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

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Abstract

This paper studies the heterogeneous effect of state-level policies on opioid prescribing by focusing on the interaction of health and labor. This paper highlights the role of opioid misuse risk perception as the point where the policies and labor environment meet. By estimating a dynamic discrete choice model of opioid misuse and work, I quantify the substitution toward illegal opioids by the policy across different types of displacement from labor. Counterfactual scenarios targeting the illegal opioid market, labor dynamics, and the opioid misuse risk perception are discussed.

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

JEL: C35, C53, C61

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1 Introduction

The opioid crisis in the United States has claimed over half a million lives from 1999 to 2020, and the mortality rate by opioid overdose is increasing every year[1]. State governments began to enact laws on prescribing opioids to tackle the opioid crisis, as well as the Prescription Drug Monitoring Program (PDMP) to restrict opioid prescribing. The state-level laws on prescribing opioids and PDMPs have one goal in common: decrease mortality from opioid overdose.

figures/opioid_deaths_by_year.png

Figure 1: Deaths by Opioid Overdose in the United States, 2000-2020

figures/state_restrictions_by_year_statenames.pr

Figure 2: States with Laws that Restricts Opioids Prescribing, 2013-2020

However, the literature paid little attention to understanding various reasons why people misuse opioids and how people would react to counterfactual policies. In this paper, I study a dynamic discrete choice framework that captures various aspects in which people may misuse prescription and illegal opioids: to cope with physical and mental health, "frustration" from labor market participation, and perceiving opioid misuse as not a great risk.

This paper highlights opioid misuse as a choice based on the interplay of state-level policies on prescribing opioids, health, and labor. It is well-documented that policies

[1] `https://www.cdc.gov/drugoverdose/deaths/opioid-overdose.html`, retrieved on September 30, 2023

like the Prescription Drug Monitoring Program (PDMP) and state-level restrictions on the initial prescribing of opioids decreased prescription rates on an extensive margin but also have unintended consequences for increasing opioid overdose deaths. However, it is not known whether these policies have heterogeneous effects across socioeconomic groups. This paper highlights these policies' unintended consequences via labor transitions.

Opioid misuse is a medical term defined as using opioids in any way not as directed by a doctor in terms of the amount, duration, frequency, and using opioids with or without a prescription. While the literature focuses on the effect of supply-side interventions on prescribing opioids, little attention is paid to understanding why people misuse opioids as a choice. Understanding opioid misuse behavior would shed light on finding a better policy for decreasing opioid misuse and overdose deaths.

The motivation for these restrictions is that excessively prescribing opioids led to increases in opioid overdose deaths. Also, these restrictions are imposed because people have a bad idea about the risk of misusing opioids.

Despite the state government's efforts to curb the trend, the mortality rate by opioid overdose has become the leading cause of death in the prime working age group. The literature on the opioid crisis has reached the consensus that opioid overdose deaths have increased because of these supply-side interventions.

While the "unintended consequence" of supply-side intervention has been well-documented, little attention is paid to how opioid misuse has changed by the policy. Surprisingly, from 2015 to 2019, opioid misuse has decreased overall. Meanwhile, opioid misuse, Opioid Use Disorder, and opioid overdose deaths are prevalent in the prime working age. Linking opioid misuse as a precursor to Opioid Use Disorder and Opioid overdose death, I ask, "Who are the winners and losers from these policies?"

This paper focuses on the interaction between opioid misuse and labor as a channel through which the policy's effect propagates. Also, this paper highlights the role of the perception of the risk of misusing opioids as amplifying the heterogeneous effect of opioid misuse and, thus, Opioid Use Disorder and overdose deaths.

I develop a dynamic discrete choice model of work and misusing opioids. The choice set for working and opioid misuse depends on the individual's displacement from the labor market and prescription to opioids. The individual understands misusing opioids may cause opioid use disorder and death by opioid overdose, but his evaluation differs by his perception of the risk of misusing opioids.

The model captures the trade-off individuals make with labor and opioid misuse, compensating for the disutility of being displaced from labor and the consequences of opioid use. The model can then quantify the substitution toward illegal opioids on the extensive margin across different types of displacement from labor. By doing so, this paper evaluates the heterogeneous effects of the recently imposed state-level policies via labor. The model can also quantify how much the change in the perception of the risk of misusing opioids affects opioid misuse.

The estimation of the model extends the "two-step" conditional choice probabilities estimator by incorporating finding the finite dependence paths with perception bias (see Arcidiacono and Miller (2011), Arcidiacono and Miller (2019), and Hwang (2020) for details). Applying the two-step CCP estimator with finite dependence with perception bias is complicated because the perceived transition probabilities change for each guess of the perception bias. This paper extends the finite dependence search process by guessing the degree of bias, search for finite dependence, estimate the structural parameters, update the bias, and continue until convergence.

