A Structural Analysis of Opioid Misuse: Labor, Health, Perception on Opioid Misuse Risk, and State-level Restrictions on Opioid Prescribing

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November 10, 2024

Abstract

This paper examines the heterogeneous responses of opioid misuse across health and labor status during 2015-2019. Three aggregate changes that characterize this period are considered: increased risk of death from opioid misuse, the spread of state-level policies on opioid prescribing, and fluctuating prices. The role of opioid misuse risk perception is highlighted as an additional channel for policy intervention. By estimating a dynamic discrete choice model of opioid misuse with stochastic perception bias, I show that labor status is just as important as health conditions in determining opioid misuse. Counterfactual analysis indicates that the decrease in opioid misuse is mainly due to the increased risk of death from opioid misuse. Policies targeting opioid prescription generally have no effect on overall misuse but alter the share of people using illegal opioids. No evidence is found for the impact of illegally traded opioid prices on opioid misuse. Lastly, correcting the perception of opioid misuse risk would be effective in decreasing opioid misuse among the unemployed and those with poor mental health, but its aggregate effect is limited due to the relative rarity of perception bias.

Keywords: opioid crisis, dynamic discrete choice, supply-side intervention, fentanyl, prescription opioids

JEL: C35, C53, C61

* jaepil.lee@cmu.edu. I thank Robert Miller, Rebecca Lessem, Anh Nguyen, John Kennan, Chris Taber, Yujung Hwang, Luming Chen, Mengqi Wang, Tianli Xia, Hyunkyeong Lim, and the seminar participants at Carnegie Mellon University and the University of Wisconsin-Madison for their comments. Tepper Healthcare Initiative provided funding for this project. This research was performed under FSRDC project #2124. Results from restricted NSDUH and NVSS are under the disclosure process. All errors are my own.

1 Introduction

There are two seemingly opposing trends in opioid misuse[1] and mortality rates from 2015 to 2019. Figures 1 and 2 show that the opioid misuse rate has been *decreasing* while mortality rates from opioid overdose have been *increasing*. These opposing trends raise several questions: What aggregate changes have contributed most to the observed trends in opioid misuse and deaths? Is there heterogeneity in opioid misuse in response to these aggregate changes? If so, how do people respond differently to these aggregate changes across health and labor status? Through which channels can policymakers intervene to decrease opioid misuse effectively? In

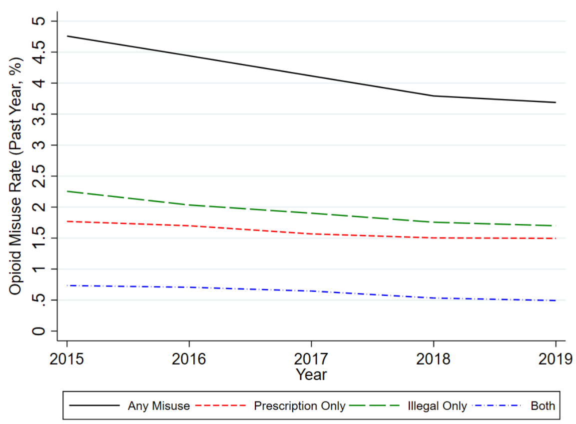

Figure 1: Opioid Misuse Rate 2015-2019, PUF NSDUH

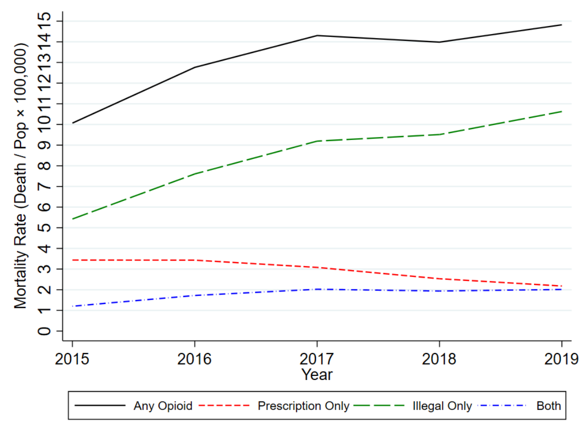

Figure 2: Mortality Rate by Opioid Overdose 2015-2019, RUF NVSS

this paper, I study opioid misuse as an economic choice that trades off today's pain-relieving effects and other rewarding properties for tomorrow's negative health and labor outcomes. I classify opioid misuse by where people obtained opioids for misuse: (i) one's own prescribed opioids, (ii) illegally traded opioids, and (iii) both prescribed and illegally traded opioids. This classification is important because it affects the probability of dying from misuse and future health outcomes. The risk of death from opioid overdose, an event that may occur when people misuse opioids, is higher if one uses illegally traded opioids due to their unregulated quality, potency, and other factors, compared to misusing one's own prescribed opioids. Although it simplifies opioid misuse on the intensive margin, this classification can capture the substitutability between prescription opioids and illegally traded opioids, which is of interest when designing policies to decrease opioid misuse and deaths.

I evaluate how three aggregate changes during 2015-2019 affected opioid misuse differently

[1]Opioid misuse is a medical term defined as using opioids not as directed by a doctor in any way. Examples include taking prescribed opioids in larger amounts, at higher frequency, for longer duration, changing the method of administration, or using illegally traded opioids.

across health and labor status. First, state-level policies aimed at controlling opioid prescribing have been widely implemented during this period. Second, the probability of dying from opioid misuse has been increasing as illegal opioids become more risky. Third, prices of illegally traded opioids at the state level have fluctuated over time. Since all of these changes occurred simultaneously, the individual effect of each change is ambiguous.

I also introduce perception bias on opioid misuse risk as a new channel that amplifies the effect of labor and health on opioid misuse. People with poorer health and unfavorable labor status tend to perceive that others are not taking a significant risk when using heroin. Motivated by this pattern, I estimate the significance of perception bias regarding opioid misuse risk in the model.

I compile several restricted data sets on opioid misuse, policies, death data, and price information to document five stylized facts. First, opioid misuse is associated with poor health and unfavorable labor status. Second, policies on opioid prescribing have decreased prescriptions on the extensive margin. Third, the mortality risk of misusing opioids has increased, mostly due to illegal opioids. Fourth, illegally traded opioid prices across states have fluctuated. Lastly, the perception of opioid misuse risk is negatively correlated with unfavorable labor and health status.

Motivated by these data patterns, I develop a dynamic model of work and opioid misuse with stochastic perception bias. The model is an infinite horizon model with endogenous mortality risk. In each period, the representative individual is informed about the probability of death from opioid misuse, his location's policy on opioid prescribing, and illegal opioid prices. His latent health status is realized based on his past year's choice of work and opioid misuse. The person may be removed from the labor force due to unemployment, inability to work because of health conditions, or retirement. Subsequently, the individual may receive prescription opioids conditional on his health, labor status, and the policies on opioid prescribing. The person then forms his perception of the risk of misusing opioids each period, conditional on his labor, health, and opioid prescription status. The individual understands that misusing opioids increases the probability of death by opioid overdose and negative health and labor outcomes in the future. However, the perceived transition probability to death by opioid misuse is discounted if the person perceives misusing opioids as not a great risk. The person then chooses to work and misuse opioids. The person can only work if he is not displaced from labor. The person can always choose to misuse opioids, but the kinds of opioid misuse vary by opioid prescription status. At the end of each period, death is stochastically realized based on his health and opioid misuse.

I estimate the model by extending the two-step conditional choice probabilities estimator to accommodate finite dependence. I first use the Expectation-Maximization algorithm to recover the probability distribution of latent health, reduced-form conditional choice probabilities, and perception bias process. Then, I recover the joint transition probability of death, labor, and health by attributing the state-level variation in opioid misuse to the marginal transition probabilities observed in other data sets. Given the recovered choice and transition probabilities, I construct a system of equations that identify the utility parameters and the size of perception bias on opioid misuse risk. The estimation method iterates between finding finite dependence paths that cancel out the ex-ante value function with a given perception bias candidate and estimating the structural parameters. The algorithm continues until the perception bias converges.

The model estimates capture the heterogeneous preferences on opioid misuse across labor and health and the significance of the perception bias. Transition probability estimates confirm that opioid misuse has negative effects on health and labor. The utility parameter estimates show that being unemployed has the strongest incentive to misuse illegal opioids. People who cannot work due to health conditions derive positive utility from opioid misuse, but the magnitude is smaller than for the unemployed. Retired individuals have negative utility from opioid misuse. Individuals with poor physical health experience disutility from misusing opioids, which could be related to an increased baseline mortality rate. People with poor mental health have positive utility from misusing opioids even when their baseline mortality rate is higher than those with good health. This heterogeneity in utility from opioid misuse indicates that supply-side interventions, such as state-level restrictions on opioid prescribing, may have differing effects on people's opioid misuse. I also find that the size of the perception bias on opioid misuse risk is significantly greater than zero, illuminating a new channel for intervention.

In counterfactual analysis, I use the 2015 population as a benchmark and apply the aggregate changes in 2018 with respect to policies, prices, and mortality risks. Counterfactual analysis shows that increasing the probability of dying from opioid misuse has the biggest effect on decreasing opioid misuse. Restricting opioid prescription increases the probability of using illegal opioids slightly, mainly among the unemployed population and those with poor mental health. Changing prices has little effect on opioid misuse. This illustrates that people have been decreasing opioid misuse by internalizing the higher risk of misuse, rather than in response to supply-side interventions by policymakers. Also, the analysis highlights that people with poor mental health and who are unemployed are the most adversely affected by the state-level policies, as they substitute toward illegal opioids, increasing their exposure to higher mortality risk.

I also evaluate the role of perception bias on opioid misuse. By collapsing the perception bias to zero, I observe a significant decrease in opioid misuse. This mostly benefits the unemployed and people with poor mental health, as they are highly associated with perception bias. However, the aggregate effect is small because the population with perception bias is about 15

My paper contributes to the economic studies on the opioid crisis by evaluating the heterogeneous effect of state-level policies on opioid prescribing via health and labor. The consensus in the literature has been that labor market conditions and the opioid crisis are correlated at a macro level (Mukherjee et al. (2023)), but empirical evidence from individual-level data shows mixed results (Maclean et al. (2021), Currie et al. (2019)). In contrast to the existing literature, my paper constructs a micro-founded model of work and opioid misuse to reveal how opioid misuse behavior varies by health and labor status. I then quantify how much health and labor motivate opioid misuse. This paper extends findings on the "unintended consequences" of supply-side interventions, such as those identified in event studies on the OxyContin reformulation in 2010 (Alpert et al. (2018)) and the implementation of the Must-Access Prescription Drug Monitoring Program (PDMP) (Kim (2021)), by characterizing the decision process of individuals and analyzing who is more affected by state-level restrictions on opioid prescribing.

My paper is closely related to Greenwood et al. (2022), Mulligan (2024), and Balestra et al. (2023). Greenwood et al. (2022) develops a Markov model of opioid use to predict the effects of policy interventions on opioid prescribing. Mulligan (2024) considers price and mortality risk changes between prescription and illegally traded opioids. Balestra et al. (2023) empirically documents how must-access PDMPs affected physicians' behavior on prescribing opioids and their effect on mortality rates. My paper encompasses all of these aspects by developing a model with changes in opioid prescription via policy, changes in illegal opioid prices, and changes in mortality risks during 2015-2019. I also consider labor and health dimensions to reveal heterogeneous responses to those changes. Moreover, I introduce perception bias to opioid misuse risk to evaluate its significance for policy intervention.

I contribute to the substance use and labor literature by developing a tractable dynamic model with stochastic perception bias. There are two approaches to modeling substance use: rational addiction (Greenwood et al. (2022), Hai and Heckman (2022), Becker and Murphy (1988)) and behavioral models (O'Donoghue and Rabin (2015), O'Donoghue and Matthew (1999)). My paper stands in the middle by introducing a perception bias that may be realized in each period depending on the individual's state. In this sense, my model approximates a dynamic model of a "sophisticated" agent with present bias, where the present self understands that his future self may also have perception bias.

My paper is also close to the recent literature in the identification and estimation of dynamic discrete choice models with unobserved heterogeneity (Hwang (2020), Hu and Shum

(2012), Kasahara and Shimotsu 2009) and unobserved choices (Hu and Xin (2023)). I utilize the approach of Hwang (2020) using proxy variables to recover the probability distribution of two-dimensional latent health status. Loosely related to Hu and Xin (2023), I attribute state-level variation in opioid misuse in repeated cross-sections to marginal transition probabilities observed in the Survey of Income and Program Participation (SIPP). By combining the two approaches, I recover the joint transition probability of labor and health by opioid misuse and estimate the dynamic model in my paper.

Third, I contribute to the literature by developing a new estimation strategy to estimate the structural parameters along with the parameter on subjective beliefs. Applying the original "two-step" CCP estimator with finite dependence (Arcidiacono and Miller (2011), Arcidiacono and Miller (2019)) is infeasible in this model because the magnitude of the perception bias is jointly estimated with utility parameters. This means that the decision weights that achieve a finite dependence path must change as we estimate the structural parameters. To overcome this challenge, I extend the estimation procedure by iterating between searching for finite dependence paths and estimating the structural parameters. This paper also simplifies the process of finding a finite dependence path. Contrary to Arcidiacono and Miller (2019), this paper uses the pseudo-inverse on the linear system of equations for the perceived transition probabilities to get the decision weights. As long as a solution to the system exists, this approach can find a finite dependence path with less computational burden.

