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

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Abstract

I study how health, labor status, and perception of the risk of opioid misuse jointly shape opioid misuse behavior and how policy can respond. I develop and estimate a dynamic model of opioid misuse and labor supply with endogenous mortality risk and misperception of the risk of opioid misuse by combining multiple restricted data sets. I decompose the effects of three aggregate changes between 2015–2019: rising opioid mortality risk, expanded state prescribing restrictions, and cross-state variation in illegal opioid prices. I find that the decline in opioid misuse rates is almost entirely explained by higher mortality risk. State restrictions on opioid prescribing reduce opioid misuse among the healthy group but push the unemployed and unhealthy toward illegal opioids, resulting in a negligible effect. The illegal opioid price plays no role. Eliminating the misperception would reduce opioid misuse by 20 percent, suggesting a new policy channel in combating the opioid epidemic.

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

JEL: C35, C53, C61

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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?

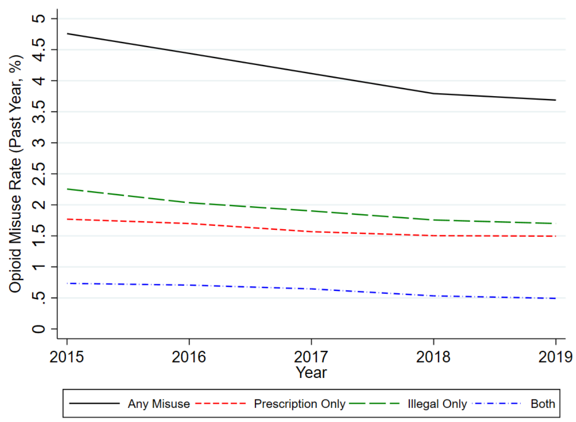

Figure 1: Opioid Misuse Rate 2015-2019, Public National Survey of Drug Use and Health

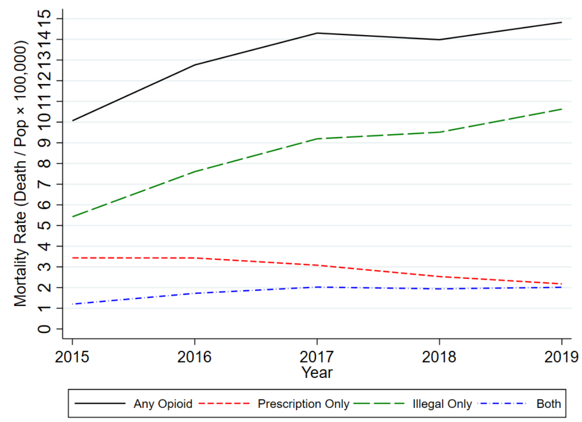

Figure 2: Mortality Rate by Opioid Overdose 2015-2019, Restricted National Vital Statistics System

In 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. Death by opioid overdose, an event that may occur when people misuse opioids, is more likely to occur if one uses illegally traded opioids due to their unregulated quality or potency compared to misusing one's own prescribed opioids. Although it simplifies opioid misuse on the intensive margin, this classification captures the substitutability between misusing prescription opioids and illegally traded opioids, which is of interest when designing policies to decrease opioid misuse and, consequently, deaths.

[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.

During 2015-2019, there were three aggregate changes that may have affected opioid misuse. 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 dangerous. 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. Moreover, these aggregate changes might have affected differently across health and labor status.

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, primarily 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 they are not displaced from their job. 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 the 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 2019 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 turn to illegally traded 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%. This illustrates that policy interventions that target the demand side can be effective in decreasing opioid misuse among those who are more susceptible to opioid misuse, rather than conventional supply-side interventions on opioid prescribing.

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. (2025)), 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. (2023a). 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. (2023a) 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 state-dependent, stochastically realized perception bias in each period, which affects how people discount future adverse effects.

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 finite dependence 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 present descriptive evidence on the relationship between opioid misuse and individual and macroeconomic factors. For individual factors, I consider labor, health, and the misperception of the risk of opioid misuse. For macroeconomic factors, I consider the probability of dying from misusing opioids, prices for illegally traded opioids, and state-level policies on opioid prescribing.

Throughout this paper, a person is classified into three groups in terms of exposure to opioids in the past 12 months. The first group is nonusers, who did not use opioids at all, neither with prescription opioids nor by misusing opioids. The second group is prescription opioid users. People in this group have received prescription opioids from their doctor, have used them as directed by the doctor, and have not misused opioids. The last group is denoted as misusers. People in this group have misused opioids in the past 12 months, and depending on where they sourced opioids, they are further classified as prescribed opioids only, illegal opioids only, or both.

2.1 Individual Factors: Health, Labor, and Misperception on the Risk of Harm from Opioid Misuse

Resonating with the "death of despair" hypothesis (Case and Deaton (2017)), I argue that individual factors such as health and labor status are associated with opioid misuse. This paper also focuses on how unfavorable health and labor status are associated with misperception of the risk of harm from misusing opioids, and how the misperception is associated with opioid misuse. In this sense, the effect of unfavorable health and labor status on opioid misuse is amplified by the misperception.

2.1.1 Health and Opioid Misuse

The primary motivation for restricting opioid prescription is that excessive opioid prescription facilitates the spread of opioid misuse. Prima facie, that seems to be true with the finding in Table 1 that the groups with higher opioid prescription rates are associated with higher opioid misuse. The table shows that people in worse health tend to be positively associated with higher opioid prescription rates and opioid misuse. Among the respondents who answered that they were in excellent health, 20% of them were prescription opioid users and about 2.5% were misusers. In contrast, about 48% of people with fair or poor health were prescription opioid users, and 5.8% were misusers.

However, it is clear that health is confounded with prescription rates, so it is unclear whether restricting the dispensing of prescription opioids will solve the opioid crisis. Reducing prescription opioids may induce the population to substitute with illegally traded opioids, which are more harmful due to their variability in quality and potency. 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 prescription opioids, but it could also be that there are other factors aside from health.

Table 1: Row Percentages of Opioid Use by Health: Nonuser, Prescription User, and Misuser

			Opioid Misuse			
			Prescribed		Not Prescribed	
	Nonuser	Rx User	Rx Only	Both	Illegal Only	Total
Excellent	76.37	21.17	0.95	0.31	1.20	100
Very Good	68.31	28.00	1.35	0.50	1.84	100
Good	60.82	34.51	1.71	0.75	2.22	100
Fair/Poor	48.08	46.08	2.79	1.00	2.05	100
All	64.78	31.18	1.58	0.61	1.85	100

Source: Restricted NSDUH, 2015-2019.

2.1.2 Labor and Opioid Misuse

In fact, labor status is just as strongly associated with opioid misuse as health, if not more. Table 2 shows the row percentages of opioid use across labor statuses. Comparing those who are "out of labor," "employed," and "unemployed," opioid prescription rates seem to be similar, ranging from 32% to 34%. However, the opioid misuse rate among the unemployed stands out, as 8.5% of the unemployed are misusers. Considering that the prescription rate and misuse rate for those who "cannot work due to health conditions" are about 50% and 5.8%, respectively, it seems clear that unfavorable labor conditions like unemployment are playing a role in opioid misuse.

Table 2: Row Percentages of Opioid Use by Labor Status: Nonuser, Prescription User, and Misuser

			Opioid Misuse			
			Prescribed		Not Prescribed	
	Nonuser	Rx User	Rx Only	Both	Illegal Only	Total
Out of labor	66.60	28.97	1.84	1.88	0.72	100
Employed	67.31	28.48	1.57	2.02	0.61	100
Unemployed	63.65	27.83	2.64	4.08	1.80	100
Unable to Work	35.61	57.88	3.42	2.06	1.03	100
Retired	63.79	34.71	0.71	0.67	0.12	100
Total	66.88	28.96	1.61	1.93	0.62	100

Source: Restricted NSDUH, 2015-2019.

Figures 3 and 4 also provide descriptive evidence that extensive opioid prescription itself may not be the only cause for opioid misuse, and labor status can be an additional candidate for the cause. The figures show opioid prescription rates and opioid misuse rates by age groups during 2015-2019. If opioid prescription is the cause of opioid misuse, then the opioid misuse rate should be increasing as people age due to higher prescription rates. However, Figure 4 shows that the majority of opioid misusers are concentrated in the prime working age. This suggests that socioeconomic factors during the prime working age, like labor status, could be driving opioid misuse rather than opioid prescription itself.

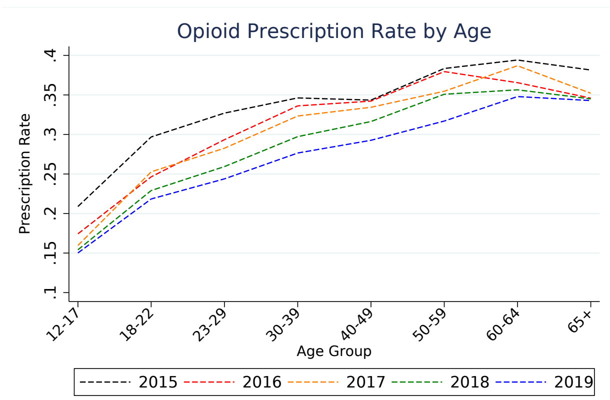

Figure 3: Opioid Prescription Rates by Age, Restricted NSDUH, 2015-2019

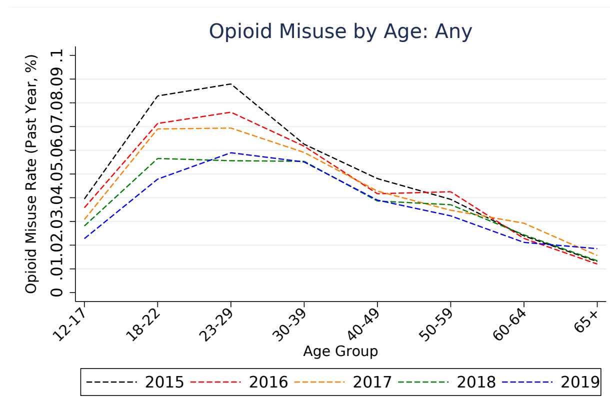

Figure 4: Opioid Misuse Rates by Age, Restricted NSDUH, 2011-2019

2.1.3 Misperception of the Risk of Harm from Misusing Opioids

The rationale for state-level policies on prescribing opioids is that people are overconfident about the risk of harm from misusing opioids. If such misperception induces opioid misuse, it might be justifiable to design a policy to correct the public's perception of opioid misuse risk. Given that, 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. In this section, I explain how I derive the misperception of the risk of harm from misusing opioids from the data and how the misperception is associated with health, labor, and ultimately, opioid misuse.

The NSDUH has two variables that measure the perception of the level of risk of harm that *other people* are taking when using illegal opioids, which is misuse by default[2]. Based on how the questions are asked, these questions do not elicit the preference to risk; instead, they ask about the perception of the amount of risk of misusing opioids. I recode the two variables into a binary variable, "a great risk" and "not a great risk." By setting "a great risk" as a benchmark, I define those who answered "not a great risk" as people with a misperception of the risk of harm when misusing opioids. Tables 3 and 4 show that the misperception of the

[2]The exact questions are, "how much do people risk harming themselves physically and in other ways when they try heroin once or twice?" and "how much do people risk harming themselves physically and in other ways when they use heroin once or twice a week?" See the appendix for more details on how I derived the binary variable I use for analysis in this paper.

Table 3: Perception of the Amount of the Risk Other People Take when Misusing Opioids

	2015	2016	2017	2018	2019	All
Great Risk	85.71	86.28	86.98	87.03	86.06	86.41
Not a Great Risk	14.29	13.72	13.02	12.97	13.94	13.59
Total	100	100	100	100	100	100

Source: Restricted NSDUH, 2015-2019.

risk of opioid misuse is an individual factor correlated to health and labor. Table 3 shows that about 13% to 14% of the population thinks that other people are not taking a great risk when using heroin, a well-known illegal opioid. The fraction of the population with misperception on the risk of opioid misuse is relatively stable in contrast to other macro trends that spiked in 2015-2019, such as mortality rates from opioid overdose with illegal opioids and the spread of state-level policies on opioid prescribing. Table 4 shows the average marginal effects of the logistic regression of the misperception on other individual socioeconomic factors. The table shows that worsened health status, as measured by lower health score and disability measures, is positively associated with misperception of the risk of opioid misuse. Also, unemployment is positively correlated with forming the misperception of the risk of opioid misuse[3].

In addition, the misperception of the risk of harm from opioid misuse is positively correlated with opioid misuse even after controlling for labor and health conditions. Table 5 shows the average marginal effects of the misperception of the risk of harm from opioid misuse on decisions on working and misusing opioids across labor separation and prescription statuses after controlling for various socioeconomic variables, including labor and health conditions. The choice set is determined by labor separation and prescription status, resulting in each row having different columns for available choices. The misperception has statistically significant positive correlations with opioid misuse across all labor and prescription statuses. As such, the misperception amplifies the effect of labor and health conditions on opioid misuse.

Combining these patterns for misperception of the risk of harm from opioid misuse, I allow the misperception to be a stochastic process where the probability of having misperception depends on other individual socioeconomic factors. The misperception captured by the variable in the NSDUH shifts the belief about the harm of opioid misuse, not the preference. In the counterfactual analysis, I shut down the misperception in the model and predict how

[3]It is noteworthy that some other factors show negative associations. For example, people who received prescription opioids tend to be less likely to form the misperception of the risk of opioid misuse. Also, other labor statuses, such as "being unable to work due to health conditions" and "retired," are negatively associated with forming the misperception. I do not take a stance on how being in those statuses can be beneficial for reducing misperception. This paper takes the variation as-is, leaving alternative explanations like hearing more about the danger of misusing opioids, conditional on these health and labor statuses aside.

Table 4: Average Marginal Effects from Logistic Regression of Misperception of the Risk from Misusing Opioids on Health, Labor, and Prescription Status

	Misperception of the Risk of Opioid Misuse			
Health				
Very Good	0.0130	0.0130	0.0135	0.0135
	(0.0028)	(0.0028)	(0.0028)	(0.0028)
Good	0.0208	0.0209	0.0215	0.0216
	(0.0030)	(0.0030)	(0.0029)	(0.0029)
Fair/Poor	0.0232	0.0234	0.0239	0.0241
	(0.0045)	(0.0045)	(0.0045)	(0.0045)
Disability Measures				
Doing Errands	0.0128	0.0128	0.0126	0.0126
	(0.0067)	(0.0067)	(0.0066)	(0.0066)
Dressing	0.0170	0.0171	0.0173	0.0174
	(0.0090)	(0.0091)	(0.0091)	(0.0091)
Walking	-0.0138	-0.0138	-0.0131	-0.0132
	(0.0048)	(0.0048)	(0.0048)	(0.0048)
Seeing	0.0143	0.0142	0.0155	0.0155
	(0.0060)	(0.0060)	(0.0060)	(0.0060)
Hearing	0.0187	0.0189	0.0184	0.0185
	(0.0061)	(0.0061)	(0.0060)	(0.0060)
Thinking	0.0195	0.0196	0.0184	0.0185
	(0.0047)	(0.0047)	(0.0047)	(0.0047)
Labor				
Unemployed	0.0312	0.0309	0.0311	0.0307
	(0.0059)	(0.0059)	(0.0059)	(0.0059)
Unable to Work	-0.0299	-0.0301	-0.0266	-0.0268
	(0.0055)	(0.0055)	(0.0057)	(0.0057)
Retired	-0.0405	-0.0404	-0.0392	-0.0392
	(0.0036)	(0.0036)	(0.0036)	(0.0036)
Work Exp	-0.0360	-0.0360	-0.0355	-0.0355
	(0.0033)	(0.0032)	(0.0032)	(0.0032)
Opioids				
Received Rx Opioids	-0.0154	-0.0156	-0.0147	-0.0149
	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Other				
College Education	0.0351	0.0352	0.0321	0.0322
	(0.0026)	(0.0026)	(0.0026)	(0.0026)
State FE	No	No	Yes	Yes
Year FE	No	Yes	No	Yes
Weighted N	1127053929			

Source: Restricted NSDUH, 2015-2019. Notes: Standard errors are in parentheses.

much opioid misuse would decrease [4].

