'|x,s_0',1}(1 - f_{d|s_0',1})\left(1 - (1-\pi\delta) f_{s_1',1}\right) \end{bmatrix} && \text{Tomorrow's Life without OUD}
\end{aligned}
$$

▸ Identification ▸ Derivation ▸ Back

Estimation: Stage 2

- Using the one-to-one mapping between CCPs and CVF differences:

$$\psi_1(x,s) - \psi_j(x,s) = v_j(x,s) - v_1(x,s)$$

$$= (\bar{y}_j(\theta^y) + u_{o,j}(\theta^o)) - (\bar{y}_1(\theta^y) - u_{o,1}(\theta^o)) \qquad \text{Today's Utility}$$

$$+\beta W \begin{bmatrix} f_{d|s_0',j} + (1-\pi\delta) f_{s_1'|j}\left(f_{d|s_1',j} - f_{d|s_0',j}\right) \\ -f_{d|s_0',1} - (1-\pi\delta) f_{s_1'|1}\left(f_{d|s_1',1} - f_{d|s_0',1}\right) \end{bmatrix} \qquad \text{Death}$$

$$+\beta(1-\pi\delta)\sum_{x'} \bar{V}(x',s_1') \begin{bmatrix} f_{x'|x,s_1',j}(1-f_{d|s_1',j}) f_{s_1',j} \\ -f_{x'|x,s_1',1}(1-f_{d|s_1',1}) f_{s_1',1} \end{bmatrix} \qquad \text{Tomorrow's Life with OUD}$$

$$+\beta\sum_{x'} \bar{V}(x',s_0') \begin{bmatrix} f_{x'|x,s_0',j}(1-f_{d|s_0',j})\left(1-(1-\pi\delta) f_{s_1',j}\right) \\ f_{x'|x,s_0',1}(1-f_{d|s_0',1})\left(1-(1-\pi\delta) f_{s_1',1}\right) \end{bmatrix} \qquad \text{Tomorrow's Life without OUD}$$

Identification Derivation Back

Estimation: Stage 2

- Using the one-to-one mapping between CCPs and CVF differences:

$$
\begin{aligned}
&\psi_1(x,s) - \psi_j(x,s) = v_j(x,s) - v_1(x,s) \\
&= (\bar{y}_j(\boldsymbol{\theta}^y) + u_{o,j}(\boldsymbol{\theta}^o)) - (\bar{y}_1(\boldsymbol{\theta}^y) - u_{o,1}(\boldsymbol{\theta}^o)) && \text{Today's Utility} \\
&+ \beta W \begin{bmatrix} f_{d|s_0',j} + (1-\pi\delta) f_{s_1'|j}\left(f_{d|s_1',j} - f_{d|s_0',j}\right) \\ -f_{d|s_0',1} - (1-\pi\delta) f_{s_1'|1}\left(f_{d|s_1',1} - f_{d|s_0',1}\right) \end{bmatrix} && \text{Death} \\
&+ \beta(1-\pi\delta) \sum_{x'} \bar{V}(x', s_1') \begin{bmatrix} f_{x'|x,s_1',j}(1 - f_{d|s_1',j}) f_{s_1',j} \\ -f_{x'|x,s_1',1}(1 - f_{d|s_1',1}) f_{s_1',1} \end{bmatrix} && \text{Tomorrow's Life with OUD} \\
&+ \beta \sum_{x'} \bar{V}(x', s_0') \begin{bmatrix} f_{x'|x,s_0',j}(1 - f_{d|s_0',j})\left(1 - (1-\pi\delta) f_{s_1',j}\right) \\ f_{x'|x,s_0',1}(1 - f_{d|s_0',1})\left(1 - (1-\pi\delta) f_{s_1',1}\right) \end{bmatrix} && \text{Tomorrow's Life without OUD}
\end{aligned}
$$