Section 2 describes the data patterns on the associations among health, labor, perception of opioid misuse risk, and policy. Section 3 presents the dynamic model of work and opioid misuse with stochastic perception bias. Section 4 discusses the identification of the model parameters. Section 5 describes the estimation procedure and results. Section 7 discusses counterfactual analysis.

2 Data Patterns

In this section, I provide descriptive evidence of how opioid misuse is associated with labor, health, policy, and the perception of the risk of opioid misuse. The data patterns come from the public National Survey of Drug Use and Health (NSDUH) and the restricted National Vital Statistics System (NVSS). The details of data sources are in the appendix.

I classify people into three groups in terms of exposure to opioids. The first group is non-users, defined as those who did not use opioids, either via prescription opioids or opioid misuse in the past 12 months. The second group is the prescription (Rx) opioid users. This group used their prescribed opioids as directed by a doctor and did not misuse opioids in the past 12 months. The third group is opioid misusers. They misused opioids in the past 12 months, and their opioid misuse can vary by where they sourced opioids for misuse.

2.1 Health and Opioid Misuse

The main motivation for restricting opioid prescription is that excessive opioid prescription facilitates prescription opioid misuse. If this is true, then groups with higher opioid prescription rates would be associated with higher opioid misuse in the data. This pattern is observed in Table 1. It shows that people in worse health tend to be positively associated with receiving prescription opioids and misusing opioids. In the NSDUH, about 20% of respondents who answered that they were in excellent health received opioids and used them as directed by a doctor in the past 12 months. About 2.6% of the respondents with excellent health have misused opioids during this period. In contrast, about 45% of people with fair or poor health have received opioids in the past 12 months and used them as directed by a doctor, and 5.9% have misused opioids.

			Opioid Misuse			
Health (4-levels)	Nonuser	Rx user	Rx Only	Illegal only	Both	Total
Excellent	76.20	21.24	0.99	1.24	0.33	100
Very Good	68.39	27.88	1.40	1.81	0.52	100
Good	60.94	34.35	1.66	2.31	0.73	100
Fair/Poor	48.19	45.91	2.76	2.09	1.06	100
All	64.85	31.05	1.59	1.88	0.62	100

Table 1: Row Percentages of Opioid Use by Health: Nonuser, Prescription User, and Opioid Misuse. PUF NSDUH, 2015-2019.

Although a higher prescription rate is associated with higher opioid misuse in Table 1, this does not show why people in worse health are misusing opioids. This could be due to having easier access to opioids, but it could also be there are other aspects associated with health. As later sections show, labor and perception bias on opioid prescribing are intertwined with this pattern.

2.2 Labor and Opioid Misuse

This paper emphasizes the role of labor status on opioid misuse. Table 2 shows the row percentages of opioid use across labor status. 57% of those who answered they “cannot work due to health reasons” have received prescription opioids and used as directed by a doctor. Such a high prescription rate is associated with higher opioid misuse, around 6.71%. However, the opioid misuse rate by the unemployed population is even higher, marking 8.47%, while their prescription rate is around the same as those who are working and who are not working by choice. Considering this, people might be misusing opioids out of frustration from the labor market outcome, similar to the "death of despair" hypothesis (Case and Deaton (2017)).

	Nonuser	Rx User	*Opioid Misuse* Rx Only	Illegal Only	Both	Total
Out of Labor	65.13	30.71	1.68	1.83	0.64	100
Working	67.41	28.34	1.58	2.05	0.63	100
Unemployed	63.87	27.67	2.56	4.12	1.79	100
Unable to Work	35.69	57.60	3.45	2.18	1.08	100
Retired	64.34	34.50	0.63	0.47	0.07	100
18-21	72.40	21.18	2.13	3.25	1.04	100
12-17	81.56	15.29	1.39	1.42	0.34	100
All	66.87	28.98	1.61	1.93	0.62	100

Table 2: Row Percentages of Opioid Use by Labor Market Displacement: Nonuser, Prescription User, and Opioid Misuse. PUF NSDUH, 2015-2019.

Table 2 also shows that labor status matters in studying opioid misuse. While 4.5% were unemployed during 2015-2019, they represent about 7.2% to 13% of opioid misusers. Similarly, while 5% of the population were unable to work due to health reasons, 6% to 11% of opioid misusers were in this category.

	Nonuser	Rx User	*Opioid Misuse* Rx Only	Illegal Only	Both	All
Out of Labor	12.79	12.60	13.48	12.40	13.21	12.74
Working	65.10	57.17	62.15	68.05	63.14	62.64
Unemployed	4.44	4.02	7.26	9.87	12.97	4.51
Unable to Work	2.85	9.61	11.23	5.99	8.98	5.18
Retired	14.82	16.60	5.88	3.69	1.70	14.94
Total	100	100	100	100	100	100

Table 3: Column Percentages of Opioid Use by Labor Market Displacement: Nonuser, Prescription User, and Misuse by Type. PUF NSDUH, 2015-2019.

Dividing the prescription patterns and opioid misuse rates by age groups further shows that higher prescription is not the sole reason for opioid misuse. Figures 3 and 4 show opioid prescription and opioid misuse rates by age groups during 2015-2019. Although prescription rates become higher as you get older, opioid misuse is only higher among young people, and older people generally do not misuse opioids.

Figures 5 and 6 further highlight that the opioid crisis applies to the prime working age. During 2015-2019, many states began to impose restrictions on prescribing opioids. In this period, the mortality rates by opioid overdose with prescription opioids were generally steady, while opioid overdose deaths by illegal opioids (e.g., fentanyl) have sharply increased. Despite the changes, the hump-shaped curve across age groups is also persistent. Notably, most of the deaths were from prime working age group.

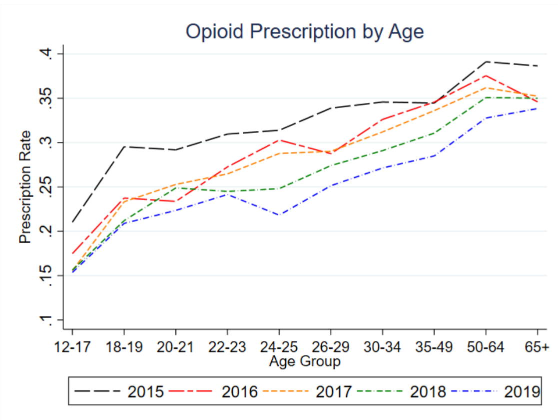

Figure 3: Prescription Rates across Age Groups, PUF NSDUH, 2015-2019

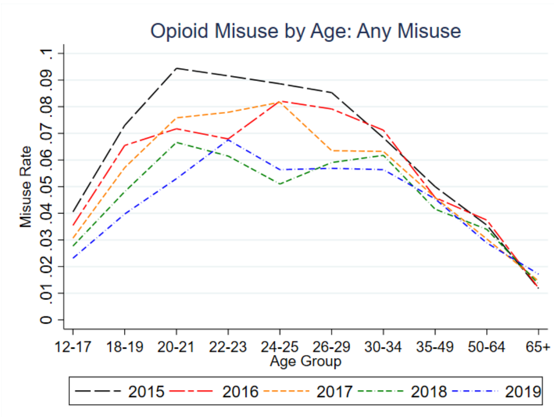

Figure 4: Mortality rates by prescription opioids across age groups, NVSS, 2011-2019

These figures, along with the associations across health and labor statuses, indicate that the opioid crisis is not just due to lax opioid prescription. Rather, the opioid crisis is a multifaceted socioeconomic problem where health and labor must also be integrated into the analysis.

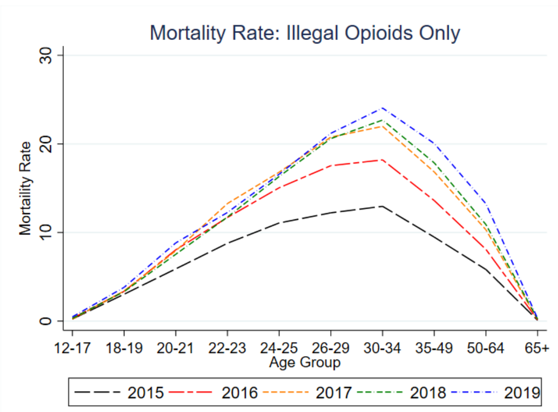

Figure 5: Prescription Rates across Age Groups, PUF NSDUH, 2015-2019

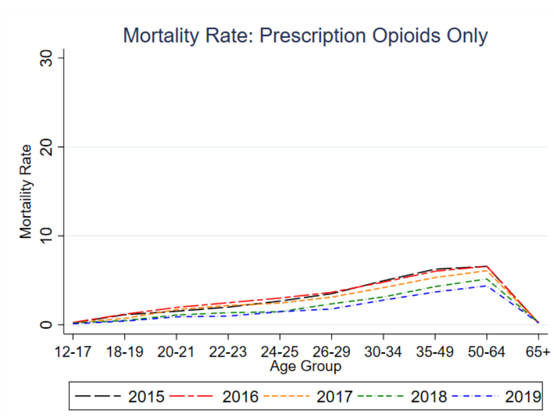

Figure 6: Mortality rates by prescription opioids across age groups, NVSS, 2011-2019

2.3 State-level Policies on Opioid Prescribing and Their Effects

We observed a surge in opioid overdose deaths during 2015-2019, after the introduction of fentanyl in the black market in the United States. I compute the statistical probability of death from opioid misuse by matching the fractions of people dying from opioid overdose with the fractions of people misusing opioids.

Table 4 shows that the probability of dying from other causes than opioid overdose has stayed constant during this period. However, the probability of dying from opioid overdose have surged, mainly led by illegal opioids becoming more lethal.

	2015	2016	2017	2018	2019
Opioid Overdose					
Prescription only	0.19	0.20	0.19	0.17	0.15
Illegal 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 4: Probability Dying from Other Causes of Death and from Opioid Overdose, PUF NSDUH & NVSS, 2015-2019

If illegal opioids have become more risky in terms of the probability of dying from them, then restricting opioid prescription at the state level may induce certain groups of people to substitute the need for opioids with illegal opioids. This is a widely accepted argument in the literature on the opioid crisis, known as the "unintended consequences" of supply-side intervention on increasing the opioid overdose deaths by illegal opioids (Kim (2021), Alpert et al. (2018)). My paper delves into the well-known unintended consequence of supply-side intervention and evaluates the heterogeneous effect of the state-level policies across labor and health statuses.

In this section, I document that the state-level policies during this period have indeed decreased opioid prescription rate and they seem to have had an "unintended consequence." I first use aggregate data to proxy for opioid prescription rate on the extensive margin. The first measure is Opioid Rx per 100 population in state s in year t, Rx/100. The second measure is the amount of opioids dispensed in state s in year-quarter t. I run two-way fixed effects regression to show that state-level restrictions indeed are associated with lower opioid dispense rate.

$$\log(y_{s,t}) = \beta_1 r_{s,t}(1 - m_{s,t}) + \beta_2 m_{s,t}(1 - r_{s,t}) + \beta_3 r_{s,t} m_{s,t} + X\beta + \alpha_s + \delta_t + \varepsilon_{s,t} \tag{1}$$

β_1, β_2, and β_3 capture the association between the state-level restrictions and the opioid pre-

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

Table 5: Two-way Fixed Effects Regression Results of the Number of Prescriptions per 100 Population and Opioids Dispensed on State-level Policies on Opioid Prescribing, CDC, ARCOS, and CPS, 2014-2019.

scription rate. While state-level restrictions and must-access PDMP seem to be uncorrelated with prescription rates, states that implement two policies together have a strong negative correlation with opioid prescriptions.

I expect that the result of logit regression of being prescribed opioids on policies using restricted NSDUH would be similar. State-level restrictions and must-access PDMP alone would have a more nuanced correlation with prescribing opioids. In contrast, when both policies are implemented, it would have a strong negative correlation with the opioid prescription rate. This correlation would also be heterogeneous across health status. One policy would have a weaker effect of reducing opioid access for those with worse health, and one might not have such an effect. However, from the observed aggregate trends, it seems intuitive to assume that the effect of policies on opioid prescription rates is the strongest when both policies are implemented.

To see whether the state-level policies on opioid prescribing is associated with mortality rates, I run a two-way fixed effect regression with mortality rates by opioid overdose as the dependent variable.

$$\mathrm{Mort}_{s,t} = \beta_1 r_{s,t}(1 - m_{s,t}) + \beta_2 m_{s,t}(1 - r_{s,t}) + \beta_3 r_{s,t} m_{s,t} + X\beta + \alpha_s + \delta_t + \varepsilon_{s,t} \tag{2}$$

As Table 6 shows, state-level policies seem to have positive association with the increase in the mortality rate by synthetic opioid overdose, which are considered to be illegally traded[2].