Table 5: Average Marginal Effects of Misperception of the Risk of Harm from Opioid Misuse on the Joint Choice of Work and Opioid Misuse

Separation from labor	Prescription Status	Joint Choice for Work and Opioid Misuse: No Work & Illegal Only	No Work & Rx Only	No Work & Both	Work & No Misuse	Work & Illegal Only	Work & Rx Only	Work & Both	
Not Separated	Not Prescribed	0.0007	-	-	-0.0120	0.0116	-	-	
		(0.0006)			(0.0034)	(0.0018)			
	Prescribed	-	0.0034	0.0030	-0.0420	-	0.0170	0.0212	
			(0.0018)	(0.0010)	(0.0062)		(0.0038)	(0.0028)	
Separated: Unemployed, Unable to Work, Retired	Not Prescribed	0.0183	-	-	-	-	-	-	-
		(0.0043)							
	Prescribed	-	0.0209	0.0178	-	-	-	-	-
			(0.0066)	(0.0035)					

Notes: Standard errors are in parentheses. Cells marked '–' denote choices that are not part of the feasible choice set. Controls include health score (4 levels), disability measure, labor status (if separated from labor), work experience, illegal opioid price, state-level policies in opioid prescribing, year fixed effects, state fixed effects, and dummy variables for age categories. See the appendix for the full result.

2.2 Macro Factors: Mortality Risk, Prices, and Policies

While there was a surge in opioid overdose deaths during 2015-2019, it is unclear how much state-level policies that reduced opioid prescribing played a role. In a counterfactual world where there were no such policies, would there have been fewer or more deaths? How much have people reduced or increased illegal opioid use due to the policies?

In this section, I show that policies have reduced opioid prescribing on the extensive margin, consistent with the literature. Also, I show that mortality rates from opioid overdose with illegal opioids are positively associated with state-level policies. While such a positive association had been stigmatized as "unintended consequences" in the literature that studies the effects of supply-side interventions from 2010 to 2013 (see Alpert et al. (2018) and Kim (2021)), I further show how the unintended consequences have been disproportionately distributed across the population in different health and labor separation statuses.

2.2.1 Mortality Risk from Opioid Misuse

In this paper, I treat opioid overdose as a random event that occurs if people misuse opioids. Accordingly, I compute the probability of dying from opioid misuse by matching the fractions of people who died from opioid overdose to the fraction of people who misused opioids, under

[4]The assumption that the misperception can be mediated by policy is consistent with the existing literature in medical science. For example, Adams et al. (2022) evaluates the efficacy of "Know the Truth," an anti-opioid campaign to middle-school students, by measuring the changed perceived risk of opioid addiction.

a few more assumptions. I first compute the share of the population that died from different causes: other causes of death, opioid overdose involving prescription opioids only, opioid overdose involving illegal opioids only, and opioid overdose involving both prescription and illegal opioids[5].

I assume that people who have misused only prescription opioids may appear in opioid overdose deaths involving prescription opioids, but not in those involving illegal opioids. Likewise, I assume that people who used only illegal opioids may appear in opioid overdose deaths involving illegal opioids, but not with prescription opioids. Those who have misused both prescription and illegal opioids may appear in any category of opioid overdose death. I also assume that everyone faces a positive probability of dying from other causes of death. Lastly, I assume that the probabilities of deaths are additive. For example, suppose the person has misused prescription opioids only. Then, his probability of death in that period is the sum of the probability of dying from other causes of death and that of dying from opioid overdose involving prescription opioids.

The following system of equations maps the fractions of the population across opioid misuse and deaths categories to the probabilities of death from opioid misuse in year t:

$$\begin{aligned}
p_{\text{OD:rx},t} &= \frac{F_{\text{OD:rx},t}}{F_{\text{drx},t} + F_{\text{bth},t}} \\
p_{\text{OD:il},t} &= \frac{F_{\text{OD:il},t}}{F_{\text{dil},t} + F_{\text{bth},t}} \\
p_{\text{OD:bth},t} &= \frac{F_{\text{OD:bth},t}}{F_{\text{bth},t}} + p_{\text{OD:rx},t} + p_{\text{OD:il},t} \\
p_{\text{OCD},t} &= F_{\text{OCD},t}.
\end{aligned}$$

Here, $F_{\text{COD},t}$ denotes the fraction of the population that died from a given cause of death in year t, and $p_{\text{COD},t}$ denotes the probability of dying from that cause. OCD refers to other causes of death; OD:rx, OD:il, and OD:bth denote opioid overdose death involving prescription opioids only, illegal opioids only, and both prescription and illegal opioids, respectively. Likewise, $F_{\text{drx},t}$, $F_{\text{dil},t}$, and $F_{\text{bth},t}$ refer to the fractions of the population who misused prescription opioids only, illegal opioids only, and both prescription and illegal opioids, respectively.

The third equation adjusts for double-counting among individuals who misuse both prescription and illegal opioids. Since such individuals may also appear in overdose deaths

[5] The National Vital Statistics System records both the cause of death and the substance detected in the body. An opioid overdose death where only prescription opioids were found indicates that the person at least misused prescription opioids, but it does not rule out that illegal opioids were also used. The categories for opioid overdose death are consistent with those commonly used in the literature on the opioid crisis.

involving only prescription opioids or only illegal opioids, the probabilities $p_{\text{OD:rx},t}$ and $p_{\text{OD:il},t}$ are subtracted so that $p_{\text{OD:bth},t}$ captures the additional probability of death uniquely attributable to misusing both prescription and illegal opioids. In that sense, the *gross* probability of death for those who misuse both prescription and illegal opioids in year t, denoted $f^d_{\text{bth},t}$, is given by:

$$f^d_{\text{bth},t} = p_{\text{OD:rx},t} + p_{\text{OD:il},t} + p_{\text{OD:bth},t}.$$

Table 6 shows the gross probability of dying from opioid misuse as a result of the mapping. The probability of dying from causes other than opioid overdose has stayed constant during this period. However, the probability of dying from an opioid overdose has been increasing, mainly due to illegal opioids becoming more dangerous.

Table 6: Probability of Dying from Other Causes of Death and from Opioid Overdose

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

Source: Public NSDUH and NVSS, 2015-2019

2.2.2 Prices for Illegal Opioids

In this paper, I treat the price of illegally traded opioids as a macroeconomic factor that shapes an individual's opioid misuse behavior. I use data from StreetRx, a project that gathers voluntary reports of illegal transactions of opioids. For each transaction, I convert the price into dollars per milligram morphine equivalent (MME) and compute the averages for each year and state. See the appendix for more details on the data cleaning procedure. Figures 5 and 6 show variation in illegal opioid prices across states between 2015 and 2019. Figure 5 shows that while the median price across states was \$0.80 per MME, prices for illegal opioids in some states, like Wyoming and Washington D.C., were consistently higher than in other states. Figure 6 shows the trajectories of illegal opioid prices for some major states in the U.S., which indicates some aggregate fluctuations over time. I use this variation to identify the price elasticity of misusing illegal opioids on the extensive margin. In the model, I assume that prices are taken as given and the individual is agnostic about the next period's illegal price, i.e., in each period, he expects that the price is held constant. Then,

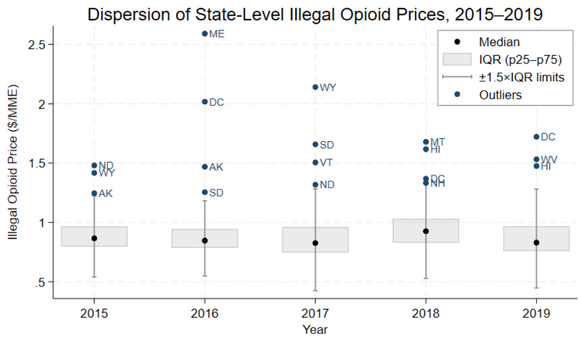

Figure 5: Dispersion of State-Level Illegal Opioid Prices, StreetRx, 2015-2019

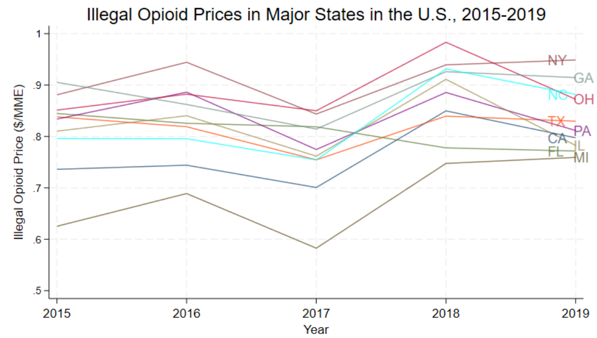

Figure 6: Illegal Opioid Prices in Major States in the U.S., StreetRx, 2015-2019

the variation between illegal opioid misuse rates and prices across years and states identifies the price elasticity of opioid misuse.

I attribute the change in prices to supply-related factors only and assume that the demand-related factors are negligible. To justify omitting the effect of demand on the illegal opioid price in this paper, I rely on the consensus on the context of the opioid crisis after 2013, when fentanyl spread in the United States. In this period, it has become extremely cheap to produce illegal opioids, as fentanyl is 99 percent cheaper compared to other illegally traded opioids (Pardo et al., 2019). People also found it easy to obtain illegal opioids; one survey by the American Psychiatric Association in 2018 reveals that "(…) nearly half feel it is extremely or somewhat easy to access opioids for illegal use."[6] Given this context, I assume that the supply curve is flat and there is no search friction to find and purchase illegal opioids.

2.2.3 State-Level Policies on Opioid Prescribing

To combat the opioid crisis during this period, many states have imposed restrictions on opioid prescribing. In this paper, I consider the two policies that were imposed during this period: state laws and the Prescription Drug Monitoring Program (PDMP). I document that both policies have decreased opioid prescribing on the extensive margin, consistent with the literature (Sacks et al. (2021), Balestra et al. (2023a)). I also show that the policies had no effect on the illegal opioid prices, which is another feature I leverage in the model.

During this period, many states began imposing state laws or requiring doctors to check the PDMP to reduce opioid misuse. The details of state laws vary; some states set the

[6] `https://www.psychiatry.org/newsroom/news-releases/nearly-one-in-three-people-know-someone-addicted-to-opioids-more-than-half-of-millennials-believe-it-is-easy-to-get-illegal-opioids`, retrieved on November 22, 2023. The site is no longer available as of October 2025. Still, the existence of the survey can be found here: `https://www.psychiatry.org/news-room/apa-public-opinion-polls/past-annual-and-monthly-polls`

Table 7: Number of States with Restrictions on Opioid Prescribing

	2015	2016	2017	2018	2019
State Law Only	5	8	11	16	18
Must-Access PDMP Only	8	8	7	5	4
Both	0	1	11	17	18
Total	13	17	29	38	40

Source: Prescription Drug Abuse Policy System (PDAPS)

maximum number of days allowed to fill per prescription, or the maximum amount of dose per prescription, etc. State laws may vary in terms of the scope of the population; the state limit may apply only to initial prescriptions or only to minors, etc. I recorded the state laws into a binary variable that takes a value of one if there is a clause that restricts the number of days per prescription to adults or everyone. PDMPs are databases that collect a patient's prescription history for doctors to decide whether the patient is suspected of abusing controlled substances or exhibiting substance use disorder. To be consistent with the literature, I consider the "must-access" PDMPs, which legally require the doctors to access the PDMP to check a patient's prescription history before prescribing controlled substances (see Kim (2021) and Sacks et al. (2021) for details). As shown in Table 7, these two policies have spread out during this period, and by 2019, 40 states had imposed at least one of the policies.

Table 8 shows the average marginal effects of state-level policies on the opioid prescription status. The logistic regressions show that both must-access PDMP and state laws are negatively associated with the probability of an individual receiving prescription opioids, although the significance and the magnitude differ slightly across different specifications in fixed effects. This finding is also consistent with the literature in health economics, where state-level policies are found to have decreased opioid prescribing on the extensive margin (Sacks et al. (2021), Balestra et al. (2023b)). Considering this pattern, the model takes into account the influence of the policies on the probability of receiving prescription opioids conditional on labor and health status.

The state-level policies are shown to be uncorrelated with illegal opioid prices in the two-way fixed effects regression. For a state s and year t, the specification of the regression is:

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

where $\bar{p}_{s,t}$ denotes the illegal opioid prices derived from StreetRx, $r_{s,t}$ denotes the state-law, $m_{s,t}$ denotes the must-access PDMPs, α_s is state-level fixed effect, and δ_t is year-level fixed effect. β_1, β_2, and β_3 capture the association between the state-level restrictions and illegal

Table 8: Average Marginal Effects of State-Level Policies and Socioeconomic Factors on Opioid Prescription Status

	Received Prescription Opioids			
Policies				
Must-Access PDMP	0.0059	0.0083	-0.0200	-0.0080
	(0.0036)	(0.0036)	(0.0075)	(0.0080)
State Law	-0.0318	-0.0164	-0.0355	-0.0061
	(0.0032)	(0.0037)	(0.0044)	(0.0059)
Labor				
Unemployed	-0.0090	-0.0098	-0.0073	-0.0082
	(0.0065)	(0.0065)	(0.0064)	(0.0065)
Unable to Work	0.1389	0.1377	0.1346	0.1342
	(0.0086)	(0.0086)	(0.0087)	(0.0086)
Retired	-0.0007	-0.0008	-0.0015	-0.0014
	(0.0046)	(0.0046)	(0.0046)	(0.0046)
Health				
Very Good	0.0720	0.0721	0.0711	0.0713
	(0.0039)	(0.0039)	(0.0039)	(0.0039)
Good	0.1250	0.1255	0.1234	0.1236
	(0.0041)	(0.0041)	(0.0041)	(0.0041)
Fair/Poor	0.1740	0.1748	0.1724	0.1728
	(0.0055)	(0.0055)	(0.0055)	(0.0055)
Disability Measures				
Doing Errands	0.0123	0.0124	0.0129	0.0129
	(0.0079)	(0.0079)	(0.0079)	(0.0079)
Dressing	0.0521	0.0521	0.0516	0.0516
	(0.0121)	(0.0122)	(0.0121)	(0.0121)
Walking	0.1334	0.1324	0.1330	0.1323
	(0.0075)	(0.0075)	(0.0074)	(0.0075)
Seeing	0.0004	0.0004	-0.0004	-0.0004
	(0.0077)	(0.0077)	(0.0077)	(0.0077)
Hearing	0.0145	0.0144	0.0124	0.0124
	(0.0077)	(0.0077)	(0.0077)	(0.0077)
Thinking	0.0655	0.0661	0.0644	0.0652
	(0.0064)	(0.0064)	(0.0063)	(0.0063)
State FE	No	No	Yes	Yes
Year FE	No	Yes	No	Yes
Weighted N	1127053929			

Restricted NSDUH, PDAPS, 2015-2019. Standard errors in parentheses.

opioid prices. Table 9 shows that the policies have statistically insignificant associations with the logs of illegally traded prices. Based on this pattern, the model in the next section treats policy and illegal opioid price as independent macroeconomic factors; that is, this paper does not extend the model to take price as an endogenous object as a function of state-level policies.

Table 9: The Result of the Two-way Fixed Effect Regression of Log of Illegally Traded Opioid Prices on State-level Policies

	log Price			
State Law Only	-0.006	-0.012	0.027	0.023
	(0.040)	(0.045)	(0.046)	(0.053)
Must-Access PDMP Only	-0.048	-0.045	-0.072	-0.065
	(0.046)	(0.046)	(0.051)	(0.053)
Both	0.002	0.001	-0.014	-0.008
	(0.040)	(0.049)	(0.045)	(0.056)
State FE	No	No	Yes	Yes
Year FE	No	Yes	No	Yes
N	250	250	250	250

StreetRx and PDAPS, 2015-2019. Standard errors in parentheses.

2.3 Summary

The data patterns show that the opioid crisis is not just a supply-side problem—it is a demand problem, too. Individual characteristics such as health, labor, and misperception of the risk of opioid misuse are shown to be associated with opioid misuse. At the same time, macroeconomic trends such as the mortality risk of opioid misuse, prices for illegal opioids, and state policies limiting opioid prescribing are also playing a role in the individual's environment, which then affects opioid misuse behavior. To understand how each macroeconomic factor, in particular state-level policies, has contributed to the observed changes during 2015-2019, it is therefore crucial to build and estimate a model of an individual's opioid misuse behavior that interacts with their individual and macroeconomic states. Moreover, the model would help us to predict the effect of a counterfactual policy where we intervene on the misperception process. To this end, I develop a dynamic discrete choice model with stochastic perception bias in the next section.