The estimation result using public data shows that the interaction of opioid misuse provides an intuition of the observed data patterns.

The counterfactual analysis shows that correcting the perception of opioid misuse risk would not reduce opioid misuse risk. Increasing illegal opioid prices would be very costly, as increasing it by 100 times decreases opioid misuse by 1%. Higher recovery rate from labor market participation constraint is estimated to show

Section 2 describes data patterns in 2015-2019 for associations across policy, health, and labor. Section 3 presents the model of work and opioid misuse with perception bias. Section 4 explains the identification of the model parameters. Section 5 describes the estimation procedure. Section 7 provides counterfactual scenarios.

2 Literature on Opioid Crisis

This paper contributes to the literature by evaluating the heterogeneous effect of health policies via labor. The paper quantifies the heterogeneous elasticities of opioid misuse across different socioeconomic status. This paper extends to findings for the "unintended consequences" of supply-side interventions from event studies like Alpert et al. (2018) (OxyContin reformulation in 2010) and Kim (2021) (Must-Access Prescription Drug Monitoring Program) by characterizing the decision process of an individual and analyzing who is more affected by the state-level restrictions on opioid prescribing.

This paper adds to the literature empirical evidence that opioid misuse and labor market conditions, on top of health and policy variations, are strongly related. The consensus in the literature seems that the labor market conditions and the opioid crisis are correlated at a macro-level, but empirical evidence from individual-level data show mixed results[2]. Papers that show a positive relationship between unfavorable macroeconomic conditions and opioid overdose include Greenwood et al. (2022), Mulligan (2022), Dow et al. (2020), Harris et al. (2020), Venkataramani et al. (2020), Park and Powell (2021), Mukherjee et al. (2023), Charles et al. (2019),Deiana and Giua (2018), Hollingsworth et al. (2017), Currie et al. (2019), Beheshti (2022), and Aliprantis et al. (2022). Papers that study the relationship between individual employment history and opioid prescriptions include Laird and Nielsen (2016) and Maclean et al. (2015).[3] This paper utilizes individual-level data on opioid misuse to quantify how much labor market conditions induce opioid misuse.

This paper is close to Greenwood et al. (2022) and Balestra et al. (2023), as I analyze opioid use behavior in conjunction with state-level restrictions on opioid prescribing and work decisions. My paper is different from Balestra et al. (2023) as I focus on the post-2014 period, where we already have illegal opioids available in

[2]See Maclean et al. (2021) for detailed discussion.

[3]On a more neutral view, Finkelstein et al. (2021) find that opioid abuse is associated with location-specific characteristics based on the Social Security Disability Insurance (SSDI) data. The authors attribute the location-specific factors to areas with higher prescription rates, but my model also captures the state-level variations in socioeconomic transitions.

the streets, and that I am focusing on the state-level restrictions rather than the Prescription Drug Monitoring Programs, which is what the literature on the opioid crisis has been focusing on. I depart from Greenwood et al. (2022) as I consider the wider variety of dynamics in terms of prescription, constraint to work, and health status. Greenwood et al. (2022) fits a Markov chain of various stages in opioid use at the aggregate economy, but I use variation in the state-level restrictions to specify the channel where the prescription policy comes in and how this policy affects various aspects of an individual. Also, I endogenize labor as a choice that interacts with opioid misuse, along with health status to capture work decision's interaction with opioid misuse. Greenwood et al. (2022) assumes that nonusers always work, which is not always the case. Also, by allowing heterogeneous opioid use behavior across age groups, I can further evaluate which group, young versus old, is more affected by the state-level policies and labor market constraints and how much. To the extent of my knowledge, only Greenwood et al. (2022) considers a dynamic model of opioid use to predict the effects of various policies on opioid use and overdose death rate. Although the approach is similar, I focus on 2015-2019 to evaluate state-level restrictions that happened during this period, allow the individuals to choose labor supply while facing labor market shocks, and allow the individuals to be heterogeneous toward risk aversion to using opioids not as directed by a doctor. These differences fit the data patterns that, the prime working age are more impacted than other age groups, while prescription rates are higher as people age, and people with lower risk aversion to using illegal opioids actually use them not as directed by a doctor. These data patterns all imply that state-level restrictions on opioid prescription are insufficient to deal with the opioid epidemic. I also provide intuition through the model that people face trade-offs between safer but more expensive prescription opioids and cheaper but more dangerous illicit opioids. Most importantly, while Greenwood et al. (2022) captures the potential complementarity of opioid use not as directed by a doctor and not working, I capture that not working due to labor market shocks and not working by choice have different effects to opioids use not as directed by a doctor.