[2]Currently, the mortality data on opioid overdose do not distinguish pharmaceutical fentanyl from illegally produced fentanyl. The CDC instead reports opioid overdose deaths by synthetic opioids except for Methadone to account for the increase in opioid overdose deaths involving fentanyl. Conversely, natural opioids, semi-natural opioids, and Methadone are considered to be prescription opioids in the mortality data. Previous studies show that synthetic opioid deaths are not correlated with fentanyl prescription rates but with the

	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 6: Two-way Fixed Effects Regression Results of Opioid Overdose Mortality Rate on State-level Policies on Opioid Prescribing, CDC, ARCOS, and CPS, 2014-2019.

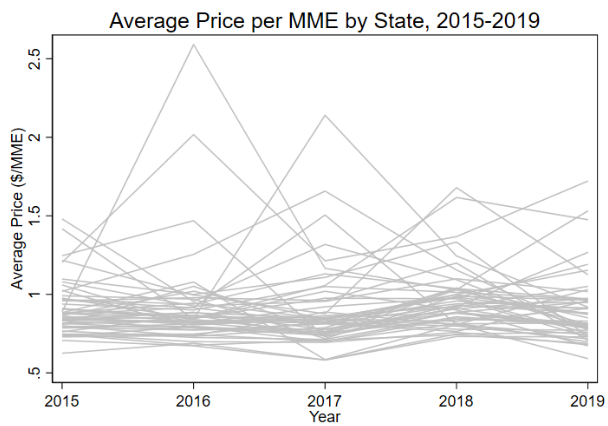

Figure 7: Average Illegal Opioid Prices by State, StreetRx, 2015-2019.

However, it is unclear exactly who substituted reduced access to prescription opioids to illegal opioids with this reduced-form result.

2.4 Illegal Opioid Prices

Figure 7 shows average prices for illegally traded opioids across states during 2015-2019 from StreetRx. While most states' prices for illegally traded opioids were below a dollar per milligram of morphine equivalent (MME), the prices fluctuated a lot during this period. I use this variation across states to see whether people changed their opioid misuse rate. I provide empirical evidence that the state-level policies do not affect prices for illegal opioids. If illegally

number of drug submissions confiscated by law enforcement that tested positive for fentanyl (see Gladden et al. (2016) and Peterson et al. (2016).)

traded opioids are derived from prescription opioids, then restricting opioid dispense via state-level policies would have a positive correlation with illegally traded opioid prices. To see this, I run a two-way fixed effects regression of the average price per MME for illegally traded opioid prices on state-level policies on opioid prescribing. Equation 3 is the specification for the regression:

$$\bar{p}_{s,t} = \beta_1 r_{s,t}(1 - m_{s,t}) + \beta_2 m_{s,t}(1 - r_{s,t}) + \beta_3 r_{s,t} m_{s,t} + X\beta + \alpha_s + \delta_t + \varepsilon_{s,t}. \quad (3)$$

β_1, β_2, and β_3 capture the association between the state-level restrictions and the average reported price for illegal trade prices. Table 7 shows that the policies have statistically insignificant associations with illegally traded prices, if not negative. Based on the empirical

	\$/MME	log(\$/MME)
State Restriction Only	-0.0563	-0.0420
	(0.0415)	(0.0374)
Must-Access PDMP Only	-0.0822	-0.0725
	(0.0456)	(0.0402)
Both	-0.0750	-0.0612
	(0.0467)	(0.0414)
Year FE	Y	Y
State FE	Y	Y
Controls	Y	Y
N	300	300

Table 7: Two-way Fixed Effect Regression Result of Average Illegally Traded Opioid Price on State-level Policies, StreetRx and CPS, 2014-2019.

evidence, I assume that the state-level restrictions only affect opioid prescription on an extensive margin and not on the prices for illegally traded opioids. This implies that I am assuming a flat supply curve for illegal opioids. This assumption is innocuous based on the characteristics of the opioid crisis during 2015-2019. After the introduction of fentanyl in the United States in 2013, illegal opioids became widely accessible. Surveys also show that "(...) nearly half feel it is extremely or somewhat easy to access opioids for illicit use" in 2018.[3]

2.5 Perception of Opioid Misuse Risk

The rationale for state-level policies on prescribing opioids is that people are overconfident about the risk of misusing opioids. If this misperception of the risk of misusing opioids

[3]https://www.psychiatry.org/news-room/news-releases/nearly-one-in-three-people-know-someone-addicted-t

induces opioid misuse, it might seem justifiable to design a policy to correct the public's perception of opioid misuse risk. Thus, my paper highlights the perception of the risk of opioid misuse as an additional channel where labor, health, and prescription of opioids may affect opioid misuse.

Table 8 shows that about 14% of the population thinks that other people are not taking a great risk when using heroin, a well-known illegal opioid. Considering that the fraction of people with opioid use disorder (i.e., addiction) is less than 1%, this discrepancy in the perception of the risk of misusing opioids may initiate opioid misuse. Table 9 shows that the

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

perception of the risk of opioid misuse is also associated with unfavorable labor status and poor health. With this regression, however, it is difficult to understand which one affected the other. It could be that people with perception bias began misusing opioids and ended up with worse labor and health outcomes, or vice versa. This why I develop a model where the causality runs both ways and runs a counterfactual analysis by shutting down the perception bias channel.

	Opioid Misuse: Not a Great Risk
Labor	
Laid Off	0.0352 (0.0058)
Unable to Work	-0.0224 (0.0062)
Retired	-0.0312 (0.0047)
Work Experience	-0.0305 (0.0034)
Health	
Very Good	0.0104 (0.0028)
Good	0.0194 (0.0030)
Fair/Poor	0.0180 (0.0038)
Opioids	
Received Rx Opioids	-0.0179 (0.0030)
Controls	Y

Table 9: Average Marginal Effects of Health, Labor, and Prescription to Opioids on Perception of Opioid Misuse Risk. PUF NSDUH 2015-2019.

2.6 Summary

The data patterns show that the opioid crisis is not a simple problem to be controlled by opioid prescription practices. The associations across health, labor, and perception of opioid misuse risk are intertwined along with aggregate changes in the probability of death from opioid misuse, policies on opioid prescribing, and prices for illegal opioids. To understand and predict the effect of policies we design, we first must understand the behavior of opioid misuse, which is affected by health, labor, and various other aspects. To uncover the "deep parameters" that shape the data patterns we see, I develop a dynamic discrete choice model where an individual is affected by the perception bias in each period in the next section.

3 Model

I consider an infinite horizon individual optimization problem with endogenous death probability. The individual is endowed with education level and state location. In each period, the individual observes the state-level restrictions on opioid prescribing and prices for illegally traded opioids. The individual expects that the policies and prices will stay the same forever. He knows his past year work experience and latent physical and mental health. In each, the individual may be displaced from labor. Then, the individual is prescribed opioids based on his latent health and state-level restrictions on opioid prescribing. Finally, he forms the perception of opioid misuse risk based on education level, labor, health, and opioid prescription. Then, he makes decisions on working and opioid misuse. He faces a risk of death in each period based on his health and opioid misuse. He continues the optimization problem until death.

3.1 State Variables and Choice Set

Location s is defined at the state level. In each year t, each location has state-level restriction $r_{s,t}$, must-access PDMP $m_{s,t}$, and price for illegally traded opioids $p^{il}_{s,t}$. The representative individual expects that he will live in that state forever. Also, the individual expects the policies and prices to stay the same forever.

The individual knows whether he has worked in the previous year or not: $\text{xp} = \mathbf{1}\{\text{Worked in the previous period}\}$.

The vector of latent health is in two dimensions, (h_1, h_2). Each dimension has two values, good and bad: $h_1 \in \{G, B\}$ and $h_2 \in \{G, B\}$. h_1 and h_2 represent physical health and mental health, respectively. For simplicity, the vector of latent health is indexed by $h = 1 + \mathbf{1}\{h_2 = B\} + 2 \times \mathbf{1}\{h_1 = B\}$.

The individual may experience displacement from labor, cw. There are three kinds of displacement from labor: unemployment, inability to work due to health conditions, and retirement.

$$cw = \begin{cases} 0 & \text{Not displaced from labor} \\ 1 & \text{Unemployed} \\ 2 & \text{Unable to work due to health conditions} \\ 3 & \text{Retired} \end{cases}$$

If the person is displaced from labor, the person cannot work during this period. If the person is not displaced from labor (cw = 0), the person can choose to work or not during this period. While retirement is not an explicit endogenous choice, its transition probability depends on the previous working decision and labor market displacement. People can return to the labor force after retirement, but this is not modeled explicitly. The transition back to the labor force after retirement is captured through the transition probability.

The individual may be prescribed opioids each period, conditional on his labor, health, and state-level policies. Denote the prescription status by rx = $\mathbf{1}\{\text{Received Prescription Opioids}\}$.[4]

Lastly, the individual forms a perception of the risk of misusing opioids, $b \in \{L, H\}$. If $b = H$, the individual expects the actual probability of dying from opioid misuse known at t. If $b = L$, the individual perceives that misusing opioids is not a great risk. In this case, the individual perceives the probability of dying from opioid misuse is lower than the actual probability by $\delta \in [0, 1]$.

The individual can choose to work and to misuse opioids each period. Denote d_w, d_o^{rx}, and d_o^{il} by

$$\begin{aligned} d_w &= \mathbf{1}\{\text{Work}\} \\ d_o^{il} &= \mathbf{1}\{\text{Use illegal opioids}\} \\ d_o^{rx} &= \mathbf{1}\{\text{Misuse prescribed opioids}\}. \end{aligned}$$

Denote all possible actions by $j = 1 + d_o^{il} + 2d_o^{rx} + 4d_w$ and let $d_j := \mathbf{1}\{\text{Chooses action } j\}$. The choice set is affected by i) being displaced from labor and ii) being prescribed opioids. If the

[4] Being prescribed opioids is exogenous to individuals conditional on state-level policies and individual state variables. This is an innocuous simplification based on the finding in the literature that doctor shopping is rare (Sacks et al. (2021)). This assumption does not rule out the role of physicians; this model aggregates physicians' practice of prescribing opioids as a function of the individual's state variables and state-level policies. Thus, this model can address counterfactual analysis of changes in physicians' opioid prescribing practices by changing the transition probability of being prescribed opioids. See Schnell (2022) for a study on physicians' behavior in prescribing opioids.

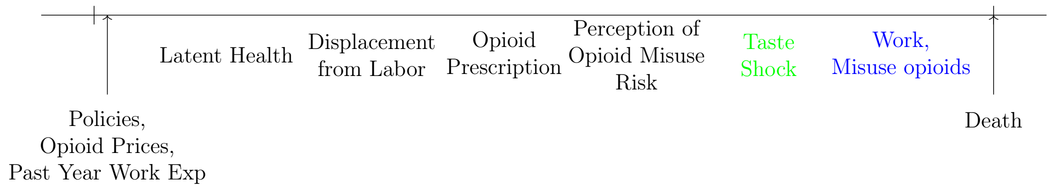

Figure 8: State Realization and Decision in Each Period

individual is displaced from labor, he cannot work during this period. Using illegal opioids is always an option regardless of receiving prescription opioids. However, the individual can misuse his prescribed opioids only if he is prescribed one. Also, if he is prescribed opioids, then he must misuse prescription opioids first before using illegal opioids. Formally, the choice set $\mathcal{J}(\mathbf{1}\{\text{cw} \neq 0\}, rx)$ is defined as:

$$\begin{aligned}
\mathcal{J}(0,0) &= \{1,2,5,6\} \\
\mathcal{J}(1,0) &= \{1,2\} \\
\mathcal{J}(0,1) &= \{1,3,4,5,7,8\} \\
\mathcal{J}(1,1) &= \{1,3,4\}.
\end{aligned}$$

The individual receives a vector of idiosyncratic shocks $(\varepsilon_1, \dots, \varepsilon_{|\mathcal{J}(\mathbf{1}\{cw \neq 0\}, rx)|})$, where each ε_j follows the i.i.d. type 1 extreme value distribution.

Once the individual chooses an action, death is realized. The probability of dying is conditional on the individual's health and decision to misuse opioids. If he dies, the problem ends with receiving a terminal disutility of death, $W = 0$.[5] Figure 8 summarizes each period's state realization and decision process. To simplify notation, I use $\Omega_{s,t} = (s, r_{s,t}, m_{s,t}, p^{il}_{s,t})$ to denote all state-level aggregate variables relevant to opioid prescriptions and opioid prices. $x = (e, \text{xp}, \text{cw}, \text{rx})$ to denote all individual-level state variables except for latent health $h = (h_1, h_2)$, the perception of opioid misuse risk b, and the vector of idiosyncratic shocks $\boldsymbol{\varepsilon}$. The state space is then defined by $\Omega = (\Omega_g, x, h, b, \boldsymbol{\varepsilon})$.