3 Model

I consider an infinite-horizon individual optimization problem with endogenous death probability. The individual is endowed with an education level and a location. In each period, the individual is informed about the probability of dying from opioid misuse. At the same time, state-level restrictions on opioid prescribing and illegal opioid prices are announced. The individual expects that the policies and prices will remain unchanged forever. He knows whether he has worked in the previous year.

In each period, the individual factors—health, labor, opioid prescription, and misperception—are revealed sequentially, with their transition probabilities based on the previous year's individual state and this year's macroeconomic factors. The model features a two-dimensional latent health state and various reasons for being separated from the labor market. Opioid prescription process approximates the physician's prescribing practice at the state-year level. Finally, the misperception of the risk of harm from opioid misuse is realized based on education, labor, health, and opioid prescription.

Then, the individual makes decisions on working and opioid misuse. The person is forward-looking and knows the future transition probabilities on health, labor, prescription, and the misperception process in the next period, conditional on this period's macroeconomic factors. The misperception of the risk of harm from opioid misuse, however, discounts the belief about the probability of death from opioid misuse. If the person survives, they continue the optimization problem and repeat it 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 to live in that state and for the policies and prices in this period to stay the same forever.

Denote the previous year's working decision as $\text{xp}_t = \mathbf{1}\{\text{Worked in } t-1\}$[7]. The work experience affects income from working and transition probabilities for health, labor, and the misperception process for this period.

The individual's health condition has two dimensions, (h_{1t}, h_{2t}). Each dimension has two values, good and bad: $h_{1t} \in \{G, B\}$ and $h_{2t} \in \{G, B\}$. Health is indexed by $h_t = \mathbf{1}\{h_{2t} = B\} + 2 \times \mathbf{1}\{h_{1t} = B\}$ where $\mathbf{1}\{x\}$ is the indicator function that equals one if the statement x is true and zero otherwise.

[7] While working experience and tenure is of great importance in labor economics, I work with a binary variable due to data restrictions.

The structure of the health condition captures opioid addiction by loading information on addiction to h_{2t}. The individual's health condition is observed by the econometrician only through proxy variables—self-reported health score and disability measures. I allow the self-reported health score and the disability measures "difficulty in doing errands alone" and "difficulty in dressing" to contain information about both health dimensions, (h_{1t}, h_{2t}). I assume that the disability measures "difficulty in seeing," "difficulty in hearing," and "difficulty in walking" to contain information about h_{1t} only, while "difficulty in thinking, concentrating, and making decisions" contains information about h_{2t} only.

Given the correlation across the proxy variables[8], I interpret h_{1t} as physical health and h_{2t} as mental health. Because "difficulty in thinking, concentrating, and making decisions" is correlated with opioid use disorder in the NSDUH, the model captures opioid addiction through h_{2t}. The estimation result also shows that opioid misuse increases the probability of transitioning to poor mental health ($h_{2t} = B$), which confirms that the addiction channel is captured in the model with the proxy variable structure.[9]

The individual may experience separation from labor, cw_t. There are three kinds of separation from labor: unemployment, being unable to work due to health conditions, and retirement.

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

If the person is separated from the labor market, they cannot work during this period. If the person is not separated from the labor market ($\mathrm{cw}_t = 0$), the person can choose to work or not during this period. Retirement is not an explicitly endogenous choice in this model, but the transition probability of retirement depends on working experience, decision to work, and labor status. People can return to the labor force after retirement, that is, no longer

[8]See Table 23 for the correlation table across health measure, disability measures, opioid use disorder, and serious psychological disorder.

[9]There are several reasons why I do not directly model Opioid Use Disorder (OUD), even though the variable the NSDUH includes the variable for it. First, the OUD variable contains incomplete information about the person's opioid addiction: the questions for determining OUD in the NSDUH are asked only if the person reported that he misused opioids in the past 12 months. Thus, the NSDUH has no information about people who had not misused opioids even though they were experiencing opioid addiction. The second reason comes from identification for transition probabilities. I identify the transition probabilities by attributing the state-level variation in marginal transition probabilities in other panel data from SIPP and MEPS to state-level variation in opioid misuse. Since I am using multiple data sources, I am restricted to use only common proxy variables for health.

separated from the labor market, and that transition is captured through the transition probability.

The individual receives prescription opioids each period, conditional on his labor, health, and state-level policies. Denote the prescription status by $\mathrm{rx}_t = \mathbf{1}\{\text{Received Rx Opioids}\}$. [10]

Lastly, the individual forms a perception of the risk of misusing opioids, $b_t \in \{L, H\}$. If $b = H$, the individual expects the actual probability of dying from opioid misuse known at t. If $b_t = L$, 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 makes the joint choice of work and opioid misuse 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 $j = 1 + d_o^{il} + 2d_o^{rx} + 4d_w$. The choice set is affected by i) being separated from labor ($\mathrm{cw}_t \neq 0$) and ii) received prescription opioids ($\mathrm{rx}_t = 1$). If the individual is separated 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 them. Also, if he is prescribed opioids, then he must misuse prescription opioids first before using illegal opioids. Formally, the choice set $\mathcal{J}(\mathbf{1}\{\mathrm{cw}_t \neq 0\}, \mathrm{rx}_t)$ 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 $\boldsymbol{\varepsilon}_t := (\varepsilon_{jt})_{j \in \mathcal{J}_t}$ where $\mathcal{J}_t = \mathcal{J}(\mathbf{1}\{\mathrm{cw}_t \neq 0\}, \mathrm{rx}_t)$ and each ε_{jt} follows the i.i.d. type 1 extreme value distribution.

[10] In this paper, receiving prescription opioids is exogenous to individuals conditional on state variables. This simplifying assumption is based on the finding in the literature that "doctor shopping" behavior 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, state-level policies, and state-level fixed effects. Thus, this model can address a counterfactual analysis of changing opioid prescribing practices by changing the probability of receiving prescription opioids. See Schnell (2022) for a structural economic study on physicians' behavior in prescribing opioids.

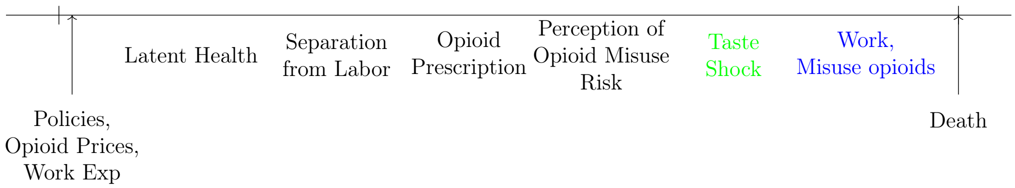

Figure 7: State Realization and Decision in Each Period

Once the individual chooses an action, death is realized based on the probability of death. The probability of dying is based on the individual's health and decision to misuse opioids. If he dies, the problem ends with receiving a terminal disutility of death, $W = 0$.[11] Figure 7 summarizes each period's state realization and decision process.

To simplify notation, let $z_{s,t} = (s, r_{s,t}, m_{s,t}, p^{il}_{s,t})$ denote all state-level macroeconomic variables relevant to opioid prescriptions and opioid prices. Let $x_t = (e, \mathrm{xp}_t, h_t, \mathrm{cw}_t, \mathrm{rx}_t, b_t)$ denote all individual-level state variables, and the vector of idiosyncratic shocks $\boldsymbol{\varepsilon}_t$. For notational simplicity, I denote $\Omega_{s,t} = (z_{s,t}, x_t)$ the state space except for $\boldsymbol{\varepsilon}_t$.

3.2 Per-period Utility

The individual receives per-period utility based on action $j \in \mathcal{J}(\mathbf{1}\{\mathrm{cw}_t \neq 0\}, \mathrm{rx}_t)$. The utility function consists of five additively separable terms: baseline utility, benefit from income, non-pecuniary utility from working, utility from opioid misuse, and idiosyncratic shock:

$$u(z_{s,t}, x_t, \boldsymbol{\varepsilon}_t, j; \boldsymbol{\theta}^y, \boldsymbol{\theta}^u) = u_0 + \alpha \log y(x_t, j; \boldsymbol{\theta}^y) + u_w(x_t, j; \boldsymbol{\theta}^w) + u_o(z_{s,t}, x_t, j; \boldsymbol{\theta}^o) + \varepsilon_{jt}. \quad (2)$$

where $y(\cdot)$ denotes the income, $u_w(\cdot)$ denotes the non-pecuniary utility from working, $u_o(\cdot)$ denotes the utility from opioid misuse. u_0 denotes the baseline utility, α is the weight on how much the individual values income compared to utility from working and opioid misuse, $\boldsymbol{\theta}^y$ is the vector of parameters that govern income process, $\boldsymbol{\theta}^u := (\boldsymbol{\theta}^w, \boldsymbol{\theta}^o)$ is the vector of parameters that govern the utility function, $\boldsymbol{\theta}^w$ and $\boldsymbol{\theta}^o$ are the vector of parameters that govern the utility from working and opioid misuse, respectively. While the baseline utility u_0 is typically not identified in dynamic discrete choice models, but if the model has a terminal state (in this case, death) and if the (dis)utility from reaching the terminal state is normalized to zero, then the constant term u_0 is identified and adjusts the effect of normalization on the decision-making process. Non-pecuniary utility from working captures the (dis)utility from working that varies across labor and health status. Utility from opioid misuse captures the incentive to misuse opioids due to poor health, unfavorable labor status, and opioid prices.

[11] While this normalization is common in economics, it imposes a strong restriction on the flow utilities. See the appendix for details on the identification of dynamic discrete choice models with a terminal state.

Misperception does not enter the flow utility; it only affects the expectation of the transition probability of death from opioid misuse.

Income is a function of the individual's choice on working and opioid misuse, health condition, prescription status, education, and work experience. Even when the individual does not work in a given period—either by choice or due to separation from the labor market—he receives a baseline of income, which varies by education level e. The functional form of the income process is

$$y(x_t, j; \boldsymbol{\theta}^y) = d_w y_w(x_t, j; \boldsymbol{\theta}^y_w) + (1 - d_w) y_{nw}(e; \boldsymbol{\theta}^y_{nw}) \tag{3}$$

$$y_w(x_t, j; \boldsymbol{\theta}^y_w) = \mathrm{x}_t^{w\top} \boldsymbol{\theta}^y_w \tag{4}$$

$$y_{nw}(e; \boldsymbol{\theta}^y_{nw}) = \mathrm{x}_t^{nw\top} \boldsymbol{\theta}^y_{nw} \tag{5}$$

where $\mathrm{x}_t^w := \big(1,\ e,\ \mathrm{xp}_t,\ e \times \mathrm{xp}_t,\ \mathrm{h}_t,\ \mathbf{1}\{h_t \neq 0\} \times \mathrm{rx}_t,\ \mathbf{1}\{h_t \neq 0\} \times \mathrm{xp}_t,\ (d_o^{rx},\ d_o^{il}) \otimes (1,\ \mathbf{1}\{h_t \neq 0\},\ \mathrm{xp}_t)\big)$ and $\mathrm{x}_t^{nw} := \big(1 - e,\ e\big)$. $\mathbf{h}_t := \big(\mathbf{1}\{h_t = 1\},\ \mathbf{1}\{h_t = 2\},\ \mathbf{1}\{h_t = 3\}\big)$. The Kronecker product $(d_o^{rx},\ d_o^{il}) \otimes (1,\ \mathbf{1}\{h_t \neq 0\},\ \mathrm{xp}_t)$ generates six interactions of opioid misuse across health and work experience. $y_w(x_t, j; \boldsymbol{\theta}^y_w)$ is income from working and $y_{nw}(e; \boldsymbol{\theta}^y_{nw})$ is baseline income when the person is not working. The first line in income from working captures the effect of education and work experience on income. The second line captures decreases in productivity due to bad health, potential productivity recovery from prescription opioids, and heterogeneity in the decrease in productivity due to bad health across work experience. The last two lines capture the potential decrease in productivity due to prescription and illegal opioid misuse, and its heterogeneity across bad health and work experience.

Non-pecuniary utility from working flexibly captures the differences in utility from working conditional on health, education, work experience, and opioid misuse:

$$u_w(x_t, j; \boldsymbol{\theta}^u) = \mathbf{1}\{d_w = 1\} \mathbf{x}_t^{w\top} \boldsymbol{\theta}^w \tag{6}$$

where $\mathbf{x}_t^{w\top} := \big(\mathbf{h}_t,\ e,\ \mathrm{xp}_t,\ e \times \mathrm{xp}_t,\ \mathbf{1}\{h_t \neq 0\}\mathrm{rx}_t,\ \mathbf{1}\{h_t \neq 0\}\mathrm{xp}_t,\ (d_o^{rx},\ d_o^{il}) \otimes (1,\ \mathbf{1}\{h_t \neq 0\},\ \mathrm{xp}_t)\big)$.

Lastly, the utility function of opioid misuse captures various socioeconomic reasons why people may find it appealing to misuse opioids:

$$u_o(\Omega_{s,t}, j; \boldsymbol{\theta}^o) = \mathbf{x}_{ot}^\top \boldsymbol{\theta}^o_d + \mathbf{1}\{d_o^{il} = 1\} p_{st}^{il} \mathbf{x}_{pt}^\top \boldsymbol{\theta}^o_p, \tag{7}$$

where $\mathbf{x}_{ot}^\top := \big(1,\ \mathbf{h}_t,\ \mathbf{e} \otimes \mathbf{cw}_t,\ \mathrm{xp}_t\big)$, $\mathbf{x}_{pt}^\top := \big(1,\ \mathbf{h}_t,\ \mathbf{cw}_t,\ \mathrm{rx}_t\big)$, $\mathbf{cw}_t := \big(\mathbf{1}\{\mathrm{cw}_t = 1\},\ \mathbf{1}\{\mathrm{cw}_t = 2\},\ \mathbf{1}\{\mathrm{cw}_t = 3\}\big)$, and $\mathbf{e} := \big(\mathbf{1}\{e = 0\}, \mathbf{1}\{e = 1\}\big)$. $d \in \{rx, bth, il\}$ stands for misusing prescription opioids only, both prescription and illegal opioids, and illegal opioids only, determined by $(d_o^{rx},\ d_o^{il})$. The Kronecker product $\mathbf{e}_t \otimes \mathbf{cw}_t$ yields the six interactions of education and the individual's status in the labor market. $\boldsymbol{\theta}_d^o$ is the vector of parameters for the preference of misusing opioids. $\boldsymbol{\theta}_p^o$ is the vector of parameters determining the price elasticity of opioid misuse on the extensive margin.

3.3 Transition Probabilities

After taking an action j, the states are realized sequentially: death, health, labor, prescription, and misperception. Death is realized conditional on health and opioid misuse. Denote $f_d(j, h_t; \boldsymbol{\theta}_t^d)$ the transition probability to death conditional on health and opioid misuse in year t:

$$f_d(j, h_t; \boldsymbol{\theta}_t^d) = \theta_1^d + \theta_2^d h_{1t} + \theta_3^d h_{2t} + \theta_{4,t}^d d_o^{rx} + \theta_{5,t}^d d_o^{il} + \theta_{6,t}^d d_o^{rx} d_o^{il}$$

where θ_1^d denotes the baseline probability of death, θ_2^d and θ_3^d denote the additional probability of death due to having worse health, and $(\theta_{4,t}^d, \theta_{5,t}^d, \theta_{6,t}^d)$ denote the probability of death from misusing prescription opioids, illegal opioids, and both prescription and illegal opioids in year t. Note that the gross increase in the probability of death from misusing both prescription opioids and illegal opioids is the sum of the last three terms: $\theta_{4,t}^d + \theta_{5,t}^d + \theta_{6,t}^d$.

If the person survives, the next period's health is realized. The transition probability of health, $f_h(h_{t+1}|j, e, h_t, \mathrm{cw}_t, \mathrm{rx}_t, \mathrm{xp}_t)$, has a multinomial logit form. For each index for the health status in the next period $k = 1, 2, 3$, the log odds of the transition probability of health in the next period is:

$$\log \frac{f_h(h_{t+1} = k|j, e, h_t, \mathrm{cw}_t, \mathrm{rx}_t, \mathrm{xp}_t; \boldsymbol{\theta}^h)}{f_h(h_{t+1} = 0|j, e, h_t, \mathrm{cw}_t, \mathrm{rx}_t, \mathrm{xp}_t; \boldsymbol{\theta}^h)} = \mathbf{x}_t^{h\top} \boldsymbol{\theta}_k^h \tag{8}$$

where $\mathbf{x}_t^h = \big(1,\ e,\ \mathbf{h}_t,\ \mathbf{cw}_t,\ \mathrm{xp}_t,\ d_w, \mathrm{rx}_t(1 - d_o^{rx}),\ \mathrm{rx}_t d_o^{rx},\ d_o^{il}\big)$. The first line captures the health transition by education and previous health status, the second line captures the expectation of the next period's health by labor status, and the third line captures the expectation of the next period's transition of health by joint choice of work and opioid misuse.