This paper complements Schnell (2022) by focusing on the demand side of using opioids and documenting the substitution mechanism between prescription opioids and illicitly traded opioids. Schnell (2022) concerns an equilibrium model of physicians and patients in a primary market considering the existence of a secondary market. While Schnell (2022) abstracts away from illicitly traded opioids like heroin and fentanyl, this paper simplifies the primary market by being prescribed an opioid as a function of the individual's health profile and state-level policy. Instead, I focus on the decision of opioid misuse along with its negative health consequences and labor supply. Also, this paper covers the entire U.S. landscape of the opioid crisis at the state level by exploiting state-level variations in state policy and state-level population distributions.

Broadly, my paper is related to economic studies in substance addiction. Since Becker and Murphy (1988), the rational addiction model has been a base model to rationalize substance addiction given observational data. Addiction studies using rational addiction framework include Greenwood et al. (2022), Hai and Heckman (2022), Dragone and Raggi (2018), Carpenter et al. (2017), Gordon and Sun (2015), Arcidiacono et al. (2007), Baltagi (2007), Gruber and Köszegi (2001), Chaloupka (1991), Grossman and Chaloupka (1998), Grossman et al. (1998), Becker and Murphy (1988), and Boyer (1983). Although slightly different, this paper shares the philosophy of 'rational self-medication' (Darden and Papageorge (2018)). We see a sharp increase in the mortality rate by synthetic opioids not only because people suffer from Opioid Use Disorder but also because they now have stricter access to safer prescription opioids. Thus, people choose to alleviate pain and withdrawal with more narcotic opioids in the short run in exchange for more harmful consequences. One of the distinct features of this class of model is that the individual accumulates addiction stock as she continues to consume the addictive good. In my model, the addiction is characterized by Opioid Use Disorder, which occurs randomly by opioid use. The heterogeneity in risk aversion to using heroin, by default illegal opioids, is incorporated to show the heterogeneous effects of state-level restrictions on different types of individuals.

This paper uses a dynamic discrete choice model to characterize opioid use behavior. As such, the paper is close to the recent work in the identification and estimation of dynamic discrete choice models with unobserved heterogeneity (**?**, Hu and Shum

(2012), Kasahara and Shimotsu 2009), partially unobserved choices **?**), unobserved heterogeneity in endogenous transition probabilities (Hwang (2020)). The difference is that the data does have what happens to the addiction state after the decision is made, but the addiction state upon choice is unobserved. Similar to Hwang (2020), the transition matrix is unobserved and similar to **?**, I do not observe the full transition probabilities due to data restrictions. This paper utilizes the two solutions to unobserved components: opioid use disorder and joint transition probability. The identification of the model relies on parametric assumptions on the joint transition probabilities, the order in which the unobserved heterogeneity and observed transition probabilities are revealed. In this sense, the paper is closely related to Hwang (2020) and **?**. Hwang (2020) considers identifying a DDC model with endogenous unobserved heterogeneity when a researcher has proxy variables for the unobserved heterogeneity at hand. **?** consider DDC models where researchers do not observe choices directly. In this paper, I use proxies to identify the individual's probability of experiencing OUD before opioid misuse.

This paper's model introduces opioid misuse risk perception as a random realization in each period. While this is a simple way to introduce a behavioral aspect to opioid misuse, estimating the DDC model with it is complicated because it distorts the actual transition probabilities in the model. In CCP estimation using finite dependence, finding the decision weights that achieves finite dependence is a function of the magnitude of the perception's effect on distorting the belief from rational belief. This paper shows that in the case where the perception bias is a random realization in each period, then we can first find finite dependence paths conditional on the person has been rational for multiple periods, and then we can find the rest of finite dependence path as a known function to the benchmark finite dependence path.

3 Data Patterns

In this section, I provide descriptive evidence of how opioid misuse is associated with labor, health, and policy. The data patterns come from the public National Survey of Drug Use and Health (NSDUH) and the public National Vital Statistics System (NVSS)[4]. The details of data sources are in the appendix.

I classify people into three groups in terms of exposure to opioids. The first group is non-users, defined as those who did not use opioids, either via prescription or misuse in the past 12 months. The second group is the prescription opioid users. This group used their prescribed opioids as directed by a doctor and did not misuse opioids in the past 12 months. The third group is opioid . They have used i) prescribed opioids not as directed by a doctor in any way, ii) used opioids that are not prescribed to them, or iii) both.

There are two direct outcomes due to opioid use: Opioid Use Disorder (OUD) and opioid overdose death[5]. Opioid Use Disorder can occur even when people are using opioids as directed by a doctor. Opioid overdose death can occur when people misuse opioids.