3.2 Per-period Utility

The individual receives per-period utility based on action $j \in \mathcal{J}(\mathbf{1}\{\text{cw} \neq 0\}, \text{rx})$. The utility function consists of four terms: utility from income, utility from working, utility from opioid

[5]While this normalization is common, this imposes a strong restriction on the flow utilities. See appendix for details.

misuse, and idiosyncratic shocks.

$$
\begin{aligned}
u_j(x, h, \Omega_{s,t}, \boldsymbol{\varepsilon}; \boldsymbol{\theta}^y, \boldsymbol{\theta}^u) = \underbrace{\theta_1^u y(x, h, d_w, d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^y)}_{\text{Pecuniary Benefit from Working}} + \underbrace{u_w(x, h, d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^u) d_w}_{\text{Non-pecuniary Utility from Working}} \\
+ \underbrace{u_o(x, h, p_{s,t}^{il}, d_w, d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^u)}_{\text{Utility from opioid misuse}} + \varepsilon_j.
\end{aligned} \tag{4}
$$

The first term captures the income process of individuals conditional on their status and opioid misuse. Non-pecuniary utility from working captures leisure or disutility from working that varies across labor and health status. Utility from opioid misuse captures incentive to misuse opioids due to bad health, bad labor status, and opioid prices. It also captures the complementarity of opioid misuse and not working.

In each period, the wage is a function of latent health, prescription, opioid misuse, education, and past year work experience.

$$
\begin{aligned}
\log y = (1 - d_w)\left(\theta_1^y(1-e) + \theta_2^y e\right) + d_w \Bigg(\theta_3^y + \sum_{m=2}^{4} \theta_{m+2}^y \mathbf{1}\{h = m\} \\
+ \sum_{m=2}^{4} \theta_{m+5}^y \mathbf{1}\{h = m\} rx + \theta_{10} d_o^{rx} + \theta_{11} d_o^{il} + \theta_{13} e + \theta_{13} xp + \theta_{14} e \times xp \Bigg) + \nu
\end{aligned} \tag{5}
$$

where $\nu \sim \mathcal{N}(0, \sigma_y^2)$ is measurement error.

3.3 Transition Probabilities

First, after making an action j, death is realized conditional on health and opioid misuse.

The first term represents the baseline probability of death. Opioid misuse increases the probability of death. Also, the probability of dying from opioid misuse differs by each period.

Prices for illegally traded opioids $p_{g,t}^{il}$, and state-level policies opioid prescribing $r_{g,t}$ and $m_{g,t}$ are announced at the beginning of each period. In each period, individuals expect that opioid prices and restrictions will stay the same in the future forever.

Then, latent health $h = (h_1, h_2)$, displacement from labor cw, prescription rx, and the perception of opioid misuse risk b are realized sequentially. First, latent health is realized whose probability is in a multinomial logit form:

$$\begin{aligned}
&\frac{P(h'=k|e,h,\text{cw},\text{rx},\text{xp},j)}{P(h'=1|e,h,\text{cw},\text{rx},\text{xp},j)} \\
&= \theta^h_{1,k} + \theta^h_{2,k} e + \sum_{m=1}^{3} \theta^h_{m+2} \mathbf{1}\{\text{cw}=m\} + \theta^h_{6,k}\text{xp} + \sum_{m=2}^{4} \theta^h_{m+5} \mathbf{1}\{h=m\} + \theta^h_{10,k}\text{rx} \\
&+ \theta^h_{11,k} d_w + \big(\theta^h_{12,k} + \theta^h_{13}\mathbf{1}\{h_1=B\} + \theta^h_{14}\mathbf{1}\{h_2=B\}\big)\mathbf{1}\{d^{rx}_o=1 \vee d^{il}_o=1\}
\end{aligned} \tag{6}$$

for $k=2,3,4$. Then, the individual may experience displacement from labor conditional on the realized latent health and previous choices. The transition probability of labor market displacement takes the following functional form:

$$\begin{aligned}
&\frac{P(\text{cw}'=k|e,h',\text{cw},\text{rx},\text{xp},j)}{P(\text{cw}'=0|e,h',\text{cw},\text{rx},\text{xp},j)} = \theta^{cw}_{1,k} + \theta^{cw}_{2,k} e + \sum_{m=1}^{3} \theta^{cw}_{m+2,k} \mathbf{1}\{\text{cw}=m\} + \theta^{cw}_{6,k}\text{xp} \\
&+ \sum_{m=2}^{4} \theta^{cw}_{m+8,k} \mathbf{1}\{h'=m\} + \theta^{cw}_{13,k}\text{rx} + \theta^{cw}_{14,k} d_w + \theta_{15,k}\mathbf{1}\{d^{rx}_o=1 \vee d^{il}_o=1\}
\end{aligned} \tag{7}$$

for $k=1,2,3$.

After health and displacement from labor are realized, the individual receives prescription drugs. The doctor prescribes opioids based on the individual's health and labor status and state-level restrictions on prescribing opioids. The probability of receiving prescription opioids in a given state location s is

$$\begin{aligned}
&\frac{P(\text{rx}=1|h,\text{cw},r_{s,t},m_{s,t},s)}{P(\text{rx}=0|h,\text{cw},r_{s,t},m_{s,t},s)} = \theta^{rx}_1 + \sum_{m=2}^{4} \theta^{rx}_m \mathbf{1}\{h=m\} + \sum_{m=1}^{3} \theta^{rx}_{m+4} \mathbf{1}\{\text{cw}=m\} + \\
&+ r_{s,t}(1-m_{s,t})\left(\theta^{rx}_8 + \sum_{m=2}^{4} \theta^{rx}_{m+7}\mathbf{1}\{h=m\}\right) + m_{s,t}(1-r_{s,t})\left(\theta^{rx}_{12} + \sum_{m=2}^{4} \theta^{rx}_{m+11}\mathbf{1}\{h=m\}\right) \\
&+ r_{s,t} m_{s,t}\left(\theta^{rx}_{16} + \sum_{m=2}^{4} \theta^{rx}_{m+15}\mathbf{1}\{h=m\}\right) + \alpha_s.
\end{aligned} \tag{8}$$

The functional form flexibly captures how the probability of receiving prescription opioids would change according to state-level policies. α_g captures the state-level fixed effects on prescribing opioids.

Lastly, the individual forms his perception of the opioid misuse risk. The probability of perceiving that misusing opioids has low risk $b = L$ is

$$\frac{P(b = L|e, h, \text{cw}, \text{rx})}{P(b = H|e, b, \text{cw}, \text{rx})} = \theta^b_1 + \theta^b_2 e + \sum_{m=2}^{4} \theta^b_{m+1} \mathbf{1}\{h = m\} + \sum_{m=1}^{3} \theta^b_{m+5} \mathbf{1}\{\text{cw} = m\} + \theta^b_9 \text{rx}. \quad (9)$$

When the individual perceives that misusing opioids has a low risk, he discounts the probability of dying from opioid misuse by δ. Equation 10 illustrates how the perception of the risk of misusing opioids affects the belief about the probability of dying from opioid misuse.

$$f_d(h, b, j, t; \boldsymbol{\theta}^d, \delta) = \theta_1 + \theta^d_2 h_1 + \theta^d_3 h_2 + (1 - \delta \mathbf{1}\{b = L\}) \left(\theta^d_{4,t} d_{rx} + \theta^d_{5,t} d_{il} + \theta^d_{6,t} d_{rx} d_{il} \right). \quad (10)$$

3.4 Value Function Representation

In each period, the individual chooses her action $j \in \mathcal{J}(\mathbf{1}\{\text{cw} \neq 0\}, rx)$ to maximize her expected discounted sum of utility until death.

$$d^*_j = \underset{j \in \mathcal{J}(\mathbf{1}\{\text{cw} \neq 0\}, \text{rx})}{\arg\max} \; \mathbb{E} \left(\sum_{t=1}^{\infty} \beta^{t-1} \left[u_j(x, h, b; \boldsymbol{\theta}^y, \boldsymbol{\theta}^u) + \varepsilon_j \right] \middle| \Omega_{s,t} \right)$$

where the expectation operator is applied to all perceived possible future realizations of future state variables conditional on the location-level aggregate variables. The Bellman representation of the optimization problem, $V(\Omega_{s,t}, x, h, b, \boldsymbol{\varepsilon})$, is

$$\begin{aligned} V(\Omega_{s,t}, x, h, b, \boldsymbol{\varepsilon}) = & \max_{j \in \mathcal{J}(\mathbf{1}\{\text{cw} \neq 0\}, rx)} u_j(x, h; \boldsymbol{\theta}^y, \boldsymbol{\theta}^u) + \varepsilon_j + \beta f_d(h, b, j, t; \boldsymbol{\theta}^d, \delta) W + \\ & \beta \left(1 - f_d(h, b, j, t; \boldsymbol{\theta}^d, \delta)\right) \sum_{x', h', b'} \mathbb{E}_{\boldsymbol{\varepsilon}'} \left[V(\Omega_{s,t}, x', h', b', \boldsymbol{\varepsilon}') \right] f(x', h', b' | \Omega_{s,t}, x, h, j) \end{aligned} \quad (11)$$

where $f(x', h', b'|\Omega_{s,t}, x, h, j)$ is the perceived transition probability of $(b', \text{rx}', \text{cw}', h')$ conditional on this period's state, choice, and survival:

$$\begin{aligned} f(x', h', b'|\Omega_{s,t}, x, h, j) = & f_b(b'|e, h', \text{cw}', \text{rx}') f_{\text{rx}}(\text{rx}'|h', \text{cw}', r_{s,t}, m_{s,t}, s) \\ & \times f_{\text{cw}}(\text{cw}'|e, h', \text{cw}, \text{rx}, \text{xp}, j) f_h(h'|e, h, \text{cw}, \text{rx}, \text{xp}, j) \end{aligned} \quad (12)$$

$f_h(h'|e, h, \text{cw}, \text{rx}, \text{xp}, j)$ is the transition probability of latent health, $f_{cw'}(\text{cw}'|e, h', \text{cw}, \text{rx}, \text{xp}, j)$ is the transition probability of labor market displacement, $f_{rx'}(\text{rx}'|h', \text{cw}', r_{s,t}, m_{s,t}, s)$ is the transition probability of being prescribed opioids, and $f_b(b'|e, h', \text{cw}', \text{rx}')$ is the transition probability of the perception of opioid misuse risk.

The choice-specific value function $v_j(\Omega_{s,t}, x, h, b)$ is then

$$
\begin{aligned}
v_j(\Omega_{s,t}, x, h, b) &= u_j(x, h; \boldsymbol{\theta}^y, \boldsymbol{\theta}^u) + \beta f_d(h, j, t; \boldsymbol{\theta}^d, \delta)W \\
&+ \beta \left(1 - f_d(h, j, t; \boldsymbol{\theta}^d, \delta)\right) \sum_{x', h', b'} \bar{V}(\Omega_{s,t}, x', h', b') f(x', h', b' | \Omega_{s,t}, x, h, j)
\end{aligned}
\tag{13}
$$

where $\bar{V}(\Omega_{s,t}, x', h', b') = \int V(\Omega_{s,t}, x', h', b', \boldsymbol{\varepsilon}')g(\boldsymbol{\varepsilon}')$ is the ex-ante value function. By the corollary 2 from Arcidiacono and Miller (2011), there exists a one-to-one mapping between the choice probabilities conditional on state $(\Omega_{s,t}, x, h, b)$ and the conditional value function, $\psi(\mathbf{p}(\Omega_{s,t}, x, h, b))$ such that

$$
\psi(\mathbf{p}(\Omega_{s,t}, x, h, b)) = \bar{V}(\Omega_{s,t}, x, h, b) - v_j(\Omega_{s,t}, x, h, b) \tag{14}
$$

where $\mathbf{p}(\Omega_{s,t}, x, h, b) := (p_1(\Omega_{s,t}, x, h, b), \ldots, p_J(\Omega_{s,t}, x, h, b))'$ is the vector of optimal choice probabilities conditional on the state $(\Omega_{s,t}, x, h, b)$,

$$
p_j(\Omega_{s,t}, x, h, b) = \int \mathbf{1}\{v_j(\Omega_{s,t}, x, h, b) - v_k(\Omega_{s,t}, x, h, b) \geq \varepsilon_k - \varepsilon_j,\ \forall j \in \mathcal{J}\} g(\boldsymbol{\varepsilon}). \tag{15}
$$

4 Identification

The model is characterized by the utility parameters $\boldsymbol{\theta}^u$, income process ($\boldsymbol{\theta}^y$,σ_y), transition probability parameters ($\boldsymbol{\theta}^d$, $\boldsymbol{\theta}^h$, $\boldsymbol{\theta}^{cw}$, $\boldsymbol{\theta}^{rx}$, α_s), stochastic process for opioid misuse perception $\boldsymbol{\theta}^b$, terminal value upon death W, and the magnitude of discounting the probability of death, δ. The discount factor is set to $\beta = 0.98$, and the distribution of choice-specific idiosyncratic shocks is assumed to follow i.i.d. type 1 extreme value.