Given the next period's health, $h_{t+1} = (h_{1,t+1},\ h_{2,t+1})$, the person's labor status in the next period cw_{t+1} is realized. The transition probability of the individual's status in the labor market, $f_{\mathrm{cw}}(\mathrm{cw}_{t+1}|j, e, h_{t+1}, \mathrm{cw}_t, \mathrm{xp}_t, \mathrm{rx}_t)$, takes the multinomial logit form, i.e., the log odds of the transition probabilities are:

$$\log \frac{f_{\mathrm{cw}}(\mathrm{cw}_{t+1} = k|j, e, h_{t+1}, \mathrm{cw}_t, \mathrm{xp}_t, \mathrm{rx}_t; \boldsymbol{\theta}^{\mathrm{cw}})}{f_{\mathrm{cw}}(\mathrm{cw}_{t+1} = 0|j, e, h_{t+1}, \mathrm{cw}_t, \mathrm{xp}_t, \mathrm{rx}_t; \boldsymbol{\theta}^{\mathrm{cw}})} = \mathbf{x}_t^{\mathrm{cw}\top} \boldsymbol{\theta}_k^{\mathrm{cw}} \tag{9}$$

for $k = 1, 2, 3$, where $\mathbf{x}_t^{\mathrm{cw}\top} = \big(\mathbf{e} \otimes (1,\ \mathbf{cw}_t),\ \mathbf{h}_{t+1},\ \mathrm{xp}_t, \mathrm{rx}_t, d_w, \mathbf{1}\{d_o^{rx} = 1 \vee d_o^{il} = 1\}\big)$. Note that the transition probability for the individual's labor status in the next period, cw_{t+1}, differs by the interactions of education and the labor status in this period.

Next, the individual receives prescription drugs based on his labor, health, and his location's policies on opioid prescribing. The individual expects the probability of receiving prescription opioids in the next period, $f_{\mathrm{rx}}(\mathrm{rx}_{t+1}|h_{t+1}, \mathrm{cw}_{t+1}, r_{s,t}, m_{s,t}, s, t)$, has a logit form. The log odds of the probability of receiving prescription opioids next year, conditional on surviving in a given state location s and year t, is:

$$\log \frac{f_{\mathrm{rx}}(\mathrm{rx}_{t+1} = 1|h_{t+1}, \mathrm{cw}_{t+1}, r_{s,t}, m_{s,t}, s, t; \boldsymbol{\theta}^{\mathrm{rx}})}{f_{\mathrm{rx}}(\mathrm{rx}_{t+1} = 0|h_{t+1}, \mathrm{cw}_{t+1}, r_{s,t}, m_{s,t}, s, t; \boldsymbol{\theta}^{\mathrm{rx}})} = \mathbf{x}_{st}^{\mathrm{rx}\top} \boldsymbol{\theta}^{\mathrm{rx}} + \zeta_s \tag{10}$$

where $x_{s,t}^{\mathrm{rx}\top} := \big(1,\ \mathbf{cw}_{t+1},\ \mathbf{h}_{t+1},\ \big(r_{s,t}(1 - m_{s,t}),\ m_{s,t}(1 - r_{s,t})\ , r_{s,t} r_{s,t}\big) \otimes \mathbf{h}_{t+1}\big)$. Note that the individual expects the state-level policies to remain the same in the next period, so state laws and must-access PDMPs in state s in year t, $r_{s,t}, m_{s,t}$, apply in the perceived transition probability of receiving prescription opioids. The functional form flexibly captures how the probability of receiving prescription opioids would change according to state-level policies. ζ_s captures the state-level fixed effects on prescribing opioids.

Lastly, the individual forms the perception of the risk of harm from opioid misuse. The probability of perceiving that misusing opioids has low risk of harm $b = L$ depends on education and in each period's health, labor, and prescription status:

$$\log \frac{f_b(b = L|e, h_{t+1}, \mathrm{cw}_{t+1}, \mathrm{rx}_{t+1}; \boldsymbol{\theta}^b)}{f_b(b = H|e, h_{t+1}, \mathrm{cw}_{t+1}, \mathrm{rx}_{t+1}; \boldsymbol{\theta}^b)} = x_{t+1}^{b\top} \boldsymbol{\theta}^b \tag{11}$$

where $\mathbf{x}_t^{b\top} := \big(1,\ e,\ \mathbf{h}_{t+1}\ , \mathbf{cw}_{t+1}, \mathrm{rx}_{t+1}\big)$. If the individual perceives that misusing opioids has a low risk of harm, he discounts the probability of dying from opioid misuse by δ[12]. Equation 12 illustrates how the perception of the risk of harm from misusing opioids affects the belief about the probability of dying from opioid misuse. The perceived probability of dying conditional on health opioid misuse at in year t, denoted by $f_d(j, t, h_t, b_t; \boldsymbol{\theta}^d, \delta)$, has the following functional form:

$$\tilde{f}_d(j, h_t, b_t; \boldsymbol{\theta}_t^d, \delta) = \theta_1 + \theta_2^d h_{1t} + \theta_3^d h_{2t} + (1 - \delta \mathbf{1}\{b_t = L\}) \left(\theta_{4t}^d d_o^{rx} + \theta_{5t}^d d_o^{il} + \theta_{6t}^d d_o^{rx} d_o^{il}\right) \tag{12}$$

[12]In effect, the model imposes that the person with misperception is overconfident about not dying from opioid misuse. While parsimonious, this model captures the degree to how people perceive the riskiness of harm from opioid misuse. Given more variables, a researcher may impose more sophisticated structure on how misperception works in the subjective beliefs about the future, for example, perception bias on the riskiness of becoming addicted to opioids, etc.

where it differs from the objective probability of death by the magnitude of the perception bias, δ, on the transition probability of death from opioid misuse. The magnitude of the perception bias is a central parameter to estimate using the data.

3.4 Value Function Representation

In each period, the individual chooses her action $j \in \mathcal{J}(\mathbf{1}\{\text{cw}_t \neq 0\}, \text{rx}_t)$ to maximize her expected discounted sum of utility until death. The optimal choice given the state $\left(\Omega_{s,t}, \boldsymbol{\varepsilon}_t\right)$, d_j^* is:

$$d_j^*(\Omega_{s,t}, \boldsymbol{\varepsilon}_t) = \underset{j \in \mathcal{J}(\text{cw}_t \neq 0, \text{rx}_t)}{\arg\max} \; \mathbb{E}\left(\sum_{t=1}^{\infty} \beta^{t-1} \left[u(\Omega_{s,t}, \boldsymbol{\varepsilon}_t, j; \boldsymbol{\theta}^y, \boldsymbol{\theta}^u) \right] \middle| \Omega_{s,t} \right)$$

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

$$\begin{aligned} V(\Omega_{s,t}, \boldsymbol{\varepsilon}_t) = \max_{j \in \mathcal{J}_t} \; & u_0 + \alpha \log y(x_t, j; \boldsymbol{\theta}^y) + u_w(x_t, j; \boldsymbol{\theta}^w) + u_o(\Omega_{s,t}, j; \boldsymbol{\theta}^o) + \varepsilon_{jt} \\ & + \beta \tilde{f}_d(j, h_t, b_t; \boldsymbol{\theta}_t^d, \delta) W \\ & + \beta \left(1 - \tilde{f}_d(j, h_t, b_t; \boldsymbol{\theta}_t^d, \delta)\right) \sum_{x_{t+1}} \bar{V}(\tilde{\Omega}_{s,t+1}) \tilde{f}(x_{t+1} | \Omega_{s,t}, j) \end{aligned} \tag{13}$$

where $\mathcal{J}_t := \mathcal{J}(\mathbf{1}\{\text{cw}_t \neq 0\}, \text{rx}_t)$, $\tilde{\Omega}_{s,t+1}$ is the year $t+1$'s state space expected by the individual living in year t and $\bar{V}(\tilde{\Omega}_{s,t+1}) := \int V(z_{s,t}, x_{t+1}, \boldsymbol{\varepsilon}_{t+1}) g(\boldsymbol{\varepsilon}_{t+1})$ is the ex-ante value function in period $t+1$ given macroeconomic state variables $z_{s,t}$. The next period's ex-ante value function contains $z_{s,t}$ because in each period t, the individual expects that macroeconomic variables will remain the same forever. $\tilde{f}(x_{t+1}|\Omega_{s,t}, j)$ is the perceived transition probability of the individual state x_{t+1}, conditional on state variables $\Omega_{s,t} = (z_{s,t}, x_t)$, choice j, and surviving this period:

$$\begin{aligned} \tilde{f}(x_{t+1}|\Omega_{s,t}, j) = & f_h(h_{t+1}|j, e, h_t, \text{cw}_t, \text{rx}_t, \text{xp}_t) \\ & \times f_{\text{cw}}(\text{cw}_{t+1}|j, e, h_{t+1}, \text{cw}_t, \text{xp}_t, \text{rx}_t) \\ & \times f_{\text{rx}}(\text{rx}_{t+1}|h_{t+1}, \text{cw}_{t+1}, r_{s,t}, m_{s,t}, s, t) \\ & \times f_b(b_{t+1}|e, h_{t+1}, \text{cw}_{t+1}, \text{rx}_{t+1}, \text{xp}_{t+1}). \end{aligned} \tag{14}$$

Denote the choice-specific value function, the indirect utility of the representative individual if he commits to choice j this period, given state $\Omega_{s,t}$ and chooses optimally from the next period, $v_j(\Omega_{s,t})$, is then

$$
\begin{aligned}
v(\Omega_{s,t}) = & u_0 + \alpha \log y(x_t, j; \boldsymbol{\theta}^y) + u_w(x_t, j; \boldsymbol{\theta}^w) + u_o(\Omega_{s,t}, j; \boldsymbol{\theta}^o) \\
& + \beta \tilde{f}_d(j, h_t, b_t; \boldsymbol{\theta}_t^d, \delta) W \\
& + \beta \left(1 - \tilde{f}_d(j, h_t, b_t; \boldsymbol{\theta}_t^d, \delta)\right) \sum_{x_{t+1}} \bar{V}(\tilde{\Omega}_{s,t+1}) \tilde{f}(x_{t+1} | \Omega_{s,t}, j).
\end{aligned}
\tag{15}
$$

Define $p_j(\Omega_{s,t})$ the probability that $j \in \mathcal{J}_t$ is the optimal choice conditional on $\Omega_{s,t}$ before observing $\boldsymbol{\varepsilon}_t$:

$$
p_j(\Omega_{s,t}) = \int \mathbf{1}\{v(\Omega_{s,t}, j) - v(\Omega_{s,t}, k) \geq \varepsilon_{k,t} - \varepsilon_{j,t},\ \forall j \in \mathcal{J}_t\} g(\boldsymbol{\varepsilon}_t). \tag{16}
$$

By Corollary 2 from Arcidiacono and Miller (2011), there exists a one-to-one mapping between the vector of conditional choice probabilities $\mathbf{p}(\Omega_{s,t}) \coloneqq \left(p_j(\Omega_{s,t})\right)_{j \in \mathcal{J}_t}$ and the vector of differences between the ex-ante value function and the choice-specific value function. Denote the vector of such mapping as $\boldsymbol{\psi}(\mathbf{p}(\Omega_{s,t})) \coloneqq \left(\psi_j(\Omega_{s,t}; \mathbf{p}(\Omega_{s,t}))\right)_{j \in \mathcal{J}_t}$. Then, for each j in the choice set $\mathcal{J}_t$, the following holds:

$$
\psi_j(\Omega_{s,t}, \mathbf{p}(\Omega_{s,t})) = \bar{V}(\Omega_{s,t}) - v(\Omega_{s,t}, j). \tag{17}
$$

By subtracting $\psi_k(\Omega_{s,t}, \mathbf{p}(\Omega_{s,t}))$ from $\psi_j(\Omega_{s,t}, \mathbf{p}(\Omega_{s,t}))$:

$$
\psi_j(\Omega_{s,t}, \mathbf{p}(\Omega_{s,t})) - \psi_k(\Omega_{s,t}, \mathbf{p}(\Omega_{s,t})) = v(\Omega_{s,t}, j) - v(\Omega_{s,t}, k). \tag{18}
$$

Equation (18) is central to identification and estimation, given that I can find the weights on the transition probabilities across the future choices available for certain ρ-periods so that the ex-ante value functions are canceled out for all states available in $(\rho + 1)$-periods ahead (Arcidiacono and Miller, 2019). In that case, equation (18) only has choice probabilities, transition probabilities, and the model primitives, which allows researchers to state identification and estimate the model primitives formally. In this paper, I focus on the 1-period finite dependence, where the model is found to have decision weights that can cancel out the ex-ante value functions two periods ahead. The identification argument from (17) follows in the next section.

4 Identification

In this section, I state the system of equations derived from 1-period finite dependence for identification and explain how the variation in the data identifies the model primitives.

The model is characterized by the utility parameters $\boldsymbol{\theta}^u$, income process $(\boldsymbol{\theta}^y, \sigma_y)$, transition probability parameters $(\boldsymbol{\theta}^d, \boldsymbol{\theta}^h, \boldsymbol{\theta}^{\text{cw}}, \boldsymbol{\theta}^{rx}, \zeta_s)$, stochastic process for the misperception of the risk of harm from opioids $\boldsymbol{\theta}^b$, terminal value upon death $W = 0$, and the magnitude of discounting the probability of death from opioid misuse under misperception, δ.

The discount factor is set to $\beta = 0.98$, and the distribution of choice-specific idiosyncratic shocks follows i.i.d. type 1 extreme value. Given the specification, there is a closed-form solution for the Hotz-Miller inversion: $\psi_k(\Omega_{s,t}, \mathbf{p}(\Omega_{s,t})) = \gamma - \log p_j(\Omega_{s,t})$.

4.1 1-Period Finite Dependence

Denote $\tilde{\Omega}_{s,t+\rho} \coloneqq (z_{s,t}, x_{t+\rho})$ the state in period $t+\rho$ of an individual living at t. By applying Theorem 1 from Arcidiacono and Miller (2019), the choice-specific value function in equation (15) can be represented as follows:

$$
\begin{aligned}
v(\Omega_{s,t}, j) =& u(\Omega_{s,t}, j; \boldsymbol{\theta}^u) + \beta \tilde{f}_d(j, h_t, b_t; \boldsymbol{\theta}^d_t, \delta) W \\
&+ \beta \sum_{x_{t+1}} \sum_{k \in \mathcal{J}_{t+1}} \begin{bmatrix} u(\tilde{\Omega}_{s,t+1}, k) + \\ \psi_k(\tilde{\Omega}_{s,t+1}, \mathbf{p}(\tilde{\Omega}_{s,t+1})) \end{bmatrix} \omega(k, x_{t+1}; \Omega_{s,t}, j) \kappa(x_{t+1} | \Omega_{s,t}, j) \\
&+ \beta^2 \sum_{x_{t+1}} \sum_{k \in \mathcal{J}'} W \tilde{f}_d(k, h_{t+1}, b_{t+1}; \boldsymbol{\theta}^d_t, \delta) \omega(k, x_{t+1}; \Omega_{s,t}, j) \kappa(x_{t+1} | \Omega_{s,t}, j) \\
&+ \beta^2 \sum_{x_{t+2}} \sum_{x_{t+1}} \sum_{k \in \mathcal{J}_{t+1}} \bar{V}(\tilde{\Omega}_{s,t+2}) \kappa(x_{t+2} | \Omega_{s,t}, j),
\end{aligned}
\tag{19}
$$

where $\left(\omega(k, x_{t+1}; \Omega_{s,t}, j)\right)_{k \in \mathcal{J}_{t+1}}$ is the vector of decision weights for all available choices $k \in \mathcal{J}_{t+1}$ at state x_{t+1} in the next period $t+1$, such that $|\omega(k, x_{t+1}; \Omega_{s,t}, j)| < \infty \ \forall \ k \in \mathcal{J}_{t+1}$ and $\sum_{k \in \mathcal{J}_{t+1}} \omega(k, x_{t+1}; \Omega_{s,t}, j) = 1$ for each $(z_{s,t}, x_{t+1}) \in \tilde{\Omega}_{s,t+1}$, and $\kappa(x_{t+\rho} | \Omega_{s,t}, j)$ is the integrated transition probabilities arriving at $x_{t+\rho}$ starting from state $\Omega_{s,t}$ and choice j given the decision weights:

$$
\kappa(x_{t+1} | \Omega_{s,t}, j) = \tilde{f}(x_{t+1} | \Omega_{s,t}, j) \left(1 - \tilde{f}_d(j, h_t, b_t; \boldsymbol{\theta}^d_t, \delta)\right) \tag{20}
$$

$$
\kappa(x_{t+2} | \Omega_{s,t}, j) = \sum_{x_{t+1}} \sum_{k \in \mathcal{J}_{t+1}} \begin{bmatrix} \tilde{f}(x_{t+2} | \tilde{\Omega}_{s,t+1}, j) \times \\ \left(1 - \tilde{f}_d(j, h_{t+1}, b_{t+1}; \boldsymbol{\theta}^d_t, \delta)\right) \end{bmatrix} \omega(k, x_{t+1}; \Omega_{s,t}, j) \kappa(x_{t+1} | \Omega_{s,t}, j). \tag{21}
$$

Note that $\tilde{f}_d(k, h_{t+1}, b_{t+1}; \boldsymbol{\theta}^d_t, \delta)$ contains $\boldsymbol{\theta}^d_t$ because it is the perceived probability of death in year $t+1$ of an individual living in t.