3.1 Opioid Use and Working Age Group

Opioid use by age profile shows that opioid misuse is not simply affected by the rate of opioid prescription. Table **??** shows the percentages of nonusers, prescription opioid users, opioid without Opioid Use Disorder, opioid with Opioid Use Disorder, and deaths during 2015-2019. From 2015 to 2019, as more states imposed restrictions on opioid prescribing, we see that smaller fractions of people are prescribed opioids and misuse opioids.

Looking at this period across ages sheds light on the skepticism that the state-level restrictions is not targeting the right group of people. Prescription opioids are more likely to be associated with older people. On average, about 15% of youths have been prescribed opioids and used as directed by a doctor in the last 12 months during 2015-2019. The exposure to prescription rate increases steadily to 35% when people

[4]Results from restricted NSDUH and NVSS pending approval for disclosure.

[5]The NSDUH from 2015 to 2019 classify people with Opioid Use Disorder as those who i) used opioids not as directed by a doctor in the past 12 months, and ii) suffered from adverse effects from opioids defined by the Diagnostic and Statistical Manual of Mental Disorders, 4th edition (DSM-IV). This excludes people who have used opioids as prescribed by their doctors and are suffering from Opioid Use Disorder. I consider this group by using NSDUH 2021.

reach 65 and over. However, the percentage of people who misuse prescription opioids or misuse opioids without her prescriptions is hump-shaped across age profiles. The percentage of people misusing opioids peak in age groups of 18-25 and 26-34, with 6.85% and 6.61%. The percentage then decreases to 1.38% amongst the elderly.

The hump-shaped trend is also in the mortality rate, highlighting the opioid epidemic's heterogeneous effect on prime working age. While overall mortality rates steadily increase from 0.02% to 4.01% across age groups, mortality rates by opioid overdose account for nearly 15% of deaths amongst 18-25, about 20% of deaths amongst 26-34, and about 10% of deaths amongst 35-49%. A similar trend is observed in Figures **??** and **??**. From 2015 to 2019, more states imposed restrictions on prescribing opioids. As time passes, while mortality rates by opioid overdose with prescription opioids are steady, those by opioid overdose with illegal opioids (e.g., fentanyl) have increased. Despite the changes, the hump-shaped curve across age groups is also persistent.

This hump-shaped trend across age profiles motivates the program evaluation of supply-side interventions through the lens of the decision process of opioid misuse. For the supply-side hypothesis to be valid, more exposure to opioids must have been increasing opioid misuse, Opioid Use Disorder, and mortality rates. However, although prescription rates are higher among the elderly, the fraction of people misusing opioids is more prevalent amongst the younger generation.

Table **??** shows that constraints to work are associated with opioid misuse. I consider two kinds of constraints to work: "laid off" and "unable to work."[6] Being laid off is strongly correlated with opioid misuse but not with the prescription of opioids. In contrast to "laid off," being unable to work is positively correlated with the prescription of opioids to relieve potential pain the individual is going through.

3.2 Opioid and Death by Opioid Overdose

Table **??** shows that the fraction of people using opioids not as directed by a doctor has been decreasing while the mortality rate from opioid overdose has been increasing

[6]"Retired" is also considered a working condition, but only when people are above 60.

during 2015-2019. The first panel shows the US population's percentage of people in terms of exposure to opioids. According to the NSDUH, about 32% of the population was prescribed opioids and used as directed by a doctor in 2015 at some point in the past 12 months. 4.76% of the population were using opioids not as directed by a doctor, either with their prescribed opioids or opioids purchased elsewhere. The percentage of people not used opioids in the past 12 months has risen to 70% in 2019, and accordingly, using opioids not as directed by a doctor declined to 3.69%. The fraction of people dying from opioids, however, has risen over the years. During 2015-2019, about 0.97% of the population died. About 1.23% of total deaths were attributed to opioid overdose deaths in 2015, while it steadily increased to 1.76% in 2019.

The mortality rate is the number of deaths divided by population multiplied by 100,000. The two-way fixed effect regression

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

As predicted in Figures **??** and **??**, the coefficients β_0 is positive for synthetic opioids, negative for heroin, and (insignificant) positive for prescription opioids.

3.3 Synthetic Opioids & Heroin vs. Prescription Opioids

The increase in the mortality rate by opioid overdose is primarily driven by synthetic opioids, which are considered to be illegally traded[7]. Hereafter, synthetic opioids and heroin are defined as illegal opioids.