There are two challenges to identifying the model. First, latent health is not directly observed in the data. To address this issue, I use proxy variables to identify and estimate the probability distribution of latent health. Second, the joint transition probabilities are not observed since the NSDUH is a repeated cross-section data. Instead, I have marginal transition probabilities in SIPP and MEPS where opioid misuse is not observed. I overcome this problem by exploiting state-level variation in opioid misuse to recover the effect of opioid misuse on transition probabilities of health, labor, and prescription.

To address the first challenge, I follow a recent work on using proxy variables for unobserved heterogeneity (Hwang (2020)). Almost all surveys collect self-reported health measures and six core disability measures. I use this information in the NSDUH to identify and estimate the probability distribution of latent health conditional on education and health measures. I recode "difficult to dress alone" and "difficult to do errands" to one variable with four values so that the number of values of the proxy variable matches the number of values in latent health. Then, the 4-level self-reported health measure and "difficult to do errands & dress alone" to proxy for the joint distribution of latent health $h = (h_1, h_2)$. I use "difficult to walk," "difficult to see" and "difficult to hear" to proxy for latent physical health h_1. Lastly, I use "difficult to think, concentrate, make decisions" to proxy for latent mental health h_2. Table 10 summarizes how this paper uses the proxy variables to recover the probability distribution of latent health.

Proxy Variables		Latent Health
Health Measure	4 Values (Ordered)	Mental & Physical Health
Difficult to Do Errands & Dress	4 Values (Unordered)	Mental & Physical Health
Difficult to Think	Binary	Mental Health
Difficult to Walk	Binary	Physical Health
Difficult to See	Binary	Physical Health
Difficult to Hear	Binary	Physical Health

Table 10: Proxy Variables for Latent Health

The identification argument follows Hwang (2020). The three conditionally independent proxies, "difficult to walk," "difficult to see," and "difficult to hear," identify the probability distribution of latent physical health. The other three proxies identify the joint probability distribution of latent health. To pin down the ordering of latent health, I assume that people who answered "yes" to "difficult to think, concentrate, and make decisions" have a higher probability of having bad mental health, and people who answered "yes" to "difficult to walk" have a higher probability of having bad physical health.

To address the second challenge, I use a state-level variation on opioid misuse and marginal transition probabilities to recover the joint transition probability function. The identification idea is similar to Hu and Xin (2023) which recovers the transition probability when the choices are completely unobserved. Hu and Xin (2023) shows that one can recover the joint transition probability if a state variable that does not enter the model has information on choices. In my paper, I attribute the state-level variation of opioid misuse rate observed in the NSDUH to the state-level variation in marginal transition probabilities to health, labor, and prescription observed in SIPP. I also use information in MEPS and NSDUH to supplement the marginal transition probability for receiving prescription opioids.

Given the conditional choice probabilities and transition probabilities, the model has two components to identify: utility parameters regarding misusing opioids θ^u and the magnitude of the perception bias δ.

The perception bias δ is identified by the exclusion restriction of the risk perception variable in flow utilities, similar to the identification result for discount factor in the dynamic discrete choice literature. The difference in the choice probabilities given the same state except for risk perception identifies the size of δ.

Lastly, the parameters that govern the utility from misusing opioids $\boldsymbol{\theta}^u$ are identified by differences in choice probabilities across different choices compared to the baseline choice $j = 1$ at a given state variable. As an example, consider the differences in conditional value function between choices j and 1 at $(\Omega_{s,t}, x, h, b)$. The Hotz-Miller inversion theorem implies that (16) holds if the idiosyncratic shocks follow i.i.d. type 1 extreme value.

$$\begin{aligned}
&\log \frac{P(d_1|\Omega_{s,t}, x, h, b)}{P(d_j|\Omega_{s,t}, x, h, b)} = v_j(\Omega_{s,t}, x, h, b) - v_1(\Omega_{s,t}, x, h, b) \\
&= u_j(x, h; \boldsymbol{\theta}^y, \boldsymbol{\theta}^u) - u_1(x, h; \boldsymbol{\theta}^y, \boldsymbol{\theta}^u) + \beta W \left(f_d(h, b, j, t; \boldsymbol{\theta}^d, \delta) - f_d(h, b, 1, t; \boldsymbol{\theta}^d, \delta) \right) \\
&+ \beta \sum_{x', h', b'} \bar{V}(\Omega_{s,t}, x', h', b') \begin{bmatrix} f(x', h', b'|\Omega_{s,t}, x, h, j) \left(1 - f_d(h, b, j, t; \boldsymbol{\theta}^d, \delta)\right) - \\ f(x', h', b'|\Omega_{s,t}, x, h, 1) \left(1 - f_d(h, b, 1, t; \boldsymbol{\theta}^d, \delta)\right) \end{bmatrix}
\end{aligned} \tag{16}$$

By equation (14), equation (17) holds for any vector of decision weights $\boldsymbol{\omega}(x', h', b'|\Omega_{s,t}, x, h, b, j) = (\omega_1(x', h', b'|\Omega_{s,t}, x, h, b, j), \ldots, \omega_{j'}(x', h', b'|\Omega_{s,t}, x, h, b, j))^\top$ such that $|\omega_{j'}(x', h', b'|\Omega_{s,t}, x, h, b, j)| < \infty$ and $\sum_{j' \in \mathcal{J}} \omega_{j'}(x', h', b'|\Omega_{s,t}, x, h, b, j) = 1$.

$$\begin{aligned}
&\bar{V}(\Omega_{s,t}, x', h', b') = \\
&\sum_{j' \in \mathcal{J}} \left(v_{j'}(\Omega_{s,t}, x', h', b') + \gamma - \log P(d_{j'}|\Omega_{s,t}, x', h', b') \right) \omega_{j'}(x', h', b'|\Omega_{s,t}, x, h, b, j).
\end{aligned} \tag{17}$$

Suppose the pair of decision weights $\boldsymbol{\omega}(x', h', b'|\Omega_{s,t}, x, h, b, j)$ and $\boldsymbol{\omega}(x', h', b'|\Omega_{s,t}, x, h, b, 1)$ satisfy a 1-period finite dependence conditional on surviving at least two periods:

$$\begin{aligned}
&\sum_{x', h', b'} \sum_{j' \in \mathcal{J}} \begin{bmatrix} f(x'', h'', b''|\Omega_{s,t}, x', h', b', j') \times \\ (1 - f_d(h', b', j', t; \boldsymbol{\theta}^d, \delta)) \end{bmatrix} \omega_{j'}(x', h', b'|\Omega_{s,t}, x, h, b, j) \begin{bmatrix} f(x', h', b'|\Omega_{s,t}, x, h, b, j) \times \\ (1 - f_d(h, b, j, t; \boldsymbol{\theta}^d, \delta)) \end{bmatrix} \\
&= \sum_{x', h', b'} \sum_{j' \in \mathcal{J}} \begin{bmatrix} f(x'', h'', b''|\Omega_{s,t}, x', h', b', j') \times \\ (1 - f_d(h', b', j', t; \boldsymbol{\theta}^d, \delta)) \end{bmatrix} \omega_{j'}(x', h', b'|\Omega_{s,t}, x, h, b, 1) \begin{bmatrix} f(x', h', b'|\Omega_{s,t}, x, h, b, 1) \times \\ (1 - f_d(h, b, 1, t; \boldsymbol{\theta}^d, \delta)) \end{bmatrix}
\end{aligned} \tag{18}$$

for all $(\Omega_{s,t}, x'', h'', b'') \in \Omega$. Then, (19) holds under the 1-period finite dependence after replacing $v_{j'}(\Omega_{s,t}, x', h', b')$ forward as the sum of flow utility $u_{j'}(x', h')$ and ex-ante value function $\bar{V}(\Omega_{s,t}, x'', h'', b'')$.

$$
\begin{aligned}
&\log \frac{P(d_1|\Omega_{s,t}, x, h, b)}{P(d_j|\Omega_{s,t}, x, h, b)} \\
&= u_j(x,h) - u_1(x,h) + \beta W \left(f_d(h,1,t;\boldsymbol{\theta}^d,\delta) - f_d(h,1,t;\boldsymbol{\theta}^d,\delta) \right) \\
&+ \beta(1 - f_d(h,j,t;\boldsymbol{\theta}^d,\delta)) \sum_{x',h',b'} \sum_{j' \in \mathcal{J}} \begin{bmatrix} u_{j'}(x',h')+ \\ \psi_{j'}(\mathbf{p}(x',h',b')) \end{bmatrix} \begin{bmatrix} \omega_{j'}(x',h',b'|\Omega_{s,t}x,h,b,j) \times \\ f(x',h',b'|\Omega_{s,t},x,h,b,j) \end{bmatrix} \\
&- \beta(1 - f_d(h,1,t;\boldsymbol{\theta}^d,\delta)) \sum_{x',h',b'} \sum_{j' \in \mathcal{J}} \begin{bmatrix} u_{j'}(x',h')+ \\ \psi_{j'}(\mathbf{p}(x',h',b')) \end{bmatrix} \begin{bmatrix} \omega_{j'}(x',h',b'|\Omega_{s,t}x,h,b,1) \times \\ f(x',h',b'|\Omega_{s,t},x,h,b,1) \end{bmatrix} \\
&+ \beta^2(1 - f_d(h,j,t;\boldsymbol{\theta}^d,\delta)) \sum_{x',h',b'} \sum_{j' \in \mathcal{J}} W f_d(h',j',t;\boldsymbol{\theta}^d,\delta) \begin{bmatrix} \omega_{j'}(x',h',b'|\Omega_{s,t}x,h,b,j) \times \\ f(x',h',b'|\Omega_{s,t},x,h,b,j) \end{bmatrix} \\
&- \beta^2(1 - f_d(h,1,t;\boldsymbol{\theta}^d,\delta)) \sum_{x',h',b'} \sum_{j' \in \mathcal{J}} W f_d(h',j',t;\boldsymbol{\theta}^d,\delta) \begin{bmatrix} \omega_{j'}(x',h',b'|\Omega_{s,t}x,h,b,1) \times \\ f(x',h',b'|\Omega_{s,t},x,h,b,1). \end{bmatrix}
\end{aligned} \tag{19}
$$

Stacking (19) for all state space and choices for all (t, s, e), I have $(400 - 128) \times 5 \times 51 \times 2 = 138,720$ equations. The utility parameters are identified as long as the system equations have a full column rank. By the exclusion restriction, δ only appears in the transition probabilities. Thus, the average of difference-in-differences of choice probabilities across b for all (x, h) identifies δ.

Theoretically, W is identified by the choice probability differences in $(x, h, b = L)$ where the choices affect the transition probability of arriving (h_1, h_2) next period. This is because the baseline mortality differs by latent health. Thus, the information about the preference of arriving across latent health status in the choice probabilities identifies W. This paper sets $W = 0$ to focus on identifying the utility parameters and the perception bias. By setting $W = 0$, the last two lines in 19 disappear with the third term in the first line. This also simplifies identification argument as this approach avoids the quadratic structure on δ generated from the last two lines.

5 Estimation

To estimate the model, I modify the two-step conditional choice probabilities estimator augmented with the Expectation-Maximization algorithm (Arcidiacono and Miller (2011)). In the first step, I estimate the distribution of the latent health state h, the probability of opioid misuse perception bias b, and reduced-form conditional choice probabilities.

In the second stage, I estimate per-period income and transition probabilities. The transition probabilities are estimated sequentially for tractability. I first estimate the transition probability for latent health. Then, given the transition parameters for latent health, I estimate the transition probability for labor market displacement. Lastly, I estimate the probability of receiving prescription opioids using the NSDUH.

In the third step, I iterate between finding the finite dependence path and estimating the structural parameters. I first pick a value for $\delta \in (0, 1)$. I then compute the decision weights to achieve one-period finite dependence (Arcidiacono and Miller (2019)) given the guess for δ. Then, the utility parameters $\boldsymbol{\theta}^u$ and perception bias δ are jointly estimated from the system of equations derived from conditional value function differences. I then update δ and decision weights. I iterate until δ converges.

5.1 First Stage: CCP-EM

In the first stage, I estimate the ex-ante distribution of latent health state conditional on education θ_q, the probability of perceiving opioid misuse as not a great risk $\boldsymbol{\theta}^b$, and reduced-form CCP's $P(d_j|\Omega_{s,t}, x, h, b)$. The integrated likelihood of observing $(b_n, \{\text{pxy}_{k,n}\}_{k=1}^6, j_n)$ conditional on $\Omega_{s,t}, x_n$ for an individual n is:

$$\begin{aligned}
&\mathcal{L}(b_n, \{\text{pxy}_{k,n}\}_{k=1}^6, j_n|\Omega_{s,t}, x_n) \\
=&\sum_{h=0}^{3} \bar{q}(h|e; \boldsymbol{\theta}^q) \prod_{\text{pxy},j,b} \left[\textstyle\prod_{k=1}^6 f_{\text{pxy}}(\text{pxy}_{k,n}|h) f_b(b_n|x_n, h; \boldsymbol{\theta}^b) P(j_n|x_n, h, b_n, \Omega_{s,t})\right]^{\mathbf{1}\{b_n, \{\text{pxy}_{k,n}\}_{k=1}^6, j_n\}}.
\end{aligned}$$

I use flexible multinomial logistic functions to estimate the reduced-form conditional choice probabilities. I utilize the EM algorithm to estimate the parameters. Table 11 shows the estimation result for unconditional latent health using public NSDUH. The proxy measurement

	Good Physical, Good Mental	Good Physical, Bad Mental	Bad Physical, Good Mental	Bad Physical, Bad Mental
No College	0.64	0.17	0.09	0.10
College	0.69	0.05	0.11	0.15

Table 11: First Stage Estimates: Unconditional Latent Health Distribution. PUF NSDUH, 2015-2019.

structure matrices show that “difficult to think” is a strong signal for bad mental and “difficult to walk” is a strong signal for bad physical health. The 4-level health measure also shows reasonable probability distribution across mental and physical health. The combined disability measure using “difficult to dress” and “difficult to do errands” only has a strong signal for bad mental and physical health, but not much for other health status. This is because there are only 2% of people who answered they have difficulty dressing alone, so answering "no" to this question does not provide information. See appendix for the results.