Identification Derivation Back

Estimation: Stage 2

- Using the one-to-one mapping between CCPs and CVF differences:

$$
\begin{aligned}
&\psi_1(x,s) - \psi_j(x,s) = v_j(x,s) - v_1(x,s) \\
&= (\bar{y}_j(\boldsymbol{\theta}^y) + u_{o,j}(\boldsymbol{\theta}^o)) - (\bar{y}_1(\boldsymbol{\theta}^y) - u_{o,1}(\boldsymbol{\theta}^o)) && \text{Today's Utility} \\
&+ \beta W \begin{bmatrix} f_{d|s_0',j} + (1-\pi\delta) f_{s_1'|j}\left(f_{d|s_1',j} - f_{d|s_0',j}\right) \\ -f_{d|s_0',1} - (1-\pi\delta) f_{s_1'|1}\left(f_{d|s_1',1} - f_{d|s_0',1}\right) \end{bmatrix} && \text{Death} \\
&+ \beta(1-\pi\delta)\sum_{x'} \bar{V}(x', s_1') \begin{bmatrix} f_{x'|x,s_1',j}(1 - f_{d|s_1',j}) f_{s_1',j} \\ -f_{x'|x,s_1',1}(1 - f_{d|s_1',1}) f_{s_1',1} \end{bmatrix} && \text{Tomorrow's Life with OUD} \\
&+ \beta \sum_{x'} \bar{V}(x', s_0') \begin{bmatrix} f_{x'|x,s_0',j}(1 - f_{d|s_0',j})\left(1 - (1-\pi\delta) f_{s_1',j}\right) \\ f_{x'|x,s_0',1}(1 - f_{d|s_0',1})\left(1 - (1-\pi\delta) f_{s_1',1}\right) \end{bmatrix} && \text{Tomorrow's Life without OUD}
\end{aligned}
$$

Identification Derivation Back

Estimation: Stage 2

- Using the one-to-one mapping between CCPs and CVF differences:

$$\psi_1(x,s) - \psi_j(x,s) = v_j(x,s) - v_1(x,s)$$

$$= \left(\bar{y}_j(\boldsymbol{\theta}^y) + u_{o,j}(\boldsymbol{\theta}^o)\right) - \left(\bar{y}_1(\boldsymbol{\theta}^y) - u_{o,1}(\boldsymbol{\theta}^o)\right) \qquad \text{Today's Utility}$$

$$+\beta W \begin{bmatrix} f_{d|s_0',j} + (1-\pi\delta) f_{s_1'|j}\left(f_{d|s_1',j} - f_{d|s_0',j}\right) \\ -f_{d|s_0',1} - (1-\pi\delta) f_{s_1'|1}\left(f_{d|s_1',1} - f_{d|s_0',1}\right) \end{bmatrix} \qquad \text{Death}$$

$$+\beta(1-\pi\delta)\sum_{x'} \bar{V}(x', s_1') \begin{bmatrix} f_{x'|x,s_1',j}(1 - f_{d|s_1',j}) f_{s_1',j} \\ -f_{x'|x,s_1',1}(1 - f_{d|s_1',1}) f_{s_1',1} \end{bmatrix} \qquad \text{Tomorrow's Life with OUD}$$

$$+\beta\sum_{x'} \bar{V}(x', s_0') \begin{bmatrix} f_{x'|x,s_0',j}(1 - f_{d|s_0',j})\left(1 - (1-\pi\delta) f_{s_1',j}\right) \\ f_{x'|x,s_0',1}(1 - f_{d|s_0',1})\left(1 - (1-\pi\delta) f_{s_1',1}\right) \end{bmatrix} \qquad \text{Tomorrow's Life without OUD}$$

Identification Derivation Back

Estimation: Stage 2

- For a given $\omega(x', s', x, s)$ where $\sum_{k \in \mathcal{J}(rx', k')} \omega_k(x', s', x, s) = 1$ and $|\omega_k(x', s', x, s)| < \infty$,

$$\bar{V}(x', s_0') = \sum_{k \in \mathcal{J}(rx', k')} \left(v_k(x', s_0') - \log P(d_k | x', s_0') \right) \omega_k(x', s_0', x, s)$$

$$\bar{V}(x', s_1') = \sum_{k \in \mathcal{J}(rx', k')} \left(v_k(x', s_1') - \log P(d_k | x', s_1') \right) \omega_k(x', s_1', x, s)$$

- Iterate $v_k(x', s')$ once more wrt utilities and future value functions
- Find the weights $\omega_k(x'', s_0'', x, s)$ that cancels out the two-period-ahead ex-ante value functions $\bar{V}(x'', s'')$
- Then, I have a moment for identifying θ^o.

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Reference I

B. Abramson, J. Boerma, and A. Tsyvinski. Macroeconomics of mental health. *NBER Working Paper*, 2024.

A. Alpert, D. Powell, and R. L. Pacula. Supply-side drug policy in the presence of substitutes: Evidence from the introduction of abuse-deterrent opioids. *American Economic Journal: Economic Policy*, 10:1–35, 2018. doi: 10.1257/pol.20170082.