Figures **??** and **??** count any deceased who are found to have illegal or prescription opioids. Figures that show mortality rates with only illegal opioids or only prescription

[7] Currently, the mortality data on opioid overdose do not distinguish pharmaceutical fentanyl from illegally produced fentanyl. The CDC instead reports opioid overdose deaths by synthetic opioids except for Methadone to account for the increase in opioid overdose deaths involving fentanyl. Conversely, natural opioids, semi-natural opioids, and Methadone are considered to be prescription opioids in the mortality data. Previous studies show that synthetic opioid deaths are not correlated with fentanyl prescription rates but with the number of drug submissions confiscated by law enforcement that tested positive for fentanyl (see Gladden et al. (2016) and Peterson et al. (2016).)

opioids further indicate that there might be substitution toward illegal opioids when prescription opioids are not provided. Recall that during 2015-2019, states began imposing restrictions on opioid prescriptions. If these were effective in prescription rates, the mortality rate by only prescription opioids would decrease, as shown in figure **??**. However, there are unintended consequences of the state-level restrictions, as shown in Figure **??**. While one may think that there is only unintended consequences of state-level policies where people are dying from illegally traded opioids, this is not the case in aggregate. During 2015-2019, people do seem to be reducing using illegally traded opioids. In this sense, this paper delves deeper into who are more substituting toward illegal opioids, i.e., getting disadvantaged to the state-level policies.

3.4 State Restrictions on Prescription Opioids

I use aggregate data to proxy for opioid prescription rate. The first measure is Opioid Rx per 100 population in state g in year t, Rx/100. The second measure is the amount of opioids dispensed in state g in year-**quarter** t. I run two-way fixed effects regression to show that state-level restrictions indeed are associated with smaller dispense of opioids.

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

β_0 captures the association between the state-level restrictions and the opioid dispense rate. The coefficient is statistically negative. I capture this decrease in the extensive margin in the model.

Lastly, I am interested in whether the prices for illegally traded opioids are correlated with the state-level restrictions on prescription opioids. I ran a two-way fixed effects regression to associate the average reported price per MME for illegally traded prices in state g and year t during 2013-2019:

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

β_0 captures the association between the state-level restrictions and the average reported price for illegal trade prices. I find a statistically insignificant estimate[8]. Based on this finding, I assume that illegal opioids have a flat supply curve so that the state-level restrictions only affect opioid prescription on an extensive margin.

These associations found in the data set are interesting but do not uncover the "deep parameters" that govern the data-generating process. Labor and opioid misuse choices are affected by labor and health conditions, and vice versa. In particular, those choices are made with consideration on its future outcomes, like adverse labor and health conditions, including Opioid Use Disorder and death. Thus, this paper builds a model of work and misusing opioids.

4 Model

The model characterizes an infinite horizon individual optimization problem with endogenous death probability. The individual is endowed with a given education and state location. In each period, the individual observes the state-level restrictions on opioid prescribing and prices for illegally traded opioids. He knows his work experience from his previous working decisions and his latent physical and mental health status. In a given period, the individual may be displaced from labor given his latent health and working decision last year. Then, the individual is prescribed opioids based on his latent health condition and state-level restrictions on opioid prescribing. Finally, he forms the perception of opioid misuse risk based on what happened during this period. Then, he makes decisions to work and to use opioids. He faces a risk of death in each period based on his health and opioid misuse. If he survives, then he continues to live with new illegal opioid prices, state-level policies, etc. The individual expects that the policies and prices will remain the same.

[8] A revised regression table pending.

4.1 State Variables and Choice Set

In each year t, each state location g has state-level restriction $r_{g,t}$, which affects opioid prescription rates at the state level by year. There are also prices at the state level for illicit opioids $p^{il}_{g,t}$.

The individual carries two states from the previous period: $xp = \mathbf{1}\{\text{Worked in the previous period}\}$ and $s = (s_1, s_2)$ where $s_1 \in \{L, H\}$ and $s_2 \in \{L, H\}$. Then, the individual stochastically experiences shocks to displacement from the labor market, cw. There are three kinds of displacement from labor:

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

Retirement occurs exogenously, and its transition probability depends on the previous working decision and past year labor market displacement.

Then, the individual is prescribed opioids represented by $rx = \mathbf{1}\{\text{Prescribed with Opioids}\}$[9]. Lastly, the individual forms opioid misuse risk perception, $\pi = \mathbf{1}\{\text{“Misusing” opioids has no great risk}\}$. If $\pi = 1$, the individual has a discrepancy in the belief from the actual probability that he will die from opioid misuse.

The individual can work or misuse opioids each period. Denote d_w, d^{rx}_o, and d^{il}_o as

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

follows:

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

Denote all possible actions by $j = 1+d_o^{il}+2d_o^{rx}+4d_w$ and let $d_j := \mathbf{1}\{\text{Chooses action } j\}$. The choice set is affected by i) being displaced from labor and ii) being prescribed opioids. If the individual is displaced from labor, he cannot work during this period. Using illegal opioids is always an option regardless of receiving prescription opioids. However, the individual can misuse his prescribed opioids only if he is prescribed one. Also, if he is prescribed opioids, then he must misuse prescription opioids first before using illegal opioids. Formally, the choice set $\mathcal{J}(\mathbf{1}\{cw \neq 0\}, rx)$ is defined as:

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

.