For simplicity in enumerating the pairs of choices for a given state $\Omega_{s,t}$, I choose $j = 1$ as the baseline choice. Then, a pair of choices 1 and j at state $\Omega_{s,t}$ is said to exhibit a 1-period finite dependence if there exist decision weights $\big(\omega(k, x_{t+1}; \Omega_{s,t}, 1)\big)_{k\in\mathcal{J}_{t+1}}$ and $\big(\omega(k, x_{t+1}; \Omega_{s,t}, j)\big)_{k\in\mathcal{J}_{t+1}}$ such that

$$\kappa(x_{t+2}|\Omega_{s,t}, 1) = \kappa(x_{t+2}|\Omega_{s,t}, j) \tag{22}$$

for all $(z_t, x_{t+2}) \in \tilde{\Omega}_{s,t+2}$. If this is the case, then the difference of choice-specific value functions between 1 and j at $\Omega_{s,t}$ has the following equality condition:

$$\begin{aligned}
&\psi_1(\Omega_{s,t}, \mathbf{p}(\Omega_{s,t})) - \psi_j(\Omega_{s,t}, \mathbf{p}(\Omega_{s,t})) = v(\Omega_{s,t}, j) - v(\Omega_{s,t}, 1)\\
&= u(\Omega_{s,t}, j; \boldsymbol{\theta}^u) - u(\Omega_{s,t}, 1; \boldsymbol{\theta}^u)\\
&+ \beta\big(\tilde{f}_d(j, h_t, b_t; \boldsymbol{\theta}^d_t, \delta) - \tilde{f}_d(i, h_t, b_t; \boldsymbol{\theta}^d_t, \delta)\big)W\\
&+ \beta \sum_{x_{t+1}} \sum_{k\in\mathcal{J}_{t+1}} \begin{bmatrix} u(\tilde{\Omega}_{s,t+1}, k)+ \\ \psi_k(\tilde{\Omega}_{s,t+1}, \mathbf{p}(\tilde{\Omega}_{s,t+1})) \end{bmatrix} \begin{bmatrix} \omega(k, x_{t+1}; \Omega_{s,t}, j)\kappa(x_{t+1}|\Omega_{s,t}, j)- \\ \omega(k, x_{t+1}; \Omega_{s,t}, 1)\kappa(x_{t+1}|\Omega_{s,t}, 1) \end{bmatrix}\\
&+ \beta^2 \sum_{x_{t+1}} \sum_{k\in\mathcal{J}_{t+1}} W\tilde{f}_d(k, h_{t+1}, b_{t+1}; \boldsymbol{\theta}^d_t, \delta) \begin{bmatrix} \omega(k, x_{t+1}; \Omega_{s,t}, j)\kappa(x_{t+1}|\Omega_{s,t}, j)- \\ \omega(k, x_{t+1}; \Omega_{s,t}, 1)\kappa(x_{t+1}|\Omega_{s,t}, 1) \end{bmatrix}.
\end{aligned} \tag{23}$$

By rearranging, the terms associated with a function of conditional choice probabilities $\boldsymbol{\psi}(\cdot, \mathbf{p}(\cdot))$ to the left-hand side and setting $W = 0$, equation (23) becomes:

$$\begin{aligned}
&\psi_1(\Omega_{s,t}, \mathbf{p}(\Omega_{s,t})) - \psi_j(\Omega_{s,t}, \mathbf{p}(\Omega_{s,t}))\\
&\quad - \beta \sum_{x_{t+1}} \sum_{k\in\mathcal{J}_{t+1}} \psi_k(\tilde{\Omega}_{s,t+1}, \mathbf{p}(\tilde{\Omega}_{s,t+1})) \begin{bmatrix} \omega(k, x_{t+1}; \Omega_{s,t}, j)\kappa(x_{t+1}|\Omega_{s,t}, j)- \\ \omega(k, x_{t+1}; \Omega_{s,t}, 1)\kappa(x_{t+1}|\Omega_{s,t}, 1) \end{bmatrix}
\end{aligned} \tag{24}$$

$$\begin{aligned}
&= u(\Omega_{s,t}, j; \boldsymbol{\theta}^u) - u(\Omega_{s,t}, 1; \boldsymbol{\theta}^u)\\
&\quad + \beta \sum_{x_{t+1}} \sum_{k\in\mathcal{J}_{t+1}} u(\tilde{\Omega}_{s,t+1}, k) \begin{bmatrix} \omega(k, x_{t+1}; \Omega_{s,t}, j)\kappa(x_{t+1}|\Omega_{s,t}, j)- \\ \omega(k, x_{t+1}; \Omega_{s,t}, 1)\kappa(x_{t+1}|\Omega_{s,t}, 1) \end{bmatrix}.
\end{aligned} \tag{25}$$

Given the decision weights that attain 1-period finite dependence and the perception bias δ, the left-hand side (24) only has conditional choice probabilities and transition probabilities. If there are at least as many equations as the number of model primitives, then the parameters are identified if (25) has full column rank. More generally, a system of equations by stacking the equations above point-identifies the model primitives if there exists a unique set of parameters that minimizes a smooth norm obtained from the system of equations[13].

4.2 Variation in the Data for Identification

While identifying the parameters for the income process $(\boldsymbol{\theta}^y, \sigma)$ is straightforward from the variation of income across state variables x_t and choices j, there are two challenges to identifying the model. First, the two-dimensional health $h_t = (h_{1t}, h_{2t})$ is not directly observed in the data; instead, I observe proxy variables: self-reported health measures and six core disability measures. Second, the transition probabilities, $(f_d, f_h, f_{\mathrm{cw}}, f_{\mathrm{rx}})$ given opioid misuse are not directly observed since the NSDUH is repeated cross-sectional data; instead, I have marginal transition probabilities from SIPP and MEPS where opioid misuse is not observed.

I resolve the first challenge by adapting a recent work on identifying dynamic discrete choice models with proxy variables (Hwang (2020)). I use the information from self-reported health and six core disabilities to identify and estimate the probability distribution of the two-dimensional health conditional on education. 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_t. I use "difficult to walk," "difficult to see" and "difficult to hear" to proxy for latent physical health h_{1t}. Lastly, I use "difficult to think, concentrate, make decisions" to proxy for latent mental health h_{2t}. Table 24 summarizes how I use the proxy variables to recover the probability distribution of health in this paper[14]. The identification argument follows Hwang (2020). Two proxy variables, self-reported health and "difficult to do errands and dress," identify the joint probability distribution of health. The three conditionally independent proxies, "difficult to walk," "difficult to see," and "difficult to hear," identify the probability distribution of the first component of two-dimensional health. Lastly, "difficult to think, concentrate, make decisions" identifies the probability distribution of the second component. 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 health in the second component, and people who answered "yes" to "difficult to walk" have a higher probability of having bad health in the first component. In this sense, I call the first component "physical health" and the second component "mental health."

[13] Stacking (23) for all individual states x and choices j for all (t, s, e), I have $(400-128)\times 5\times 51\times 2 = 138,720$ equality constraints for this model.

[14] I choose these variables for proxies because they are all the variables that NSDUH, SIPP, and MEPS have in common for health. If the NSDUH were a panel data or if the three data sets have more variables in common, one may find more complex dynamics of health from opioid misuse.

To address the second challenge, I exploit 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 of a dynamic discrete choice model 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 in opioid misuse rates observed in the NSDUH to the state-level variation in marginal transition probabilities to health and labor in SIPP. For example, suppose there are two people whose individual factors are the same in two states, but opioid misuse rates differ. Then, the structure of the joint transition probability captures the differences in marginal transition probabilities for health and labor, conditional on the individual factor, as the effect of opioid misuse on the transition probability. Then, I use information from MEPS and NSDUH to recover the perceived probability of receiving prescription opioids in the next period.

Given the conditional choice probabilities and transition probabilities, two components remain to be identified: utility parameters $\boldsymbol{\theta}^u$ and the magnitude of discounting the probability of dying from opioid misuse $\delta \in (0, 1)$. δ is identified by the exclusion restriction for the misperception variable b in flow utilities, similar to Abbring et al. (2019). If b does not enter the flow utilities, then the observed differences in conditional choice probabilities across b at the same state variables except for b identify the size of δ. Lastly, the utility parameters $\boldsymbol{\theta}^u$ are identified following the typical identification argument in the dynamic discrete choice literature. The differences in conditional choice probabilities across different choices compared to the baseline choice $j = 1$ at a given state identify the difference of the flow utility functions across choices, given the rest of the model primitives[15].

5 Estimation

The identification argument in the previous section relies on finding the decision weights for each pair of choices per state. The decision weights are essentially a function of transition probabilities because they are computed by equating the integrated transition probability arriving at each attainable state two periods later. In usual dynamic discrete choice models

[15] W can be identified by the conditional choice probability differences where the choices affect the transition probability of arriving (h_{1t}, h_{2t}) in the next period. This is because the baseline mortality rate differs by the two-dimensional health status. Thus, the information about the preference for being exposed to different transition probabilities in health across different choices identifies W. For intuitive interpretability, I set $W = 0$ and instead allow the baseline utility conditional on surviving as a parameter in the utility function. See the appendix for the details on the observational equivalence in the class of dynamic discrete choice models with a terminal state.

where we assume rational expectations, the transition probabilities are found solely from the variation in the data. In that case, estimation is straightforward as in Arcidiacono and Miller (2019): estimate the transition probabilities, compute the decision weights as a function of the known transition probabilities, and estimate the model primitives using a minimum distance estimator.

The crucial difference in my model against the usual dynamic discrete choice models is that the perceived transition probability of dying from misusing opioids varies by the magnitude of discounting the probability by δ, which is a model primitive and also a component for transition probabilities. This creates a challenge in estimating the model, since the left-hand side of the equation (23) now contains the unknown component, δ.

To overcome this challenge, I extend 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 two-dimensional health h_t, the probability of opioid misuse perception bias b, and reduced-form conditional choice probabilities via the EM algorithm. In the second stage, I estimate the income process and joint transition probabilities. 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 that achieve 1-period finite dependence (Arcidiacono and Miller (2019)) given the guess for δ. Then, the utility parameters $\boldsymbol{\theta}^u$ and the magnitude of discounting the transition probability of dying from opioid misuse 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. To my knowledge, this method is the first approach in the literature to use the two-step CCP estimator on a class of dynamic discrete choice models with subjective beliefs.

5.1 First Stage: EM Algorithm

In the first stage, I estimate the prior distribution of the two-dimensional health conditional on education $\bar{q}(h_t|e)$, the parameters that govern the probability of perceiving misusing opioids as not a great risk of harm $\boldsymbol{\theta}^b$, and reduced-form CCPs $P_j(\Omega_{s,t})$ via the EM algorithm[16].

For each sample n in period t, denote the set of proxy variables by $\{\text{pxy}_{k,n,t}\}_{k=1}^{6}$. The marginal likelihood of observing $(b_{n,t}, \{\text{pxy}_{n,k,t}\}_{k=1}^{6}, j_{n,t})$, conditional on the sample n's state

[16]See Arcidiacono and Miller (2011) and Hwang (2020) for details on using the EM algorithm in the context of estimating dynamic discrete choice models.

$\Omega_{n,s,t}$, is:

$$\mathcal{L}_{n,t}(b_{n,t}, \{\mathrm{pxy}_{k,n,t}\}_{k=1}^{6}, j_{n,t}|\Omega_{n,s,t}) = \sum_{h_t=0}^{3} \bar{q}(h_t|e) \left[\prod_{k=1}^{6} f_{\mathrm{pxy}}(\mathrm{pxy}_{n,k}|h_t)\right] f_b(b_{n,t}|x_{n,t}; \boldsymbol{\theta}^b) p_j(\Omega_{s,t}).$$

Thus, the marginal likelihood of the data is

$$\mathcal{L} = \prod_{t=2015}^{2019} \prod_{n=1}^{N_t} \mathcal{L}_{n,t}(b_{n,t}, \{\mathrm{pxy}_{k,n,t}\}_{k=1}^{6}, j_{n,t}|\Omega_{n,s,t}),$$

where N_t is the number of samples in year t. I use flexible multinomial logistic functions to estimate the reduced-form conditional choice probabilities.

Table 10 shows the estimation result for the prior distribution of health conditional on education. The estimates indicate that in the model, individuals with a college degree are expected to have better health, as evidenced by the predicted fraction of people with good physical and mental health. People without a college degree are expected to have poorer mental health, and people with a college degree are expected to have poorer physical health.

Table 10: Prior Latent Health Distribution Conditional on Education

	Latent Health (Physical, Mental)			
	(Good, Good)	(Good, Bad)	(Bad, Good)	(Bad, Bad)
No College	0.5813	0.2578	0.0248	0.1361
College	0.6857	0.0551	0.1358	0.1234

Table 11 shows the proxy measurement structure matrices. The table shows that “difficult to think” is a strong signal for bad mental health h_2 and “difficult to walk” is a strong signal for bad physical health h_1. The 4-level health measure also shows a reasonable probability distribution across mental and physical health[17].

Given the distribution of latent health $h_{n,t}$, I estimate the log income process using the sample in the NSDUH. The NSDUH asks the respondents to report their aggregate income in intervals. Denote the actual income of the same n at t as $y_{n,t}$. From equation (3), the observed log income has the following functional form:

$$\log y_{n,t}(x_{n,t}, j_{n,t}; \boldsymbol{\theta}^y) = d_w \mathrm{x}_{n,t}^{w\top} \boldsymbol{\theta}_w^y + (1 - d_w)\mathrm{x}_{n,t}^{nw\top} \boldsymbol{\theta}_{nw}^y + \eta_{n,t}$$

[17]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 only 2% of people reported difficulty dressing alone, so answering “no” to this question does not provide much information. See the appendix for the summary statistics.

Table 11: Proxy Measurement Structure Matrices $\mathrm{P}(\mathrm{pxy}|h = (h_1, h_2))$

Latent Health (Physical, Mental)	Health Score			
	Excellent	Very Good	Good	Fair/Poor
Good, Good	0.28	0.45	0.23	0.03
Good, Bad	0.01	0.16	0.53	0.30
Bad, Good	0.00	0.18	0.67	0.14
Bad, Bad	0.03	0.09	0.25	0.63
Latent Health (Physical, Mental)	Difficult to (Do Errands, Dressing)			
	(No, No)	(Yes, No)	(No, Yes)	(Yes, Yes)
Good, Good	1.00	0.00	0.00	0.00
Good, Bad	0.95	0.05	0.00	0.00
Bad, Good	1.00	0.00	0.00	0.00
Bad, Bad	0.51	0.22	0.08	0.18
	Difficult to See			
Physical Health	No	Yes		
Good	0.98	0.02		
Bad	0.79	0.21		
	Difficult to Hear			
Physical Health	No	Yes		
Good	0.97	0.03		
Bad	0.78	0.22		
	Difficult to Walk			
Physical Health	No	Yes		
Good	0.99	0.01		
Bad	0.27	0.73		
	Difficult to Think			
Mental Health	No	Yes		
Good	0.98	0.02		
Bad	0.79	0.21		

where $\eta^y_{n,t} \sim \mathcal{N}(0, \sigma_y^2)$ is the measurement error. The likelihood of observing the log wage interval $(y^l_{n,t}, y^u_{n,t})$ given $(x_{n,t}, j_{n,t})$ for a sample n in year t is thus

$$\mathcal{L}^y_{n,t}(\left(y^l_{n,t}, y^u_{n,t}\right) | x_{x,t}, j_{n,t}; \boldsymbol{\theta}^y) = \Phi\left(\frac{y^u_{n,t} - y_{n,t}(x_{n,t}, j_{n,t}; \boldsymbol{\theta}^y)}{\sigma_y}\right) - \Phi\left(\frac{y^l_n - y_{n,t}(x_{n,t}, j_{n,t}; \boldsymbol{\theta}^y)}{\sigma_y}\right).$$

I estimate $\boldsymbol{\theta}^y$ via maximum likelihood estimation. Table 12 shows intuitive estimates for the income process. People lose productivity when they are in poorer health or when they misuse opioids. Using prescription opioids as directed by a doctor when people are in worse health partially recovers productivity. Education and work experience both have positive effects on productivity, and they have a complementary effect.