Given the latent health distribution, I estimate the log income process for the NSDUH sample. The NSDUH asks the respondents to report their aggregate income in intervals. I divide full-time workers' income by 52×40 and part-time worker's income by 52×20. I assume that the latent log income has the following functional form:

$$\begin{aligned}\log w_{n,t} &= (1-d_w)\left(\theta_1^y(1-e)+\theta_2^y e\right)+d_w\Bigg(\theta_3^y+\sum_{m=1}^{3}\theta_{m+3}^y\mathbf{1}\{h=m\}+\sum_{m=1}^{3}\theta_{m+6}\mathbf{1}\{h=m\}\mathrm{rx}\\ &\quad+\theta_{10}d_o^{rx}+\theta_{11}d_o^{il}+\theta_{12}^y e+\theta_{13}^y\mathrm{xp}+\theta_{14}^y\mathrm{xp}\times e\Bigg)+\nu_n\\ &:= x_y^\top\boldsymbol{\theta}^y\end{aligned}$$

where $\nu_n \sim \mathcal{N}(0,\sigma_y^2)$. The likelihood of observing the log wage bin (w_n^l, w_n^u) is

$$L_n(w_n^l, w_n^u|x_y;\boldsymbol{\theta}^y)=\Phi\left(\frac{w_n^u-x_y^\top\boldsymbol{\theta}^y}{\sigma_y}\right)-\Phi\left(\frac{w_n^l-x_y^\top\boldsymbol{\theta}^y}{\sigma_y}\right).$$

I estimate $\boldsymbol{\theta}^y$ via MLE. Table 12 shows the estimates for log income process. People lose productivity when they are in worse health and also when they misuse opioids. Prescription to opioids when people are in worse health recovers some productivity. Education and past year work experience both have positive effects on productivity and they are complementary.

5.2 Second Stage: Transition Probabilities

Given the first stage estimates, I estimate parameters for transition probability of death $\boldsymbol{\theta}^d$, health $\boldsymbol{\theta}^h$, labor market displacement $\boldsymbol{\theta}^{cw}$, and prescription $\boldsymbol{\theta}^{rx}$ and α_s^{rx} by sequentially applying minimum distance estimators. First, the following equations are used to estimate the probability of dying conditional on latent health and opioid misuse for each state location

	Estimate
Baseline	
No College Degree	1.12
College Degree	2.21
Working	
Constant	1.72
Good Physical, Bad Mental	-0.02
Bad Physical, Good Mental	-0.02
Bad Physical, Bad Mental	-0.03
Prescription Opioid Misuse	-0.06
Illegal Opioid Misuse	-0.20
Good Physical, Bad Mental × Rx	0.04
Bad Physical, Good Mental × Rx	0.03
Bad Physical, Bad Mental × Rx	0.05
College Degree	0.35
Past Year Work Experience	1.05
College Degree × Past Year Work Experience	0.38
SD of Measurement Error σ_y	1.21

Table 12: Estimates for Log Income, PUF NSDUH 2015-2019.

s and year t:

$$\begin{aligned}
P_d^{ocd}(s,t) &= \sum_{h_1=0,1,h_2=0,1} f_d^{ocd}(h_1,h_2;\boldsymbol{\theta}^d)P(h_1,h_2|s,t) \\
P_d^{rx}(s,t) &= \sum_{k=0,1} f_d^{rx}(d_o^{rx}=1,d_o^{il}=k;\boldsymbol{\theta}^d)P(d_o^{rx}=1,d_o^{il}=k|s,t) \\
P_d^{il}(s,t) &= \sum_{k=0,1} f_d^{il}(d_o^{rx}=k,d_o^{il}=1;\boldsymbol{\theta}^d)P(d_o^{rx}=k,d_o^{il}=1|s,t) \\
P_d^{bth}(s,t) &= f_d^{bth}(d_o^{rx}=1,d_o^{il}=1;\boldsymbol{\theta}^d)P(d_o^{rx}=1,d_o^{il}=1|s,t).
\end{aligned}$$

The fractions on the left-hand side come from the restricted NVSS and the state-level population estimates from the Census. The distribution of opioid misuse and the predicted distribution of latent health come from the NSDUH. The identification of the probability of death conditional on health comes from the state-level variation in latent health. Likewise, the identification of the probability of death conditional on opioid misuse comes from the state-level variation in opioid misuse rate and mortality rates. The probability of death from other causes of death besides opioid misuse varies only by latent health status, not by year or state. Table 13 shows that people generally die in about 0.6 percent probability. Having bad physical health increases the probability of dying by 2.35 percent point. Having bad mental health also increases the probability of dying by 1.28 percent point. Opioid misuse also increases the probability of dying from opioid overdose, and this varies by year. In 2015, using illegal opioids increased the probability of death by 0.25 percent point, whereas it increased to 0.64 percent point in 2019. The probability of dying from misusing prescription opioids was stable during this period. Next, I estimate the transition probability of latent

Other Causes of Death		*Opioid Misuse*	2015	2016	2017	2018	2019
Baseline	0.59	Prescription 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 13: Estimates for Probability of Death (Percent), Public NSDUH and Restricted NVSS, 2015-2019.

health. I use SIPP and MEPS to compute the marginal transition probabilities of latent health. I then use state-level variation in opioid misuse and prescription rates from NSDUH to identify the effect of opioid misuse on the transition probability of latent health. The following equations are constructed by combining SIPP, MEPS, and NSDUH:

$$P(h'|h, \mathrm{cw}, \mathrm{xp}, d_w, s, t, e) = \sum_{\mathrm{rx}, d_o^{rx}, d_o^{il}} f_h(h'|e, h, \mathrm{cw}, \mathrm{rx}, \mathrm{xp}, d_w, d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^h) \times (1 - \hat{f}_d(h, b = H, j, t; \boldsymbol{\theta}^d, \delta = 0)) \times \hat{P}(\mathrm{rx}, d_o^{rx}, d_o^{il}|h, \mathrm{cw}, \mathrm{xp}, d_w, s, t, e) \tag{20}$$

$$P(h'|h, \mathrm{cw}, \mathrm{rx}, \mathrm{xp}, d_w, t, e) = \sum_{\mathrm{rx}, d_o^{rx}, d_o^{il}} f_h(h'|e, h, \mathrm{cw}, \mathrm{rx}, \mathrm{xp}, d_w, d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^h) \times (1 - \hat{f}_d(h, b = H, j, t; \boldsymbol{\theta}^d, \delta = 0)) \times \hat{P}(\mathrm{rx}, d_o^{rx}, d_o^{il}|h, \mathrm{cw}, \mathrm{rx}, \mathrm{xp}, d_w, t, e) \tag{21}$$

where $\hat{f}_d$ is the fitted objective probability of death. Equation 20 helps identify the transition probability of the latent health state by opioid misuse by using the state-level variation in opioid misuse and marginal transition probabilities from SIPP. Equations 20 and 21 identify the transition probability of the latent health state conditional on being prescribed with opioids from MEPS.

Similarly, I estimate the transition probability of labor market displacement. I take the transition probability estimates for latent health as given and find the parameters that minimize the distance given by the following equations:

$$\hat{P}(\mathrm{cw}'|h', \mathrm{cw}, \mathrm{xp}, d_w, s, t, e) = \sum_{h, \mathrm{rx}, d_o^{rx}, d_o^{il}} f_{cw}(\mathrm{cw}'|e, h', \mathrm{cw}, \mathrm{rx}, \mathrm{xp}, d_w, d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^{cw}) \hat{f}_h \tilde{f}_d \hat{P}(\mathrm{rx}, d_o^{rx}, d_o^{il}|h, \mathrm{cw}, \mathrm{xp}, d_w, s, t, e) \tag{22}$$

$$\hat{P}(\text{cw}'|e,h',\text{cw},\text{rx},\text{xp},d_w,t,e) = \sum_{h,\text{rx},d_o^{rx},d_o^{il}} f_{cw}(\text{cw}'|e,h',\text{cw},\text{rx},\text{xp},d_w,d_o^{rx},d_o^{il};\boldsymbol{\theta}^{cw}) \hat{f}_h \tilde{f}_d \hat{P}(\text{rx},d_o^{rx},d_o^{il}|h,\text{cw},\text{rx},\text{xp},d_w,t,e) \tag{23}$$

Lastly, I estimate the probability of receiving prescription opioids via MLE. I use the state-level variation in policies and opioid prescription rates in the NSDUH to identify the effect of policies on prescription on the extensive margin. I suspect the transition parameters show negative signs for the unemployed as found in the regressions using public NSDUH. People who cannot work due to health problems are expected to receive prescription opioids at a much higher rate, and similar argument holds for those with worse latent health status. From the regression results in the data pattern section, I expect that the probability of receiving prescription opioids decreases as state-level restrictions and must-access PDMP's are introduced. Its effect across latent health should be different by which policies are implemented.

5.3 Third Stage: Iterated Minimum Distance Estimator

In the final stage, I use the system of equations constructed by stacking (19) for all states and choices to estimate the structural parameters. I start with $\delta = 0.25$ and iterate until convergence. I suspect the utility parameters align with data patterns observed in the public NSDUH.

First, as per parameter estimates for labor participation in Hwang (2020), I suspect that the utility parameter for working is positive. Worse health, low education, and no past year experience increase the disutility of working. It is unclear whether the prescription of opioids increases the preference to work or not.

Since the overall opioid misuse rate is low, I expect the constant term to be negative. I suspect that people with lower education show a higher preference for opioid misuse, and people with no past year of work experience have a larger preference for opioid misuse. From the data patterns in the NSDUH, I expect that opioid misuse and not working are complementary, which is consistent with Greenwood et al. (2022). Unemployed people have a strong preference for opioid misuse, which indicates that when opioid prescription rates are lowered, they are most likely to substitute for illegal opioids. I expect that those in worse mental health would have a stronger preference to misuse opioids than those who are in worse physical health. It is unclear whether those who have both bad mental and physical health have a strong preference for opioid misuse compared to those with only bad physical or mental health. While I expect that the coefficient for prices are negative, if the endogeneity issue on prices is not well-addressed, it could have a positive sign.

Given the estimates on the primitives, I solve the model via contraction mapping. The model fits the data well. I compute the predicted choice probabilities to the NDSUH sample in 2015-2019 across labor status and 4-level health measures. I also compare the observed choice probabilities with those predicted by the model by “difficult to think” and “difficult to walk.” The model is consistent with the data patterns.

	Estimate		*Opioid Misuse*		
			Rx Only	*Both*	*Illegal Only*
Income from Work	(+)	Constant	(-)	(-)	(-)
Utility from Working		No College Degree	(+)	(+)	(+)
Constant	(+)	No Past Year Work Exp	(+)	(+)	(+)
No College Degree	(-)	Not Working	(+)	(+)	(+)
No Past Year Work Exp	(-)	Laid off	(+)	(+)	(+)
Bad Physical Health Only	(-)	Unable to Work	(+)	(+)	(+)
Bad Mental Health Only	(-)	Retired	(-)	(-)	(-)
Both Bad Physical and Mental Health	(-)	Bad Physical Health Only	(+)	(+)	(+)
Rx $\times$ Bad Physical Health Only	(+)	Bad Mental Health Only	(+)	(+)	(+)
Rx $\times$ Bad Mental Health Only	(+)	Both Bad Physical & Mental	(+)	(+)	(+)
Rx $\times$ Both Bad Physical & Mental	(+)				
Perception Bias δ	(+)	Illegal Opioid Price	$\times$	(-)	(-)

Table 14: Utility Parameter and Perception Bias Estimates

6 Counterfactuals

I use the 2015 population as the benchmark and apply aggregate changes observed in 2018. I consider three counterfactual scenarios to decompose the effect of aggregate changes.

First, I impose the probability of death by applying the probability of death from opioid misuse in 2018 on the 2015 population. I expect that opioid misuse will decrease, especially in illegal opioid use, as people internalize the increased risk of opioid misuse.

Second, I changed the state-level restrictions on opioid prescribing with those in 2018. The effect is ambiguous because this only changes the expectation of receiving prescription opioids, not the prescription status itself.

Third, I change the state-level prices to the 2018 level. From the reduced form patterns, I expect that opioid misuse has little effect.