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

Once the individual chooses an action, death is realized. The probability of dying is conditional on the individual's health and decision to misuse opioids. If he dies, the problem ends with receiving a terminal disutility of death, $W = 0$. Figure (**??**) summarizes the decision process in each period.

For simplify notation, I will use $\Omega_g = (g, r_{g,t}, p_{g,t}^{il}, p_t^{rx})$ to denote all variables relevant to opioid prescriptions and prices, $\Omega_a = (a, e, xp, cw, bh, rx)$ to denote all state variables except for Opioid Use Disorder s, the perception of the risk of misusing opioids π, and the vector of idiosyncratic shocks $\boldsymbol{\varepsilon}$. Thus, the state space is defined by $\Omega = (\Omega_g, \Omega_a, s, \pi_o, \boldsymbol{\varepsilon})$.

4.2 Per-period Utility

The individual receives a flow utility in each age based on her action $j \in \mathcal{J}(\mathbf{1}(cw \neq 0, rx))$. The utility function consists of four additively separable terms: baseline income, income from working, utility from opioid "misuse", and choice-specific idiosyncratic error:

$$u_j(\Omega_a, s, \pi, \boldsymbol{\varepsilon}; \boldsymbol{\theta}^y, \boldsymbol{\theta}^w, \boldsymbol{\theta}^o) = \underbrace{\bar{y}(\Omega_a; \boldsymbol{\theta}^y)}_{\text{Baseline Income}} + \underbrace{y(\Omega_a, s, d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^w) d_w}_{\text{Income from Working}} + \underbrace{u_o(\Omega_a, \Omega_g, s, d_w, d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^o)}_{\text{Utility from "misusing" opioids}} + \varepsilon_j.$$

Each term in the utility function has the following functional form:

$$\begin{aligned}
y(\Omega_a, s, d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^w) =& \theta_1^w + \theta_2^w e + \theta_3^w \frac{a}{10} + \theta_4^w (\frac{a}{10})^2 + \theta_5^w \mathbf{1}\{a = 65\} \\
&+ \theta_6^w \frac{a}{10} e + \theta_7^w (\frac{a}{10})^2 e + \theta_8^w \mathbf{1}\{a = 65\} e \\
&+ \theta_9^w bh + \theta_{10}^w s + \theta_{11}^w bh\, rx + \theta_{12}^w bh\, d_o^{rx} + \theta_{13}^w d_o^{il} + \theta_{14}^w d_o^{rx}\, d_o^{il} \\
u_o(\Omega_a, \Omega_g, s, d_w, d_o^{rx}, d_o^{il}) =& \sum_{k=1}^{2} \mathbf{1}\{cw = k\} (\theta_{3k-2}^o d_o^{il} + \theta_{3k-1}^o d_o^{rx} + \theta_{3k}^o\, d_o^{rx}\, d_o^{il}) \\
&+ bh(\theta_7^o d_o^{il} + \theta_8^o d_o^{rx} + \theta_9^o d_o^{rx}\, d_o^{il}) \\
&+ s(\theta_{10}^o (1 - d_o^{il}) + \theta_{11}^o (1 - d_o^{rx}) + \theta_{12}^o (1 - d_o^{rx})\, (1 - d_o^{il})) \\
&+ (1 - d_w)(\theta_{13}^o d_o^{il} + \theta_{14}^o d_o^{rx} + \theta_{15}^o d_o^{rx}\, d_o^{il}) \\
&+ \theta_{16} rx p_t^{rx} + \theta_{17} d_o^{il} p_{g,t}^{il}
\end{aligned}$$

The baseline income $\bar{y}(\Omega_a; \boldsymbol{\theta}_0^y)$ approximates earnings over the life cycle outside of working. Income from working $y(\Omega_a, s, d_o^{rx}, d_o^{il}; \boldsymbol{\theta}_0^y)$ captures not only direct income from working conditional on the individual's state variables, but also potential changes in productivity from opioid prescription, opioid use disorder, and opioid "misuse". Utility from opioid "misuse" captures various potential reasons why people "misuse" opioids. The first line captures how much people "misuse" opioids to compensate for the disutility of being displaced from labor. The second line captures the utility of "misusing" opioids when people are in bad health. The third line captures the disutility of not "misusing" opioids when the individual has Opioid Use Disorder. The fourth line captures the complementarity of "misusing" opioids and leisure (not working). The last line captures the implied monetary cost of using opioids measured with opioid prices.