P. Arcidiacono and R. A. Miller. Conditional choice probability estimation of dynamic discrete choice models with unobserved heterogeneity. *Econometrica*, 79:1823–1867, 2011. doi: 10.3982/ecta7743.

P. Arcidiacono and R. A. Miller. Nonstationary dynamic models with finite dependence. *Quantitative Economics*, 10:853–890, 2019. doi: 10.3982/qe626.

P. Arcidiacono and R. A. Miller. Identifying dynamic discrete choice models off short panels. *Journal of Econometrics*, 215:473–485, 2020. doi: 10.1016/j.jeconom.2018.12.025.

P. Arcidiacono, H. Sieg, and F. Sloan. Living rationally under the volcano? an empirical analysis of heavy drinking and smoking. *International Economic Review*, 48:37–65, 2007. doi: 10.1111/j.1468-2354.2007.00417.x.

S. Balestra, H. Liebert, N. Maestas, and T. Sherry. Behavioral responses to supply-side drug policy during the opioid epidemic. Technical report, 2023.

D. Beheshti. The impact of opioids on the labor market: Evidence from drug rescheduling. Technical report, 2022.

W. H. Dow, A. Godøy, C. Lowenstein, and M. Reich. Can labor market policies reduce deaths of despair? *Journal of Health Economics*, 74:102372, 2020. doi: 10.1016/j.jhealeco.2020.102372.

Reference II

H. Fang and Y. Wang. Estimating dynamic discrete choice models with hyperbolic discounting, with an application to mammography decisions. *International Economic Review*, 56:565–596, 2015.

R. Hai and J. J. Heckman. The causal effects of youth cigarette addiction and education. Technical report, National Bureau of Economic Research, 2022.

Y. Hu and M. Shum. Nonparametric identification of dynamic models with unobserved state variables. *Journal of Econometrics*, 171:32–44, 2012. doi: 10.1016/j.jeconom.2012.05.023.

Y. Hu and Y. Xin. Identification and estimation of dynamic structural models with unobserved choices. Technical report, SSRN, 2023. URL `https://ssrn.com/abstra`.

Y. Hwang. Identification and estimation of a dynamic discrete choice model with an endogenous time-varying unobservable state using proxies. Technical report, SSRN, 2020.

B. Kim. Must-access prescription drug monitoring programs and the opioid overdose epidemic: The unintended consequences. *Journal of Health Economics*, 75:102408, 2021. doi: 10.1016/j.jhealeco.2020.102408.

J. Mallatt. Policy-induced substitution to illicit drugs and implications for law enforcement activity. *American Journal of Health Economics*, 8:30–64, 2022. doi: 10.1086/716462.

A. Mukherjee, D. W. Sacks, and H. Yoo. The effects of the opioid crisis on employment: Evidence from labor market flows. *Journal of Human Resources*, 2023. doi: 10.3886/e182342v1.

C. B. Mulligan. Prices and policies in opioid markets. *Journal of Political Economy*, pages 000–000, 2024. doi: 10.1086/730381.

T. O'Donoghue and M. Rabin. Present bias: Lessons learned and to be learned. *American Economic Review*, 105:273–279, 2015. doi: 10.1257/aer.p20151085.

Reference III

S. Park and D. Powell. Is the rise in illicit opioids affecting labor supply and disability claiming rates? *Journal of Health Economics*, 76:102430, 2021. doi: 10.1016/j.jhealeco.2021.102430.

D. W. Sacks, A. Hollingsworth, T. Nguyen, and K. Simon. Can policy affect initiation of addictive substance use? evidence from opioid prescribing. *Journal of Health Economics*, 76:102397, 2021. doi: 10.1016/j.jhealeco.2020.102397.

M. Schnell. Physician behavior in the presence of a secondary market: The case of prescription opioids. Technical report, Princeton University, 2022. URL https://static1.squarespace.com/static/572372e7c2ea51b309e9991a/t/62a361101fa2c47a22943335/1654874393320/Schnell_06102022.pdf.

M. Schnell and J. Currie. Addressing the opioid epidemic: Is there a role for physician education? *American Journal of Health Economics*, 4:383–410, 2018. doi: 10.1162/ajhe_a_00113.