Table 12: Estimates for Log Income

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

Note: Standard errors in parentheses are computed by bootstrapping 30 times.

5.2 Second Stage: Transition Probabilities

Given the first stage estimates, I estimate parameters for the transition probabilities of death $\boldsymbol{\theta}^d$, health $\boldsymbol{\theta}^h$, labor $\boldsymbol{\theta}^{\text{cw}}$, and prescription $\boldsymbol{\theta}^{\text{rx}}$ and ζ_s by applying minimum distance estimators sequentially.

The transition probability of death due to health conditions and opioid misuse in each period t is estimated by matching the fractions of population dying from different causes of death and fraction of populations misusing opioids. For location s and year t, denote $F_{s,t}^{\text{OCD}}$ the fraction of population who died from causes other than opioid misuse and $F_{s,t}^{\text{OD:rx}}$, $F_{s,t}^{\text{OD:il}}$, $F_{s,t}^{\text{bth}}$ are the fractions of population who died from opioid overdose involving prescription opioids only, illegal opioid only, and both prescription and illegal opioids, respectively. Also, denote $F_{s,t}^{h_1}$ the fraction of population who has bad physical health and $F_{s,t}^{h_2}$ the fraction of population who has bad mental health. Lastly, denote $F_{s,t}^{\text{rx}}$, $F_{s,t}^{\text{il}}$, and $F_{s,t}^{\text{bth}}$ the fractions of population who misused prescription opioids only, illegal opioids only, and both prescription and illegal opioids. Then, given the functional form on the transition probability of death, the following equations hold for each location s and year t:

$$
\begin{aligned}
F_{s,t}^{\text{OCD}} &= \theta_1^d + \theta_2^d F_{s,t}^{h_1} + \theta_3^d F_{s,t}^{h_2} + \eta_{s,t}^{\text{OCD}} \\
F_{s,t}^{\text{OD:rx}} &= \theta_{4,t}^d \left(F_{s,t}^{\text{rx}} + F_{s,t}^{\text{bth}} \right) + \eta_{s,t}^{\text{rx}} \\
F_{s,t}^{\text{OD:il}} &= \theta_{5,t}^d \left(F_{s,t}^{\text{il}} + F_{s,t}^{\text{bth}} \right) + \eta_{s,t}^{\text{il}} \\
F_{s,t}^{\text{OD:bth}} &= \theta_{6,t}^d F_{s,t}^{\text{bth}} + \eta_{s,t}^{\text{bth}}
\end{aligned}
$$

where $\eta_{s,t}^{\text{OCD}}$, $\eta_{s,t}^{\text{rx}}$, $\eta_{s,t}^{\text{il}}$, and $\eta_{s,t}^{\text{bth}}$ are zero-mean measurement errors. $\boldsymbol{\theta}^d$ is found by minimizing the Euclidean norm of the vector of $\eta_{s,t}$'s by stacking the equations above across s and t:

$$
\hat{\boldsymbol{\theta}}^d = \arg\min_{\boldsymbol{\theta}^d} \sum_{s,t} \left(\eta_{s,t}^{\text{OCD}} \right)^2 + \left(\eta_{s,t}^{\text{rx}} \right)^2 + \left(\eta_{s,t}^{\text{il}} \right)^2 + \left(\eta_{s,t}^{\text{bth}} \right)^2 . \tag{26}
$$

The fractions on the left-hand side come from the restricted NVSS, and the state-level population estimates come from the Census. The distribution of opioid misuse comes directly from the NSDUH, and the predicted distribution of latent health is based on the estimates in the first stage. The identification of the probability of death conditional on health comes from the variation in latent health across s and t. The identification of the probability of death from opioid misuse comes from the state-level variation in opioid misuse rate and mortality rates in each year. Table 13 shows the estimation result. First, all people face 0.6 percent as the baseline probability of death. Having bad physical health increases the probability of death by 2.35 percentage points. Having bad mental health also increases the probability of death by 1.28 percentage points. Opioid misuse also increases the probability of dying from opioid overdose, which varies by year. In 2015, using illegal opioids increased the probability of death by 0.25 percentage point, whereas it increased to 0.64 percentage point in 2019. The probability of dying from misusing prescription opioids was stable during this period.

Table 13: Estimates for Probability of Death in Percent

Other Causes of Death		*Opioid Overdose*	2015	2016	2017	2018	2019
Baseline	0.59	Rx Opioids only	0.19	0.20	0.19	0.17	0.15
Bad Physical Health	2.35	Illegal Opioids 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

Notes: Derived Using Restricted NSDUH and NVSS, 2015-2019.

Next, I estimate the transition probability of latent health. The marginal transition probabilities of latent health come from the SIPP and MEPS data. I observe $\Omega_t^{\text{SIPP}} := (d_w, \{\text{pxy}_k\}_{k=1}^6, \text{cw}_t, \text{xp}_t, s, t, e)$ from SIPP and $\Omega_t^{\text{MEPS}} := (\{\text{pxy}_k\}_{k=1}^6, d_w, \text{cw}_t, \text{xp}_t, \text{rx}_t, t, e)$ from MEPS. The posterior distribution of latent health is computed for SIPP and MEPS samples by integrating out the posterior distribution of latent health predicted by the estimates from the first stage:

$$\hat{q}^{\text{SIPP}}(h_t|\Omega_t^{\text{SIPP}}) = \sum_{d_o^{rx}, d_o^{il}, \text{rx}_t, b_t} \hat{q}(h_t|\Omega_{s,t})\hat{P}(d_o^{rx}, d_o^{il}, \text{rx}_t, b_t|\Omega_t^{\text{SIPP}}) \tag{27}$$

$$\hat{q}^{\text{MEPS}}(h_t|\Omega_t^{\text{MEPS}}) = \sum_{d_o^{rx}, d_o^{il}, s, b_t} \hat{q}(h_t|\Omega_{s,t})\hat{P}(d_o^{rx}, d_o^{il}, s, b_t|\Omega_t^{\text{MEPS}}), \tag{28}$$

where $\hat{q}(h_t|\Omega_{s,t})$ is the posterior distribution of latent health from the first stage and $\hat{P}(y_t|x_t)$ is the cell estimator for the fraction of population of y_t conditional on x_t from the NSDUH.

State-level variation in opioid misuse and prescription rates from NSDUH identifies the effect of opioid misuse on the transition probability of latent health. For each vector of observed state and choice Ω_t^{SIPP} and Ω_t^{MEPS}, the following transition probabilities must hold:

$$\begin{aligned} F_h^{\text{SIPP}}(h_{t+1}|h_t, \Omega_t^{\text{SIPP}}) = \sum_{\text{rx}_t, d_o^{rx}, d_o^{il}} & f_h(h_{t+1}|j, e, h_t, \text{cw}_t, \text{rx}_t, \text{xp}_t; \boldsymbol{\theta}^h) \times \left(1 - \hat{f}_d(j, h_t; \boldsymbol{\theta}_t^d)\right) \times \\ & \hat{P}(\text{rx}_t, d_o^{rx}, d_o^{il}|h_t, \Omega_t^{\text{SIPP}})\hat{q}^{\text{SIPP}}(h_t|\Omega_t^{\text{SIPP}}) + \eta^h_{\Omega_t^{\text{SIPP}}} \end{aligned} \tag{29}$$

$$\begin{aligned} F_h^{\text{MEPS}}(h_{t+1}|h_t, \Omega_t^{\text{MEPS}}) = \sum_{\text{rx}_t, d_o^{rx}, d_o^{il}} & f_h(h_{t+1}|j, e, h_t, \text{cw}_t, \text{rx}_t, \text{xp}_t; \boldsymbol{\theta}^h) \times \left(1 - \hat{f}_d(j, h_t; \boldsymbol{\theta}_t^d)\right) \times \\ & \hat{P}(\text{rx}_t, d_o^{rx}, d_o^{il}|h_t, \Omega_t^{\text{MEPS}})\hat{q}^{\text{MEPS}}(h_t|\Omega_t^{\text{MEPS}}) + \eta^h_{\Omega_t^{\text{MEPS}}}, \end{aligned} \tag{30}$$

where $\eta^h_{\Omega_t^{\text{SIPP}}}$ and $\eta^h_{\Omega_t^{\text{MEPS}}}$ are i.i.d. errors with zero mean, and $\hat{f}_d(j, h_t; \boldsymbol{\theta}_t^d)$ is the fitted probability of death from health and opioid misuse in year t. Equation 29 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 29 and 30 identify the transition probability of the latent health state conditional on being prescribed 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:

$$F_{\mathrm{cw}}^{\mathrm{cw}}(\mathrm{cw}_{t+1}|h_{t+1},\Omega_t^{\mathrm{SIPP}}) = \sum_{h,\mathrm{rx},d_o^{rx},d_o^{il}} f_{cw}(\mathrm{cw}_{t+1}|e,h_{t+1},\mathrm{cw}_t,\mathrm{rx}_t,\mathrm{xp}_t,d_w,d_o^{rx},d_o^{il};\boldsymbol{\theta}^{cw}) \hat{f}_h(1-\hat{f}_d(j,h_t;\boldsymbol{\theta}_t^d)\hat{P}(\mathrm{rx},d_o^{rx},d_o^{il}|h,\mathrm{cw},\mathrm{xp},d_w,s,t,e) \tag{31}$$

$$F_{\mathrm{cw}}^{\mathrm{cw}}(\mathrm{cw}_{t+1}|h_{t+1},\Omega_t^{\mathrm{MEPS}}) = \sum_{h,\mathrm{rx},d_o^{rx},d_o^{il}} f_{cw}(\mathrm{cw}'|e,h',\mathrm{cw},\mathrm{rx},\mathrm{xp},d_w,d_o^{rx},d_o^{il};\boldsymbol{\theta}^{cw}) \hat{f}_h\tilde{f}_d\hat{P}(\mathrm{rx},d_o^{rx},d_o^{il}|h,\mathrm{cw},\mathrm{rx},\mathrm{xp},d_w,t,e) \tag{32}$$

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 laws and must-access PDMP's are introduced. Their effect across latent health should be different depending on 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 (**??**) for all states and choices to estimate the structural parameters. I start with $\delta = 0.50$ and iterate until convergence.

5.4 Result and Model Fit: Predicted Opioid Misuse across Health and Labor Statuses

Table 17 shows the utility parameter estimates. The third column shows that without opioid prescription, having bad mental health and being separated from the labor market increases

Table 14: Transition Probability Estimates for Latent Health Status Conditional on Surviving

	Latent Health (Physical, Mental)		
	(Good, Bad)	(Bad, Good)	(Bad, Bad)
Constant	−0.9019	−4.0012	−1.8499
College	−2.1581	−0.8425	−1.0144
Latent Health			
(Good, Bad)	0.5479	0.4470	0.7338
(Bad, Bad)	0.4806	1.4842	1.3359
(Bad, Bad)	0.6836	1.3791	2.1625
Labor			
Unemployed	0.0623	−0.0811	−0.7025
Unable to Work	0.7480	1.6705	1.6441
Retired	0.0365	1.2441	0.6238
Work Exp	−0.1395	−0.1790	−0.6934
Opioid & Work			
Work	−0.1010	0.6473	−0.3420
Rx'd, No Misuse	−0.0479	0.2908	0.2891
Misuse Rx Opioids	0.3361	0.1758	0.5184
Use Illegal Opioids	0.1253	−0.6348	−0.4812

Notes: Latent health is a two-dimensional variable, (h_1, h_2). The transition probability function for latent health, conditional on surviving this period, has a multinomial logistic functional form where (Good, Good) is the baseline latent health.

Table 15: Transition Probability Estimates for Labor Status

	Labor Status		
	Unemployed	Unable to Work	Retired
No College			
Constant	−2.4538	−1.5689	−1.5520
Unemployed	1.3365	−0.7197	−0.6655
Unable to Work	0.3120	2.1772	1.2566
Retired	0.4216	0.6478	3.9195
College			
Constant	−2.7907	−2.5833	−1.6623
Unemployed	1.4002	−0.3265	0.0538
Unable to Work	0.5139	3.2868	1.4719
Retired	−0.3637	1.0723	3.6767
Next Period's Latent Health			
(Good,Bad)	0.0903	0.3048	0.0542
(Bad,Good)	0.0165	0.3663	0.2609
(Bad,Bad)	0.1172	0.8607	0.3575
Other			
Work Exp	−0.2467	−0.7129	−0.9034
Received Rx	0.2260	0.1269	0.2256
Opioid & Work			
Work	−1.1529	−2.0954	1.3532
Any Opioid Misuse	−0.2003	0.2103	−0.0175

Table 16: Transition Probability Estimates for Opioid Prescription

	Estimates
Constant	-0.686
Next Period's Labor	
Unemployed	0.002
Unable to Work	0.823
Retired	0.056
Next Period's Latent Health	
(Good, Bad)	0.297
(Bad, Good)	0.722
(Bad, Bad)	0.918
Policies × Latent Health	
Must-Access PDMP Only	-0.140
× (Good, Bad)	0.074
× (Bad, Good)	0.048
× (Bad, Bad)	-0.046
State-level Law Only	-0.185
× (Good, Bad)	-0.004
× (Bad, Good)	-0.041
× (Bad, Bad)	-0.050
Both Policies	-0.228
× (Good, Bad)	0.099
× (Bad, Good)	0.042
× (Bad, Bad)	-0.124
State Fixed Effects	Yes

Table 17: Utility Parameters and Perception Bias Estimates

	Opioid Misuse								
	Prescribed		Not Prescribed						
	Rx Only	Both	Illegal Only		Price		Work		Work
Health				*Health*		*Health*		*Rx Misuse*	
(Good, Bad)	-0.32	-0.30	1.02	(Good, Bad)	0.17	(Good, Bad)	-0.62	Constant	1.25
(Bad, Good)	-1.16	-2.12	0.10	(Bad, Good)	0.12	(Bad, Good)	-3.36	× Bad Health	2.03
(Bad, Bad)	-0.47	-0.55	1.69	(Bad, Bad)	-0.14	(Bad, Bad)	-3.01	× Work Exp	-0.20
No College				*Labor*		*Edu & Exp*		*Illegal Use*	
Unemployed	1.43	0.39	1.37	Unemployed	0.44	College	0.67	Constant	1.29
Unable to Work	0.84	1.78	1.45	Unable to Work	-1.33	Work Exp	-5.97	× Bad Health	0.37
Retired	-0.77	-0.73	0.62	Retired	-0.21	College × Exp	-0.16	× Work Exp	0.31
College ×				*Other*		*Bad Health ×*			
Unemployed	0.39	1.95	1.35	Rx'd Opioids	-0.15	Rx'd Opioids	-0.69		
Unable to Work	0.22	2.20	2.32	Constant	-0.03	Work Exp	2.24		
Retired	-0.18	-0.68	0.67						
Other								Baseline Utility u_0	0.58
Work Exp	0.21	0.73	-0.42					Labor Income α	2.27
Constant	-3.00	-3.30	-3.70					Perception Bias δ	0.71

the preference to use illegally traded opioids. The increase in the preference to use illegally traded opioids when the person only experiences bad physical health is small.

The first two columns apply to the situation when people receive prescription opioids. The first three rows in the first column show that people would no longer prefer to misuse prescription opioids or use illegally traded opioids. This also resonates with

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 from "difficult to think" and "difficult to walk." The model is consistent with the data patterns.