To summarize, I expect to conclude that people have been decreasing opioid misuse by internalizing the risk of opioid misuse, not by policies on opioid prescribing or changes in opioid prices. Policies on opioid prescribing have generally had a shuffling effect on who substitutes illegal opioids.

I also examine the role of perception bias in the model by setting $\delta = 0$. This shuts down the role of perception bias of opioid misuse risk, showing the theoretical upper bound of the policy intervention on correcting perception bias. I compute the decrease in opioid misuse across labor and health status to see which group will decrease opioid misuse the most. I expect to find that the unemployed and those with bad mental health have the largest decrease in opioid misuse, largely because they have a higher probability of perceiving opioid misuse as not a great risk. However, as the probability of the perception bias itself is rare, I find that correcting the perception bias decreases opioid misuse by a small amount in the population.

7 Conclusion

This paper studies how people misuse opioids by considering policies, prices, and mortality risks as aggregate changes. Modeling opioid misuse as a choice between today's pain relief or euphoria and tomorrow's negative outcomes, this paper quantifies the behavior of opioid misuse along with labor. I find that people experiencing unemployment or bad health are more likely to misuse opioids. People with bad physical health is estimated to be unlikely to misuse opioids as their baseline probability of death is already higher.

I decompose the effect of aggregate changes between 2015 and 2018 and see what affected the observed decrease in opioid misuse and increased opioid mortality rate. It turns out that the increase in the probability of death has the strongest effect on decreasing opioid misuse, as people internalize the increased risk when deciding to misuse opioids or not. State-level policies seem to reshuffle who will misuse opioids or not, and its effect on decreasing opioids seems to be marginal. I find that illegal opioid prices seem to have no effect.

The perception bias to opioid misuse risk turns out to be significant for increasing the probability of opioid misuse, as it almost completely discounts the increased risk of death from opioid misuse. As the probability of experiencing the perception bias is higher among the unemployed and those with bad mental health, correcting the perception bias is predicted to decrease opioid misuse in those groups. However, since perception bias is relatively rare shock, the overall effect is estimated to be small.

8 Appendix

8.1 Identification

In this section, I discuss identifying a dynamic discrete choice model with perception bias on the terminal state with a simpler setting. I first describe how the terminal state's payoff adds to nonparametric underidentification in dynamic discrete choice models. Then, I illustrate what perception bias in this paper represents.

Consider an observable state space relevant to the flow utility $\mathcal{X} = \{1, 2, \ldots, X\}$. The choice set is denoted by $\mathcal{J} = \{1, 2, \ldots, J\}$. Denote the vector of idiosyncratic shocks per period as $\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_J)$. A state is then defined by a tuple $(x, \boldsymbol{\varepsilon})$. Denote W as the terminal state, and with abuse of notation, W represents a value that the individual receives upon arriving at the terminal state. (x', ε') is realized only after it is determined that the individual does not arrive at W this period. Denote the transition probability of arriving at W given (x, j) as $f_W(x, j)$. The transition probability of arriving at x' given (x, j) is $(1 - f_W(x, j))f(x'|x, j)$.

Arcidiacono and Miller (2020) shows the observational equivalence theorem that a researcher must know the true payoff for a normalizing action in every state and time in a classic dynamic discrete choice model to identify the payoff function. Adding a terminal state adds an additional primitive in the model as the terminal state itself is a state. I show the observational equivalence result in this setting by directly applying Theorem 1 in Arcidiacono and Miller (2020).

Define the transition probability at $\tau + 1$ upon survival by $\kappa^*_\tau(x|x_t, j)$ and the transition probability of dying at $\tau+1$ by $\kappa_\tau^W(x|x_t,j)$.

$$\kappa_\tau^*(x_{\tau+1}|x_t,j) = \begin{cases}(1-f_W(x_t,j))f_\tau(x_{\tau+1}|x_t,j) & \text{if } \tau=t \\ \sum_{x=1}^X \kappa_{\tau-1}^*(x|x_t,j)(1-f_W(x_\tau,l(x,\tau)))f_\tau(x_{\tau+1}|x,l(x,\tau)) & \text{if } \tau>t\end{cases} \tag{24}$$

$$\kappa_\tau^W(x_t,j) = \begin{cases} f_W(x_t,j) & \text{if } \tau=t \\ \kappa_{\tau-1}^*(x|x_t,j)f_W(x,l(x,\tau)) & \text{if } \tau>t\end{cases} \tag{25}$$

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

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

Denote the payoff of the normalizing action at a state x at time t by $u^*_{l(x,t)}(x_t)$. Then, the following holds:

Corollary 1 *For each $R=1,2,\ldots,$ define an alternative payoff function for all $x\in\mathcal{X}$, $j\in\mathcal{J}$ and $t=1,2,\ldots,R$:*

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

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).

The corollary above shows that setting the terminal value W to zero is not an innocuous assumption if a true payoff exists. By setting W to zero, we are parametrizing the flow payoff function to reflect the terminal value the individual collects when she arrives at the terminal state from each (x,j,t).

As this corollary is a direct application of Arcidiacono and Miller (2020), it inherits the identification result as well—We must know the true payoff for the normalizing action for each state and time, and we must also know the true payoff at the terminal state.

In practice, we impose a much stronger parametric assumption than imposing a known payoff for a normalizing action at each state and time. In this case, one can even identify and estimate the value of W. Identification and estimation of the terminal value W may be considered if the econometrician wants to find a scrap value in bus engine replacement, entry/exit game, etc. However, assuming a zero value at the terminal state is common in labor economics.

In this paper, I add perception bias to the transition probability to the terminal state. Essentially, perception bias in this framework is a stochastic state-dependent discount factor on transition probabilities. Abbring and Daljord (2020) proposes an identification strategy to identify the discount factor in a classic dynamic discrete choice model. They propose a restriction in the utility function where a pair of states and choices has the same utility value, but the choice probabilities differ. Then, we can attribute the difference in the conditional choice probabilities to the effect of the discount factor. This restriction can be achieved if there is an excluded variable in the utility function in the state space. Then, the difference in choice probabilities across the excluded variable identifies the varying belief in the transition probabilities.

Let's consider another observable variable $s \in \{0, 1\}$, which does not enter the flow utility and only affects the belief on the transition probability of arriving at the terminal state W. The perception bias s discounts the subjective belief about the transition probability of arriving at W given (x, s) by (1-δ). Denote the transition probability of arriving at (x', s') conditional on not arriving at the terminal state W by $f(x', s'|x, s, j) = (1 - (1 - \delta s) f_W(x, j))\, f(x', s'|x, j)$.

The value function $V(x, s, \boldsymbol{\varepsilon})$ is then

$$
\begin{aligned}
V(x, s, \boldsymbol{\varepsilon}) = \max_{j \in \mathcal{J}} \, & u_j(x) + \varepsilon_j + \beta(1 - \delta s) f_W(x, j) W + \\
& \beta \left(1 - (1 - \delta s) f_W(x, j)\right) \sum_{x', s'} \bar{V}(x', s') f(x', s'|x, j)
\end{aligned}
$$

where $\bar{V}(x, s) = \int V(x, s, \boldsymbol{\varepsilon}) G(\boldsymbol{\varepsilon})$ is the ex-ante value function. By Lemma 1 in Arcidiacono and Miller (2011), I represent the ex-ante value function as the sum of the choice-specific conditional value function and its counterpart to the unique mapping from the vector of conditional choice probabilities to the conditional value function $\psi(\mathbf{p}(x,s))$:

$$
\begin{aligned}
\bar{V}(x,s) &= \psi_j(\mathbf{p}(x,s)) + v_j(x,s) \\
&= \psi_j(\mathbf{p}(x,s)) + u_j(x) + \beta(1-\delta s) f_W(x,j) W \\
&+ \beta\left(1-(1-\delta s) f_W(x,j)\right) \sum_{x',s'} \bar{V}(x',s') f(x',s'|x,j) \\
&= \psi_j(\mathbf{p}(x,s)) + u_j(x) + \beta f_W(x,j) W - \beta\delta s f_W(x,j) W \\
&+ \beta\left(1-(1-\delta s) f_W(x,j)\right) \sum_{x',s'} \bar{V}(x',s') f(x',s'|x,j) \\
&= \psi_j(\mathbf{p}(x,s)) + u_j(x) + \beta \sum_{x',s'} \bar{V}(x',s') f(x',s'|x,j)(1-f^W(x,j)) \\
&+ \beta\delta s f^W(x,j) \sum_{x',s'} \bar{V}(x',s') f(x',s'|x,j) \\
&+ \beta f^W(x,j)(1-\delta s) W
\end{aligned}
$$

The first line in the last equation represents the conditional value function of an individual when $s = 0$. The effect of s on the conditional choice probabilities given the same state and choice (x, j) has two channels. The second line in the last equation shows the change in choice probabilities by discounting the continuation value when $s = 1$. The third line represents the change in choice probabilities by discounting the terminal state's value. This shows another reason why one must be careful when treating $W = 0$. If the data generating process is $W \neq 0$, then parameterizing W to zero will load the effect of s on the choice probabilities solely to discounting the continuation ex-ante value function. As a result, the flow utility function will reflect the lost information by parameterizing W to zero.

8.2 Data

The main data set in this paper is the restricted-access National Survey of Drug Use and Health (NSDUH) during 2015-2019. It surveys about 65,000 individuals annually each year collecting information about substance use in the last 12 months, such as substance use in any way not as directed by a doctor, substance use disorder, perceived risk of using substances, etc. The survey also collects socioeconomic variables like employment, education, age, income, perceived health, etc. Although NSDUH is a unique data set on substance use, it is repeated cross-sections. This hinders inference on the dynamic decision process of individuals without merging it with auxiliary panel data. For details of how each variable in this paper's model is measured, see section 8.2.1.

I supplement the restricted-access NSDUH with the public-access Medical Expenditure

Panel Survey (MEPS) 2015-2019. The survey samples around 12,000 individuals and collects information for two years over five rounds. The survey collects information on medicine prescriptions and other socioeconomic variables such as employment, education, age, income, perceived health, etc. I use this panel data to form transition probabilities of individuals I observe in the NSUDH.

Additionally, I use the Survey of Income and Program Participation (SIPP) 2015-2019. The SIPP captures the state-level variation in socioeconomic status. The MEPS and the SIPP jointly provide the marginal transition probabilities for the dynamic model discussed in this paper.

I collect information on mortality from the restricted-access Multiple Causes of Death files from the National Vital Statistics System (NVSS) 2000-2019. The data set contains everyone deceased during this period, about 2.5 million each year. The file contains the Underlying Cause of Death (UCD), Multiple Causes of Death (MCD), education, and age.

I collect the history of state-level restrictions on opioid prescription from the Prescription Drug Abuse Policy System (PDAPS) from 2014 to 2019 maintained by the Center for Public Health Law Research at Temple University. I also used Westlaw to track the data for state-level restrictions already in place in 2014. The data set covers characteristics of laws implemented in each state in terms of the effective date, coverage (e.g., all opioids prescription or initial prescription), duration, quantity, total dosage (in terms of MME), exceptions, and penalties.

The aggregate data on opioid prescription rates come from the Centers for Disease Control and Prevention (CDC) and the Automation of Reports and Consolidated Orders System (ARCOS) by the Drug Enforcement Agency (DEA). CDC provides the number of opioid prescriptions per 100 population at the county and state levels each year[6]. ARCOS posts opioids dispensed by pharmacies in each county and state in terms of Milligrams of Morphine Equivalent (MME)[7]. These data together provide a big picture of the prevalence of prescription opioids through the primary market. While the ARCOS data shows how much opioids are dispensed through prescription, it is difficult to see the amount of opioids distributed to each person given a prescription for opioids. Likewise, while the CDC data shows how many people received prescriptions for opioids, it is difficult to see whether the amount of opioids per capita given prescription has changed over time. Balestra et al. (2023) argues that PDMP affected the extensive margin on the number of prescriptions but not on the intensive margin, the amount of opioids dispensed given prescription.

[6] https://www.cdc.gov/drugoverdose/rxrate-maps/

[7] I thank David Beheshti for sharing the digitized data for 2000-2017. I extended the data set up to 2018-2019 for this paper.

Transactions in the secondary market are difficult to observe because they are illegal. The best available data, to my knowledge, is the crowd-sourced StreetRx program 2013-2021 collected by Rocky Mountain Poison & Drug Safety under Denver Health. The data contains information on the location, time, drug classification, product name, active ingredient, total cost, dosage form (e.g., capsule, patch, spray), price per milligram, dose per unit, and whether the recorded transaction is a bulk purchase or not. The data set is used to see how prices change to state-level restrictions. Given that these are illicit transactions of drugs, the reported products may be counterfeit; thus, the record reflects what the buyers think they bought. Thus, the quality of those drugs varies. As the data set relies on people's voluntary reporting, the frequency of records does not necessarily represent the prevalence of each type of illicit opioid. I collect price per milligram morphine equivalents (MME) from this data set by merging MME conversion charts from the CDC, Medicare, and UK National Health Services.