4.3 Transition Probabilities

The transitions for the state variables are defined as follows. First, after making an action j, death is realized this period.

$$f(dth|a, e, s', d_{rx}, d_{il}; \boldsymbol{\theta}^d) = \sum_{c \in D} f(c|a, e, s', d_{rx}, d_{il}; \theta^d_c)$$

where each cause of death takes the following functional form:

$$\begin{aligned}
f_d(dth_{ocd}|a, e, s', d_{rx}, d_{il}; \theta^d_{ocd}) &= \frac{\exp(x'_{ocd}\theta^d)}{1 + \exp(x'_{ocd}\theta^d)} \\
f_d(dth_{rx}|s', d_{rx}, d_{il}; \theta^d_{rx}) &= \theta^d_{rx} d_{rx} + \theta^d_s s' \\
f_d(dth_{il}|s', d_{rx}, d_{il}; \theta^d_{il}) &= \theta^d_{il} d_{il} + \theta^d_s s' \\
f_d(dth_{bth}|s', d_{rx}, d_{il}; \theta^d_{bth}) &= \theta^d_{bth} d_{rx} d_{il} + \theta^d_s s'
\end{aligned}$$

where $x_{ocd} = [1, e, \left(\frac{a}{10}\right), \left(\frac{a}{10}\right)^2, \mathbf{1}(a = 65), \left(\frac{a}{10}\right) e, \left(\frac{a}{10}\right)^2 e, \mathbf{1}(a = 65)e]$. The functional form implies that everyone faces some probability of death by other causes of death, and "misusing" opioids linearly increases the probability of death. Opioid Use Disorder also increases the probability of dying separately from opioid "misuse" to capture the differential effects of varying intensities of opioid "misuse" on death. If the individual dies, he receives a fixed terminal value, W.

If the individual survives, he becomes one year older and moves to the next period.

Prices for prescribed opioids p^{rx}_t, illegally traded opioids $p^{il}_{g,t}$, and state-level restrictions on prescribing opioids $r_{g,t}$ are announced at the beginning of the next period. In each period, individuals expect that opioid prices and restrictions will be the same in the future.

The individual's latent health is realized first. Then, displacement from labor cw, prescription rx, and perception of opioid misuse risk are realized sequentially. Each state transition has the following functional form:

$$\frac{p(\mathrm{cw}'_k|s', \mathrm{cw}, \mathrm{rx}, e, d_w, d_{rx}, d_{il})}{p(\mathrm{cw}'_1|s', \mathrm{cw}, \mathrm{rx}, e, d_w, d_{rx}, d_{il})} =$$

$$\theta_0 + \sum_{k=2}^{4} \delta_{s'}\theta_{k-1} + \sum_{k=2}^{4} \delta_{\mathrm{cw}'}\theta_{k+3} + \mathrm{rx}\theta_8 + e\theta_9 + d_w\theta_{10} + d_{rx}\theta_{11} + d_{il}\theta_{12}$$

where $i = \sum_{k=0}^{3} \mathbf{1}\{cw' = k\} + 4\mathbf{1}\{bh' = 1\}$, and $x_{cw,bh} = [1, \mathbf{1}\{cw = 1\}, \mathbf{1}\{cw = 2\}, \mathbf{1}\{cw = 3\}, bh, rx, \frac{a}{10}, (\frac{a}{10})^2, \mathbf{1}\{a = 65\}, e, s', d_w, d_o^{rx}, d_o^{il}]$, and $\theta_i^{cw,bh}$ is a vector of coefficients for each outcome of (cw', bh') indexed by i. State fixed effects $\alpha_g^{cw,bh}$ take into account the log-odds differences in the baseline category, (cw', bh')[10]. There are additional restrictions in the transition probabilities on (cw', bh'). The individual retires exogenously.

The doctor prescribes opioids based on the individual's condition and state-level restrictions on prescribing opioids. The probability of being prescribed opioid in a given state location g is

$$f(\mathrm{rx}'|s'_k, \mathrm{cw}', \mathrm{rx}, e, \mathrm{xp}, m_{g,t}, r_{g,t}) = \frac{\exp(x\theta_{rx})}{1 + \exp(x\theta_{rx})}$$

. The vector of states governing opioid prescribing x_{rx} captures various reasons why one might have received prescription opioids that the latent health variable s cannot capture alone.

Lastly, the individual forms her perception of the risk of "misusing" opioids based on her state. The probability of an individual perceiving that misusing opioids is not

[10] One can include $\sum_{j=1}^{7} \sum_{g=1}^{50} \theta_{j,g}^{cw,bh} \mathbf{1}\{(cw, bh) = j\}\mathbf{1}_g$ to capture the variations to the transition probabilities more flexibly across state locations. I omit this interaction term due to data limitations.