The model fits the opioid misuse rate generally well across health and labor. The model over-predicts the opioid misuse rate for "unable to work" and "retired."

	Data			Model		
	Rx Only	Both	Illegal Only	Rx Only	Both	Illegal Only
Proxy: Health (4-level)						
Excellent	0.95	0.31	1.20	0.97	0.48	0.97
Very Good	1.35	0.50	1.84	1.19	0.71	1.39
Good	1.71	0.75	2.22	1.88	1.41	3.04
Fair/Poor	2.79	1.00	2.55	2.01	2.20	6.73
Labor Status						
No Displacement	1.60	0.63	2.00	1.91	1.41	2.13
Unemployed	2.64	1.80	4.07	0.79	0.17	3.59
Unable to Work	3.42	1.03	2.06	0.03	0.72	5.89
Retired	1.71	0.11	0.67	0.03	0.01	3.13

Table 18: Model Fit: Predicted Opioid Misuse by Health and Labor (in Percent), NSDUH 2015-2019

6 Counterfactuals

For counterfactual analysis, I use the 2015 population as a benchmark and decompose the three aggregate changes during 2015-2019: i) increase in the probability of death from opioid misuse, ii) expansion of state-level policies on opioid prescribing, and iii) illicit opioid prices. To do so, I first cast all three effects on the 2015 population and see how much they would have changed their opioid misuse. Then, I also check how the 2015 population would have misused opioids given each element of the aggregate change in 2019. Lastly, I shut down the misperception channel by setting the misperception bias parameter $\delta = 0$ and see how much opioid misuse would decrease.

6.1 Decomposition of the Effects of the Aggregate Changes

Table 19 shows the predicted opioid misuse rate in 2015. The model predicts that about 7.64% of the 2015 population would misuse opioids. The model predicts that people with bad mental health and people who are unable to work are the people who are most likely to misuse opioids. The opioid misuse rate in 2015 decreases by 44% if given the environment in 2019.

The increase in the probability of death from illegal opioid use decreases the opioid misuse rate by 42% by decreasing illegal opioid use. Expansion of state policies does not decrease aggregate opioid misuse rate. Opioid misuse rate for people with unfavorable labor conditions increases. Opioid misuse rate for people with good health decreases. Changes in prices for illegally traded opioids are ineffective. For the decomposition exercise, I first impose the probability of death from opioid misuse in 2019 to the 2015 sample. The expected change in opioid misuse rate is [number not disclosed yet], which is almost all of the predicted change in opioid misuse rate by imposing the 2019 environment. Thus, I conclude that the observed decrease in opioid misuse rate is entirely driven by the probability of dying from opioid misuse. The question is then what was the effect of state-level restrictions on opioid prescribing on opioid misuse. By imposing the state-level policies in 2019 to the 2015 sample, I find that people who are either not separate from the labor market and people who have good physical and mental health reduced opioid misuse. However, those who have been separate from the labor market and those who have bad mental health significantly increase opioid misuse, especially by substituting to illegally traded opioids. The increase in opioid misuse rate among people who are in worse labor and health statuses offset the decrease in opioid misuse rate by the majority of the population, which resulted in no aggregate change in opioid misuse rate. This implies that the state-level policies have had *unequal* unintended consequences that the literature has not been able to disentangle. State-level policies that restrict access to prescription opioids force people who have a stronger motivation to use opioids to substitute for illegally traded opioids, and in the presence of illegally traded opioids becoming more dangerous to use, these people are dying more because of the restrictions. Third, I change the state-level prices to the 2019 level. I find that the change in opioid misuse rate by changing the prices in 2015 to 2019 is negligible. This could be because while the signs of the estimates for price elasticity to illegally traded opioids are reasonable, the size is relatively smaller than other factors. Also, the change in price levels between 2015 and 2019 is smaller despite the fluctuation from 2015 to 2019. To check whether the level change is too small to detect the effect, I also increased the price level by 10 times. As the change in opioid misuse rate is still very small, I conclude that there is no effect of change in price on opioid misuse rate.

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

Table 19: Predicted Opioid Misuse Rate in 2015 in Percent

	Net Effect				Increased Mortality Risk				State-Level Policies				Illicit Opioid Prices			
Latent Health	Rx Only	Both	Illegal Only	Total	Rx Only	Both	Illegal Only	Total	Rx Only	Both	Illegal Only	Total	Rx Only	Both	Illegal Only	Total
(Good, Good)	32.94	-64.10	-66.67	-39.30	35.29	-62.82	-66.67	-38.34	-2.35	-2.56	0.67	-0.96	0.00	-1.28	-0.67	-0.58
(Good, Bad)	40.50	-60.50	-60.74	-44.61	42.15	-59.94	-60.74	-44.22	-1.24	-1.68	0.22	-0.46	0.00	0.00	0.22	0.00
(Bad, Good)	35.56	-67.19	-64.14	-54.34	38.89	-66.41	-64.14	-53.76	-2.22	-3.13	0.46	-0.23	0.00	-0.78	-0.46	-0.35
(Bad, Bad)	63.64	-63.43	-54.75	-52.84	66.23	-62.57	-54.05	-52.01	-1.30	-2.29	0.44	0.10	0.00	-1.14	-1.44	-1.37
Labor	Rx Only	Both	Illegal Only	Total	Rx Only	Both	Illegal Only	Total	Rx Only	Both	Illegal Only	Total	Rx Only	Both	Illegal Only	Total
No Separation	32.94	-64.94	-59.78	-41.99	42.94	-61.99	-61.43	-39.63	-7.06	-7.38	4.41	-2.11	0.59	-0.37	0.28	-0.12
Unemployed	18.42	-64.29	-54.85	-46.88	27.63	-60.71	-57.67	-48.07	-6.58	-7.14	4.76	2.83	0.00	3.57	1.94	1.64
Unable to Work	21.43	-64.62	-53.04	-51.53	26.19	-60.00	-55.10	-52.49	-4.76	-4.62	9.62	7.17	0.00	-5.38	-3.89	-4.02
Retired	16.67	-65.21	-55.31	-53.32	22.22	-61.49	-57.35	-54.84	-11.11	-5.26	5.92	4.93	0.00	0.00	-0.82	-0.76
All	31.06	-64.73	-57.78	-44.30	40.91	-61.84	-59.67	-42.73	-7.58	-7.25	5.42	-0.26	0.00	-2.90	-0.47	-0.39

Table 20: 2015 Population's Change in Opioid Misuse Rate Given 2019's Environment (in Percent)

6.2 Counterfactual: Correcting the Perception Bias

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. The model predicts that shutting down the perception bias channel would decrease the opioid misuse rate by [number not disclosed yet]. While this effect is universal, the effect's size does differ by health and labor status. While the population with good physical and mental health and those not separated from the labor market would benefit the most from the change, people in worse labor and health statuses benefit from this change. This indicates that policymakers may be able to design a cost-effective policy to decrease the opioid misuse rate by targeting more vulnerable populations.

How much would "correcting" the perception bias to 0 decrease opioid misuse? The opioid misuse rate decreases by almost 20%. What has driven the observed change in opioid misuse from 2015 to 2019? State policies induced people with worse health and labor status to use illegal opioids. People reduced opioid misuse by internalizing the increase in the probability of death. Illegal opioid prices do not have a significant effect on opioid misuse. Correcting the perception bias would reduce opioid misuse rate by 20%.

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

Table 21: 2015 Population's Change in Opioid Misuse Rate Given $\delta = 0$ (in Percent)

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 2019 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.

8 Appendix

8.1 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 8.1.1.

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[18]. ARCOS posts opioids dispensed by pharmacies in each county and state in terms of Milligrams of Morphine Equivalent (MME)[19]. 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. (2023a) 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.

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

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

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

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.

8.1.1 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.

8.2 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 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.

Table 22: Summary Statistics of the Restricted NSDUH Samples 23 or Older

	2015	2016	2017	2018	2019
Opioid Use					
Nonuser	0.6175 (0.0037)	0.6361 (0.0033)	0.6438 (0.0034)	0.6615 (0.0034)	0.6789 (0.0034)
Rx User	0.3619 (0.0036)	0.3444 (0.0033)	0.3376 (0.0034)	0.3215 (0.0033)	0.3040 (0.0034)
Misuser	0.0451 (0.0013)	0.0424 (0.0012)	0.0408 (0.0012)	0.0369 (0.0013)	0.0372 (0.0013)
- Rx Only	0.0172 (0.0009)	0.0162 (0.0008)	0.0160 (0.0008)	0.0146 (0.0008)	0.0153 (0.0008)
- Illegal Only	0.0206 (0.0009)	0.0194 (0.0009)	0.0186 (0.0008)	0.0170 (0.0009)	0.0171 (0.0009)
- Both	0.0074 (0.0005)	0.0067 (0.0005)	0.0062 (0.0005)	0.0053 (0.0005)	0.0049 (0.0004)
Heroin: Not a Great Risk	0.1429 (0.0025)	0.1372 (0.0024)	0.1302 (0.0025)	0.1297 (0.0025)	0.1395 (0.0024)
Lifetime Opioid Use before Past Year					
Never Used Opioids	0.3162 (0.0037)	0.3283 (0.0035)	0.3290 (0.0037)	0.3430 (0.0036)	0.3574 (0.0037)
Ever Used Opioids	0.5752 (0.0038)	0.5639 (0.0035)	0.5625 (0.0039)	0.5517 (0.0038)	0.5369 (0.0038)
Ever Misused Opioids	0.1086 (0.0021)	0.1078 (0.0020)	0.1085 (0.0022)	0.1053 (0.0022)	0.1057 (0.0021)
Health (4-levels)					
Excellent	0.2078 (0.0030)	0.2012 (0.0029)	0.2055 (0.0030)	0.2016 (0.0031)	0.1968 (0.0030)
Very Good	0.3508 (0.0034)	0.3543 (0.0034)	0.3610 (0.0033)	0.3538 (0.0035)	0.3560 (0.0037)
Good	0.2964 (0.0033)	0.2984 (0.0035)	0.2896 (0.0032)	0.2991 (0.0034)	0.3014 (0.0034)
Fair/Poor	0.1450 (0.0029)	0.1462 (0.0027)	0.1440 (0.0029)	0.1455 (0.0029)	0.1458 (0.0029)
Disability Measures					
Difficult to Think	0.0679 (0.0018)	0.0671 (0.0017)	0.0731 (0.0019)	0.0697 (0.0017)	0.0754 (0.0018)
Difficult to Do Errands	0.0522 (0.0017)	0.0536 (0.0017)	0.0513 (0.0016)	0.0513 (0.0017)	0.0528 (0.0016)
Difficult to Dress	0.0285 (0.0013)	0.0278 (0.0013)	0.0266 (0.0012)	0.0284 (0.0013)	0.0263 (0.0012)
Difficult to Walk	0.0986 (0.0024)	0.0976 (0.0023)	0.0936 (0.0023)	0.0950 (0.0025)	0.0917 (0.0023)
Difficult to See	0.0446 (0.0015)	0.0437 (0.0016)	0.0429 (0.0015)	0.0445 (0.0016)	0.0451 (0.0015)
Difficult to Hear	0.0556 (0.0019)	0.0563 (0.0018)	0.0583 (0.0019)	0.0573 (0.0018)	0.0574 (0.0019)
Employment					
Work Experience	0.6632 (0.0039)	0.6644 (0.0039)	0.6722 (0.0039)	0.6621 (0.0039)	0.6659 (0.0038)
Working	0.6218 (0.0040)	0.6216 (0.0038)	0.6288 (0.0039)	0.6250 (0.0039)	0.6266 (0.0039)
Not Working	0.3782 (0.0040)	0.3784 (0.0038)	0.3712 (0.0039)	0.3750 (0.0039)	0.3734 (0.0039)
Separation from Labor Market					
No Separation	0.7199 (0.0038)	0.7198 (0.0036)	0.7262 (0.0039)	0.7268 (0.0038)	0.7235 (0.0037)
Unemployed	0.0475 (0.0014)	0.0469 (0.0014)	0.0422 (0.0013)	0.0403 (0.0014)	0.0402 (0.0013)
Unable to Work	0.0570 (0.0017)	0.0545 (0.0018)	0.0498 (0.0016)	0.0504 (0.0018)	0.0508 (0.0017)
Retired	0.1757 (0.0037)	0.1788 (0.0035)	0.1819 (0.0036)	0.1825 (0.0036)	0.1856 (0.0035)
Income					
Less than $10,000	0.1879 (0.0030)	0.1850 (0.0029)	0.1727 (0.0028)	0.1704 (0.0027)	0.1624 (0.0027)
$10,000-$19,999	0.1873 (0.0030)	0.1796 (0.0028)	0.1762 (0.0029)	0.1729 (0.0030)	0.1647 (0.0029)
$20,000-$29,999	0.1390 (0.0025)	0.1375 (0.0024)	0.1336 (0.0025)	0.1377 (0.0026)	0.1352 (0.0025)
$30,000-$39,999	0.1115 (0.0022)	0.1109 (0.0022)	0.1170 (0.0023)	0.1110 (0.0023)	0.1170 (0.0024)
$40,000-$49,999	0.0971 (0.0020)	0.0992 (0.0022)	0.0939 (0.0021)	0.0961 (0.0020)	0.0994 (0.0022)
$50,000-$74,999	0.1286 (0.0024)	0.1313 (0.0025)	0.1349 (0.0025)	0.1390 (0.0025)	0.1414 (0.0025)
$75,000 or more	0.0638 (0.0018)	0.0686 (0.0019)	0.0688 (0.0019)	0.0727 (0.0020)	0.0726 (0.0019)
Age Category					
23-29	0.1385 (0.0022)	0.1375 (0.0021)	0.1374 (0.0024)	0.1335 (0.0023)	0.1340 (0.0022)
30-39	0.1836 (0.0026)	0.1880 (0.0026)	0.1880 (0.0027)	0.1941 (0.0026)	0.1906 (0.0026)
40-49	0.1845 (0.0026)	0.1781 (0.0024)	0.1765 (0.0024)	0.1715 (0.0025)	0.1724 (0.0025)
50-59	0.1993 (0.0033)	0.1958 (0.0032)	0.1899 (0.0033)	0.1861 (0.0031)	0.1827 (0.0033)
60-64	0.0841 (0.0024)	0.0857 (0.0023)	0.0885 (0.0022)	0.0896 (0.0024)	0.0898 (0.0025)
65+	0.2100 (0.0040)	0.2149 (0.0038)	0.2197 (0.0040)	0.2253 (0.0041)	0.2305 (0.0040)
Other					
College Education	0.3252 (0.0045)	0.3335 (0.0044)	0.3480 (0.0047)	0.3436 (0.0048)	0.3552 (0.0047)
Serious Psychological Disorder	0.0927 (0.0018)	0.0950 (0.0019)	0.0979 (0.0020)	0.1007 (0.0020)	0.1099 (0.0021)
Male	0.4794 (0.0035)	0.4790 (0.0034)	0.4795 (0.0033)	0.4797 (0.0034)	0.4802 (0.0033)
Weighted N	221392159	223204946	225894659	227327608	229234558

Note: The samples in the restricted NSDUH are weighted by survey weights, as required by the SAMHSA.

Table 23: Correlation Table across Proxy Variables, Serious Psychological Disorder, Opioid Use Disorder, and Opioid Misuse History, Restricted NSDUH

	Health	Errand	Dress	Walk	See	Hear	Think	SPD	OUD
Errand	0.2426								
	(0.0000)								
Dress	0.1995	0.4731							
	(0.0000)	(0.0000)							
Walk	0.3271	0.4349	0.4379						
	(0.0000)	(0.0000)	(0.0000)						
See	0.1388	0.1929	0.1553	0.2029					
	(0.0000)	(0.0000)	(0.0000)	(0.0000)					
Hear	0.1156	0.1183	0.1107	0.1927	0.1870				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
Think	0.1863	0.3377	0.2177	0.2299	0.1764	0.1156			
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
SPD	0.1339	0.1926	0.1053	0.0907	0.0746	0.0140	0.3047		
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
OUD	0.0507	0.0565	0.0294	0.0246	0.0189	0.0050	0.0760	0.1166	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0246)	(0.0000)	(0.0000)	
Ever	0.0443	0.0468	0.0259	0.0040	0.0148	-0.0070	0.0894	0.1609	0.2413
	(0.0000)	(0.0000)	(0.0000)	(0.0707)	(0.0000)	(0.0016)	(0.0000)	(0.0000)	(0.0000)

Notes: SPD stands for Serious Psychological Disorder, OUD stands for Opioid Use Disorder (recorded only when the person responded they misused opioids in the past 12 months), Ever stands for "ever misused opioids".