8.2.1 National Survey of Drug Use and Health

People are categorized into three types based on their opioid use: nonuser, prescription user, and misuser. Misusers are further determined whether they experience Opioid Use Disorder. Also, the misusers report whether this year is the first year they misused opioids. The variable, "ever misused opioids," is derived from this question. In the NSDUH, reported personal/family income consists of a lot of sources: i) Income earned at a job or business, ii) Social Security/Railroad Retirement/Social Security Income/Food Stamps/Cash Assistance/Other non-monetary welfare, iii) Retirement, disability, or survivor pension, iv) Unemployment or worker's compensation, v) Veteran's Administration payments, vi) Child support, vii) Alimony, viii) Interest income, ix) Dividends from stocks or mutual funds, x) Income from rental properties, royalties, estates or trusts.

The NSDUH collects when the respondent last misused a substance. The respondent answers in one of four options: within 30 days, more than 30 days ago but within the past 12 months, more than 12 months ago, or never used/misused.

8.3 Mortality Data for Opioid Overdose

The Centers for Disease Control and Prevention (CDC) defines the deaths by opioid overuse with the following Underlying Cause of Death - International Classification of Diseases (UCD-ICD-10) codes: X40-X44: accidental poisoning by and exposure to drug, X60-X64: intentional self-poisoning by and exposure to drug, X85: assault by drugs, medicaments and biological substances "homicide," and Y10-Y14: poisoning by and exposure to drugs

	2015	2016	2017	2018	2019
Opioid Use					
Did Not Use Opioids	0.615	0.637	0.645	0.662	0.682
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
Used Prescribed Opioids	0.363	0.343	0.336	0.321	0.301
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
Misused Opioids	0.046	0.044	0.040	0.038	0.038
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
-Prescribed Opioids Only	0.017	0.017	0.015	0.015	0.015
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
-Illegally Purchased Opioids Only	0.021	0.020	0.018	0.017	0.017
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
-Both	0.007	0.007	0.007	0.005	0.005
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Opioid Use Disorder from Opioid Misuse	0.009	0.008	0.008	0.008	0.007
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ever Misused Opioids	0.109	0.108	0.109	0.104	0.106
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Perceives Low Risk of Using Heroin	0.144	0.139	0.132	0.131	0.142
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Employment					
Past Year Work Experience	0.666	0.666	0.674	0.664	0.666
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Working	0.623	0.623	0.630	0.627	0.628
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Not Working	0.377	0.377	0.370	0.373	0.372
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Displacement from Labor					
No Displacement	0.753	0.749	0.757	0.756	0.754
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)
No Job Available/Laid Off	0.049	0.048	0.045	0.042	0.042
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Unable to Work due to Health Conditions	0.055	0.055	0.050	0.050	0.050
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Retired	0.143	0.148	0.149	0.152	0.155
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
Education					
College Degree	0.322	0.332	0.346	0.341	0.354
	(0.005)	(0.004)	(0.006)	(0.006)	(0.004)
Health					
Excellent	0.211	0.204	0.204	0.204	0.199
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Very Good	0.348	0.354	0.362	0.352	0.354
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Good	0.296	0.296	0.289	0.301	0.302
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Fair/Poor	0.145	0.145	0.144	0.143	0.146
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Disabiility Measures					
Difficult to Do Errands Alone	0.053	0.053	0.052	0.052	0.054
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Difficult to Dress or Take Bath Alone	0.029	0.027	0.026	0.029	0.026
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Difficult to Concentrate, Remember, Make Decisions	0.068	0.069	0.073	0.070	0.076
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Difficult to Walk	0.098	0.098	0.094	0.095	0.091
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
Difficult to See	0.045	0.044	0.044	0.045	0.044
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Difficult to Hear	0.055	0.055	0.058	0.059	0.058
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Serious Psychological Disorder	0.096	0.099	0.101	0.103	0.113
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Income					
Less than $10,000	0.192	0.189	0.179	0.174	0.165
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$10,000-$19,999	0.190	0.182	0.178	0.177	0.167
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
$20,000-$29,999	0.138	0.139	0.137	0.138	0.136
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
$30,000-$39,999	0.111	0.111	0.116	0.112	0.119
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
$40,000-$49,999	0.098	0.097	0.092	0.096	0.099
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$50,000-$74,999	0.128	0.130	0.135	0.140	0.142
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
$75,000 or more	0.143	0.152	0.163	0.165	0.172
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Age Category					
22-25	0.079	0.077	0.075	0.073	0.071
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
26-34	0.170	0.171	0.172	0.173	0.173
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
35-49	0.268	0.267	0.265	0.264	0.261
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
50-64	0.277	0.274	0.271	0.268	0.269
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
65 or more	0.207	0.211	0.217	0.222	0.226
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Male	0.480	0.479	0.480	0.480	0.481
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
Weighted N	225589179	227503829	230096972	231663237	233060904

Table 15: Summary Statistics of the NSDUH Samples 22 or older. NSDUH Public Use Files, 2015-2019

with undetermined intent. I count those with the following Multiple Cause of Death codes: T40.0: Opium, T40.1: Heroin, T40.2: Other opioids, T40.3: Methadone, T40.4: Other synthetic narcotics, T40.6: Other and unspecified narcotics. Prescription opioids: T40.2, T40.3. Synthetic opioids other than Methadone (mostly fentanyl): T40.4.

8.4 StreetRx

Each opioid has a different strength, so Morphine Milligram Equivalents (MME) are used for comparison. I convert MME for each opioid using three references: CDC's guidance in prescribing opioids[8], a conversion chart from Utah Department of Health and Human Services[9], Washington Health Care Authority's conversion table[10]. One milligram of Diamorphine, or heroin, is converted to 3 MME according to the UK National Health Services[11].

In StreetRx, 63.96% of fentanyl transaction records do not have a milligram dosage for each unit even though the records have a dosage for microgram (mcg) per hour. This is because fentanyl patches differ by effective duration. According to the latest available version of the MME conversion chart from the Utah Department of Health and Human Services, one patch typically lasts for three days. I impute the milligram dosage data for fentanyl patches by `dosage/mcg` $\times$ 0.001 $\times$ 24 $\times$ 3 $\times$ `MME`. I also impute the milligram dosage for lozenge/troche, powder, and sprays according to the other comparable records in the data set. The imputation recovers 1,329 price data, leaving 82 missing records out of 2,206 for fentanyl transactions.

The formula for computing the amount of opioids is

$$\text{Strength per Unit} \times \text{Number of Units} \times \text{MME Conversion Factor.}$$

8.5 Estimates

All results come from public NSDUH and restricted NVSS. The results from the restricted NSDUH and restricted NVSS are pending disclosure approval. In particular, transition probability estimates are omitted.

[8] `https://www.cdc.gov/opioids/providers/prescribing/guideline.html`, retrieved October 5, 2022

[9] `https://medicaid.utah.gov/Documents/files/Opioid-Morphine-EQ-Conversion-Factors.pdf`, retrieved October 5, 2022

[10] `https://www.hca.wa.gov/assets/billers-and-providers/HCA-MME-conversion.xlsx`, retrieved October 5, 2022

[11] `https://www.gloshospitals.nhs.uk/gps/treatment-guidelines/opioid-equivalence-chart/`, retrieved October 5, 2022

	Responses			
Health Score	Excellent	Very Good	Good	Fair/Poor
Good Physical, Good Mental	0.28	0.44	0.24	0.04
Good Physical, Bad Mental	0.02	0.12	0.55	0.31
Bad Physical, Good Mental	0.01	0.10	0.44	0.43
Bad Physical, Bad Mental	0.03	0.08	0.24	0.63
Difficult to Do Errands and Dress	(N,N)	(Y,N)	(N,Y)	(Y,Y)
Good Physical, Good Mental	0.99	0.00	0.01	0.00
Good Physical, Bad Mental	0.95	0.05	0.00	0.00
Bad Physical, Good Mental	1.00	0.00	0.00	0.00
Bad Physical, Bad Mental	0.23	0.22	0.10	0.45

Table 16: Proxy Measurement Structure Matrix: 4-level Health Measure, Difficult to do Errands & Dressing, PUF NSDUH, 2015-2019.

Difficult to Think	No	Yes
Good Mental Health	0.98	0.02
Bad Mental Health	0.76	0.24

Table 17: Proxy Measurement Structure Matrix: Difficult to Think, PUF NSDUH, 2015-2019.

	No	Yes
Difficult to Walk		
Good Physical Health	0.99	0.01
Bad Physical Health	0.29	0.71
Difficult to See		
Good Physical Health	0.98	0.02
Bad Physical Health	0.79	0.21
Difficult to Hear		
Good Physical Health	0.96	0.04
Bad Physical Health	0.78	0.22

Table 18: Proxy Measurement Structure Matrix: Difficult to Walk, Difficult to See and Difficult to Hear, PUF NSDUH, 2015-2019.

				Opioid Misuse		
Labor Status		Nonuser	Rx User	Rx Only	Illegal Only	Both
Not Displaced	Not Working					
	Working					
Unemployed						
Unable to Work						
Retired						

Table 19: Model Fit: NSDUH 2015-2019 across Labor Status

Health Measure	Nonuser	Prescription User	Opioid Misuse Rx Only	Illegal Only	Both
Excellent					
Very Good					
Good					
Fair/Poor					

Table 20: Model Fit: NSDUH 2015-2019 across Health Measure (4-levels)

Difficult to Do Errands & Dress	Nonuser	Rx User	Opioid Misuse Rx Only	Illegal Only	Both
(N,N)					
(Y,N)					
(N,Y)					
(Y,Y)					

Table 21: Model Fit: NSDUH 2015-2019 across Health Measure (4-levels)

Disability Measure		Nonuser	Rx User	Opioid Misuse Rx Only	Illegal Only	Both
Difficult to Think	No					
	Yes					
Difficult to Walk	No					
	Yes					

Table 22: Model Fit: NSDUH 2015-2019 across Disability Measures

Latent Health	Nonuser	Rx User	Opioid Misuse Rx Only	Illegal Only	Both
Good Physical, Good Mental					
Good Physical, Bad Mental					
Bad Physical, Good Mental					
Bad Physical, Bad Mental					

Table 23: Model Fit: NSDUH 2015-2019 across Latent Health

8.6 Counterfactuals

Latent Health	Nonuser	Rx User	Opioid Misuse Rx Only	Illegal Only	Both
Good Physical, Good Mental					
Good Physical, Bad Mental					
Bad Physical, Good Mental					
Bad Physical, Bad Mental					

Table 24: Counterfactual 1: Choice Probabilities on Work and Opioid Misuse Given 2018's Probability of Death across Latent Health Status

Labor Status		Nonuser	Rx User	Opioid Misuse Rx Only	Illegal Only	Both
Not Displaced	Not Working					
	Working					
Unemployed						
Unable to Work						
Retired						

Table 25: Counterfactual 1: Choice Probabilities on Work and Opioid Misuse Given 2018's Probability of Death across Labor Status

Latent Health	Nonuser	Rx User	Opioid Misuse Rx Only	Illegal Only	Both
Good Physical, Good Mental					
Good Physical, Bad Mental					
Bad Physical, Good Mental					
Bad Physical, Bad Mental					

Table 26: Counterfactual 2: Choice Probabilities on Work and Opioid Misuse Given 2018's State-level Policies on Opioid Prescribing across Latent Health Status

Labor Status		Nonuser	Rx User	Opioid Misuse Rx Only	Illegal Only	Both
Not Displaced	Not Working					
	Working					
Unemployed						
Unable to Work						
Retired						

Table 27: Counterfactual 2: Choice Probabilities on Work and Opioid Misuse Given 2018's State-level Policies on Opioid Prescribing across Labor Status

Latent Health	Nonuser	Rx User	Opioid Misuse Rx Only	Illegal Only	Both
Good Physical, Good Mental					
Good Physical, Bad Mental					
Bad Physical, Good Mental					
Bad Physical, Bad Mental					

Table 28: Counterfactual 3: Choice Probabilities on Work and Opioid Misuse Given 2018's Opioid Prices across Latent Health Status

Labor Status		Nonuser	Rx User	Opioid Misuse Rx Only	Illegal Only	Both
Not Displaced	Not Working					
	Working					
Unemployed						
Unable to Work						
Retired						

Table 29: Counterfactual 3: Choice Probabilities on Work and Opioid Misuse Given 2018's Opioid Prices across Labor Status

Latent Health	Nonuser	Rx User	Opioid Misuse Rx Only	Illegal Only	Both
Good Physical, Good Mental					
Good Physical, Bad Mental					
Bad Physical, Good Mental					
Bad Physical, Bad Mental					

Table 30: Counterfactual 4: Choice Probabilities on Opioid Misuse by setting the Perception Bias $\delta = 0$ across Latent Health Status

Labor Status		Nonuser	Rx User	Opioid Misuse Rx Only	Illegal Only	Both
Not Displaced	Not Working					
	Working					
Unemployed						
Unable to Work						
Retired						

Table 31: Counterfactual 4: Choice Probabilities on Opioid Misuse by setting the Perception Bias $\delta = 0$ across Labor Status

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