Table 24: Proxy Variables for Latent Health

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

Table 25: Row Percentages of Opioid Use by Disability. Restricted NSDUH, 2015-2019.

				Opioid Misuse			
				Prescribed		Not Prescribed	
		Nonuser	Rx User	Rx Only	Both	Illegal Only	Total
Do Errands	No	66.12	30.07	1.45	0.56	1.81	100
	Yes	40.62	51.18	3.95	1.56	2.68	100
Dressing	No	65.67	30.41	1.49	0.59	1.84	100
	Yes	33.76	58.00	4.95	1.29	2.01	100
Seeing	No	67.32	28.74	1.45	0.60	1.88	100
	Yes	40.72	54.23	2.83	0.67	1.54	100
Hearing	No	65.35	30.69	1.53	0.60	1.83	100
	Yes	52.46	41.68	2.69	0.84	2.32	100
Walking	No	65.34	30.62	1.57	0.61	1.86	100
	Yes	55.66	40.36	1.76	0.54	1.68	100
Thinking	No	66.22	30.16	1.39	0.51	1.72	100
	Yes	45.88	44.53	4.12	1.87	3.60	100

8.3 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[20], a conversion chart from Utah Department of Health and Human Services[21], Washington Health Care Authority's conversion table[22]. One milligram of Diamorphine, or heroin, is converted to 3 MME according to the UK National Health Services[23].

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 $\texttt{dosage/mcg} \times 0.001 \times 24 \times 3 \times \texttt{MME}$. 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.

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

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

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

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

Table 26: Average Marginal Effect of Socioeconomic Factors on Work and Opioid Misuse: Not Separated from the Labor Market and Not Received Prescription Opioids

	No Work & Illegal Only	Work & No Misuse	Work & Illegal Only
Health Measure			
Very Good	0.0013	-0.0024	0.0091
	(0.0004)	(0.0028)	(0.0013)
Good	0.0025	-0.0220	0.0157
	(0.0006)	(0.0033)	(0.0017)
Fair/Poor	0.0047	-0.0446	0.0184
	(0.0010)	(0.0055)	(0.0027)
Disability Measures			
Do Errands	0.0025	-0.0235	0.0099
	(0.0013)	(0.0089)	(0.0043)
Dress	0.0052	0.0012	-0.0061
	(0.0036)	(0.0153)	(0.0049)
Walking	-0.0005	-0.0386	0.0185
	(0.0012)	(0.0098)	(0.0076)
Seeing	0.0033	-0.0206	0.0082
	(0.0017)	(0.0079)	(0.0042)
Hearing	0.0005	0.0139	-0.0010
	(0.0013)	(0.0079)	(0.0043)
Thinking	0.0036	-0.0207	0.0220
	(0.0014)	(0.0063)	(0.0038)
Labor			
Work Exp	-0.0120	0.6299	0.0174
	(0.0012)	(0.0057)	(0.0013)
Opioids			
Heroin: Not as Great Risk	0.0007	-0.0120	0.0116
	(0.0006)	(0.0034)	(0.0018)
Policy: State Law	0.0007	-0.0003	-0.0012
	(0.0009)	(0.0042)	(0.0021)
Policy: Must-Access PDMP	0.0012	-0.0022	0.0018
	(0.0016)	(0.0059)	(0.0030)
Illegal Opioid Price	-0.0031	-0.0058	-0.0006
	(0.0026)	(0.0110)	(0.0061)
Other			
College Education	-0.0023	0.0459	-0.0089
	(0.0005)	(0.0025)	(0.0012)
Age Category: 30-39	-0.0003	0.0049	-0.0044
	(0.0007)	(0.0033)	(0.0019)
Age Category: 40-49	-0.0016	0.0239	-0.0160
	(0.0008)	(0.0032)	(0.0017)
Age Category: 50-59	-0.0024	0.0389	-0.0213
	(0.0009)	(0.0039)	(0.0020)
Age Category: 60-64	-0.0037	0.0465	-0.0296
	(0.0009)	(0.0056)	(0.0024)
Age Category: 65+	-0.0037	0.0508	-0.0335
	(0.0008)	(0.0048)	(0.0021)
State FE		Yes	
Year FE		Yes	
Weighted N		564194611	

Source: Restricted NSDUH, 2015-2019. Standard errors in parentheses.

Table 27: Average Marginal Effect of Socioeconomic Factors on Work and Opioid Misuse: Not Separated from the Labor Market and Received Prescription Opioids

	No Work & Rx Only	No Work & Both	Work & No Misuse	Work & Rx Only	Work & Both
Health Measure					
Very Good	-0.0007	-0.0000	-0.0046	0.0064	0.0018
	(0.0015)	(0.0008)	(0.0057)	(0.0032)	(0.0019)
Good	0.0008	0.0014	-0.0237	0.0084	0.0070
	(0.0015)	(0.0009)	(0.0062)	(0.0034)	(0.0021)
Fair/Poor	0.0043	0.0018	-0.0469	0.0150	0.0096
	(0.0020)	(0.0010)	(0.0082)	(0.0051)	(0.0031)
Disability Measure					
Errands	-0.0002	0.0030	-0.0481	0.0114	0.0121
	(0.0016)	(0.0020)	(0.0117)	(0.0077)	(0.0045)
Dress	0.0033	-0.0014	-0.0279	0.0312	0.0135
	(0.0035)	(0.0011)	(0.0196)	(0.0149)	(0.0084)
Walking	-0.0009	-0.0021	-0.0033	0.0018	-0.0077
	(0.0019)	(0.0005)	(0.0102)	(0.0068)	(0.0022)
Seeing	-0.0005	0.0027	-0.0171	-0.0003	-0.0071
	(0.0019)	(0.0019)	(0.0106)	(0.0073)	(0.0023)
Hearing	0.0019	-0.0014	-0.0069	-0.0023	0.0051
	(0.0035)	(0.0012)	(0.0119)	(0.0071)	(0.0049)
Thinking	0.0033	0.0017	-0.0456	0.0273	0.0129
	(0.0017)	(0.0011)	(0.0088)	(0.0063)	(0.0032)
Labor					
Work Exp	-0.0318	-0.0115	0.5921	0.0247	0.0089
	(0.0029)	(0.0016)	(0.0088)	(0.0028)	(0.0016)
Opioids					
Heroin: Not as Great Risk	0.0034	0.0030	-0.0420	0.0170	0.0212
	(0.0018)	(0.0010)	(0.0062)	(0.0038)	(0.0028)
Policy: State Law	-0.0011	0.0021	0.0145	-0.0040	-0.0005
	(0.0017)	(0.0014)	(0.0067)	(0.0042)	(0.0025)
Policy: MA-PDMP	-0.0013	-0.0010	-0.0081	0.0093	0.0034
	(0.0021)	(0.0011)	(0.0102)	(0.0070)	(0.0038)
Illegal Opioid Prices	0.0011	-0.0069	-0.0118	0.0021	0.0009
	(0.0050)	(0.0030)	(0.0209)	(0.0108)	(0.0076)
Other					
College Education	-0.0037	-0.0021	0.0359	0.0084	-0.0047
	(0.0011)	(0.0006)	(0.0045)	(0.0028)	(0.0016)
Age Category: 30-39	-0.0028	-0.0002	0.0266	-0.0160	-0.0081
	(0.0015)	(0.0010)	(0.0058)	(0.0036)	(0.0026)
Age Category: 40-49	-0.0048	-0.0019	0.0622	-0.0232	-0.0189
	(0.0016)	(0.0009)	(0.0058)	(0.0036)	(0.0025)
Age Category: 50-59	-0.0061	-0.0027	0.0813	-0.0305	-0.0202
	(0.0018)	(0.0010)	(0.0067)	(0.0043)	(0.0029)
Age Category: 60-64	-0.0098	-0.0041	0.1049	-0.0285	-0.0278
	(0.0019)	(0.0011)	(0.0094)	(0.0061)	(0.0030)
Age Category: 65+	-0.0085	-0.0049	0.1039	-0.0438	-0.0322
	(0.0020)	(0.0007)	(0.0094)	(0.0051)	(0.0021)
State FE	Yes				
Year FE	Yes				
Weighted N	250949682				

Source: Restricted NSDUH, 2015-2019. Standard errors in parentheses.

Table 28: Average Marginal Effect of Socioeconomic Factors on Work and Opioid Misuse: Separated from the Labor Market and Not Received Prescription Opioids

	No Work & Illegal Only
Health Measure	
Very Good	0.0137
	(0.0029)
Good	0.0176
	(0.0030)
Fair/Poor	0.0179
	(0.0035)
Disability Measures	
Do Errands	0.0027
	(0.0038)
Dress	0.0014
	(0.0056)
Walking	0.0042
	(0.0041)
Seeing	-0.0073
	(0.0034)
Hearing	0.0138
	(0.0063)
Thinking	0.0139
	(0.0039)
Labor	
Unable to Work	-0.0005
	(0.0041)
Retired	-0.0073
	(0.0061)
Work Exp	0.0034
	(0.0029)
Opioids	
Heroin: not as Great Risk	0.0183
	(0.0043)
Policy: State Law	0.0026
	(0.0045)
Policy: MA-PDMP	-0.0045
	(0.0054)
Illegal Opioid Prices	0.0005
	(0.0107)
Other	
College Education	0.0003
	(0.0035)
Age Category: 30-39	-0.0002
	(0.0075)
Age Category: 40-49	-0.0261
	(0.0084)
Age Category: 50-59	-0.0316
	(0.0105)
Age Category: 60-64	-0.0490
	(0.0124)
Age Category: 65+	-0.0588
	(0.0132)
State FE	Yes
Year FE	Yes
Weighted N	186788971

Source: Restricted NSDUH, 2015-2019.
Notes: Standard errors are in parentheses. These effects are computed among the population who are not separated from the labor market. Thus, there are no variables for different types of separation from the labor market in this table. Controls include illegal opioid price, state-level policies in opioid prescribing, year fixed effects, state fixed effects, and cate-

Table 29: Average Marginal Effect of Socioeconomic Factors on Work and Opioid Misuse: Separated from the Labor Market and Received Prescription Opioids

	No Work & Misuse: Rx Only	No Work & Misuse: Both
Health Measure		
Very Good	0.0040	0.0078
	(0.0074)	(0.0036)
Good	0.0063	0.0059
	(0.0066)	(0.0035)
Fair/Poor	0.0104	0.0072
	(0.0070)	(0.0036)
Disability Measures		
Errands	0.0085	0.0025
	(0.0065)	(0.0034)
Dress	0.0174	0.0022
	(0.0077)	(0.0038)
Walking	-0.0024	-0.0023
	(0.0051)	(0.0030)
Seeing	0.0083	0.0012
	(0.0065)	(0.0037)
Hearing	-0.0002	0.0019
	(0.0062)	(0.0040)
Thinking	0.0150	0.0092
	(0.0054)	(0.0036)
Labor		
Unable to Work	-0.0194	-0.0147
	(0.0094)	(0.0044)
Retired	-0.0354	-0.0141
	(0.0114)	(0.0057)
Work Exp	0.0147	0.0015
	(0.0073)	(0.0022)
Opioids		
Heroin: Not as Great Risk	0.0209	0.0178
	(0.0066)	(0.0035)
Policy: State Law	0.0042	0.0021
	(0.0074)	(0.0033)
Policy: MA-PDMP	-0.0005	-0.0031
	(0.0097)	(0.0045)
Illegal Opioid Prices	-0.0078	-0.0189
	(0.0201)	(0.0109)
Other		
College Education	-0.0046	-0.0011
	(0.0056)	(0.0028)
Age Category: 30-39	-0.0030	0.0006
	(0.0077)	(0.0065)
Age Category: 40-49	-0.0129	-0.0160
	(0.0079)	(0.0076)
Age Category: 50-59	-0.0145	-0.0199
	(0.0084)	(0.0088)
Age Category: 60-64	-0.0251	-0.0284
	(0.0092)	(0.0096)
Age Category: 65+	-0.0241	-0.0338
	(0.0106)	(0.0093)
State FE	Yes	
Year FE	Yes	
Weighted N	125120666	

Source: Restricted NSDUH, 2015-2019.
Notes: Standard errors are in parentheses. These effects are computed among the population who are not separated from the labor market. Thus, there are no variables for different types of separation from the labor market in this table. Controls include illegal opioid price, state-level policies in opioid prescribing, year fixed effects, state fixed effects, and categorical variables for age. See the appendix for the full result.

The formula for computing the amount of opioids is

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

8.4 Estimates

Full results from the restricted NSDUH and NVSS are pending disclosure approval (paused due to recent federal administration restructuring).

Table 30: Prior Distribution of Latent Health by Education $\mathrm{P}(h = (h_1, h_2)|e)$

	Latent Health (Physical, Mental)			
	(Good, Good)	(Good, Bad)	(Bad, Good)	(Bad, Bad)
No College	0.5813	0.2578	0.0248	0.1361
College	0.6857	0.0551	0.1358	0.1234

References

Abbring, J., \. \. Daljord, and F. Iskhakov (2019). Identifying present-biased discount functions in dynamic discrete choice models. Technical report.

Adams, E. T., R. L. Nabi, S. M. Noar, R. Evans, and L. Widman (2022). How emotional shifts effect youth perceptions of opioid risk and efficacy: Testing a know the truth campaign narrative. *Health Communication 37*(14), 1820–1831.

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

Arcidiacono, P. and R. A. Miller (2011). Conditional choice probability estimation of dynamic discrete choice models with unobserved heterogeneity. *Econometrica 79*, 1823–1867.

Arcidiacono, P. and R. A. Miller (2019). Nonstationary dynamic models with finite dependence. *Quantitative Economics 10*, 853–890.

Balestra, S., H. Liebert, N. Maestas, and T. Sherry (2023a). Behavioral responses to supply-side drug policy during the opioid epidemic. SSRN Electronic Journal.

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

Becker, G. S. and K. M. Murphy (1988). A theory of rational addiction. *Journal of Political Economy 96*, 675–700.

Case, A. and A. Deaton (2017). Mortality and morbidity in the 21st century. *Brookings Papers on Economic Activity 2017*, 397.

Currie, J., J. Jin, and M. Schnell (2019). Health and labor markets - us employment and opioids: Is there a connection? *Research in Labor Economics 47*, 253–280.

Greenwood, J., N. Guner, and K. A. Kopecky (2022). The downward spiral. Technical report, SSRN.

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

Hu, Y. and M. Shum (2012). Nonparametric identification of dynamic models with unobserved state variables. *Journal of Econometrics 171*, 32–44.

Hu, Y. and Y. Xin (2023). Identification and estimation of dynamic structural models with unobserved choices. Technical report, SSRN.

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

Kasahara, H. and K. Shimotsu (2009). Nonparametric identification of finite mixture models of dynamic discrete choices. *Econometrica 77*, 135–175.

Kim, B. (2021). Must-access prescription drug monitoring programs and the opioid overdose epidemic: The unintended consequences. *Journal of Health Economics 75*, 102408.

Maclean, J. C., J. Mallatt, C. J. Ruhm, and K. Simon (2021). Economic studies on the opioid crisis: Cost, causes, and policy responses.

Mukherjee, A., D. W. Sacks, and H. Yoo (2025). The effects of the opioid crisis on employment: Evidence from labor market flows. *Journal of Human Resources 60*(3), 780–811.

Mulligan, C. B. (2024). Prices and policies in opioid markets. *Journal of Political Economy 132*(10), 3461–3499.

O'Donoghue, T. and R. Matthew (1999). Doing it now or later. *American Economic Review 89*, 103–124.

O'Donoghue, T. and M. Rabin (2015). Present bias: Lessons learned and to be learned. *American Economic Review 105*, 273–279.

Pardo, B., J. Taylor, J. P. Caulkins, B. Kilmer, P. Reuter, and B. D. Stein (2019). The future of fentanyl. Technical report, RAND Corporation.

Sacks, D. W., A. Hollingsworth, T. Nguyen, and K. Simon (2021). Can policy affect initiation of addictive substance use? evidence from opioid prescribing. *Journal of Health Economics 76*, 102397.

Schnell, M. (2022). Physician behavior in the presence of a secondary market: The case of prescription opioids. Technical report, Princeton University.