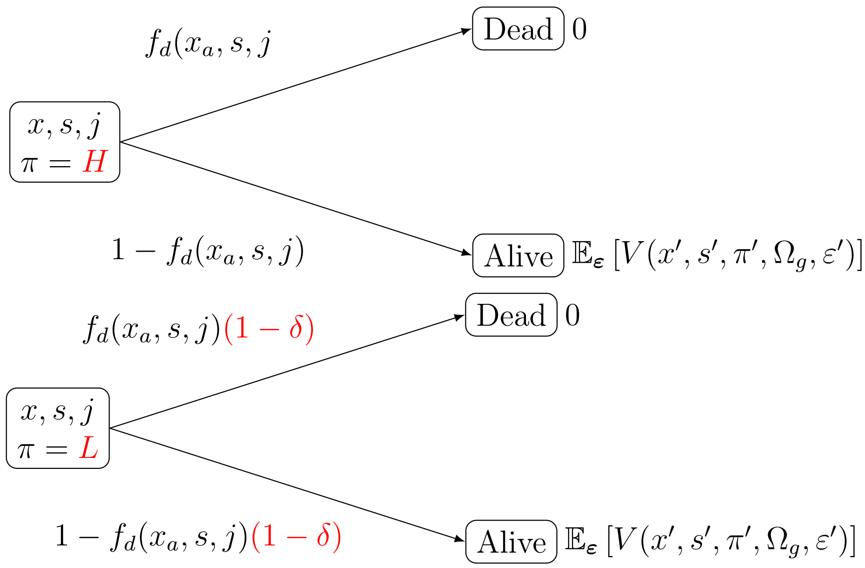

Figure 3: Changes in the Expectation on the Mortality Rate by Perception of Opioid Misuse Risk.

a great risk is

$$f(\pi' = 1 | cw', bh', rx', s'; \theta^{\pi}) = \frac{\exp(x_{\pi}\theta^{\pi})}{1 + \exp(x_{\pi}\theta^{\pi})}$$

where $x_{\pi} = [1, \mathbf{1}(cw' = 1), \mathbf{1}(cw' = 2), \mathbf{1}(cw' = 3), bh', rx', s', \frac{a}{10}, (\frac{a}{10})^2, \mathbf{1}\{a = 65\}]$[11]. When the individual perceives a lower risk of misusing opioids ($\pi = 1$), he expects a lower probability of getting Opioid Use Disorder by δ. Figure 3 illustrates how the perception of the risk of misusing opioids perturbs the belief about the future.

4.4 Value Function Representation

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

$$d_j^* = \underset{j \in \mathcal{J}(\mathbf{1}\{cw \neq 0\}, rx)}{\arg\max} \ \mathbb{E}\left(\sum_{t=1}^{\infty} \beta^{t-1} \left[u_j(\Omega_a, s, \pi; \boldsymbol{\theta}^y, \boldsymbol{\theta}^w, \boldsymbol{\theta}^o) + \varepsilon_j \right] \middle| \Omega_g \right)$$

[11] One can extend this by adding a state-level fixed effect to take into account for state-level variations in the perception of the riskiness of opioids due to different landscape of the opioid crisis across states. For example, the population in West Virginia may have significantly different views on misusing opioids than people in Pennsylvania.

where the expectation operator is applied to all possible future realizations of future state variables. The Bellman representation of the optimization problem, $V(\Omega_g, \Omega_a, s, \pi, \boldsymbol{\varepsilon})$, is

$$
\begin{aligned}
&V(\Omega_g, x, s, \pi, \boldsymbol{\varepsilon}) = \max_{j \in \mathcal{J}(\mathbf{1}\{cw \neq 0\}, rx)} u_j(x, s, ; \boldsymbol{\theta}^y, \boldsymbol{\theta}^w, \boldsymbol{\theta}^o) + \varepsilon_j \\
&\beta(1 - \pi\delta) f_{d|s_1', j} W + \\
&\beta \left(1 - (1 - \pi\delta) f_{d|s_1', j}\right) \sum_{\Omega_g', \Omega_a', \pi'} \mathbb{E}_{\boldsymbol{\varepsilon}'} \left[V(\Omega_g', x', \pi', s', \boldsymbol{\varepsilon}')\right] f_\pi(x', s') f_{rx'}(rx, cw', s', j) f_{cw'}(rx, cw, s', j) f_{s'}(rx, c
\end{aligned}
\tag{1}
$$

where δ represents the magnitude of discounting the probability of experiencing opioid use disorder.

5 Identification

The model is defined by the following parameters: utility parameters ($\boldsymbol{\theta}^y$, σ_y, $\boldsymbol{\theta}^o$), transition probability parameters ($\boldsymbol{\theta}^d$, $\boldsymbol{\theta}^s$, $\boldsymbol{\theta}^{cw}$, $\boldsymbol{\theta}^{rx}$, γ, α_g^{rx}), stochastic process for opioid misuse perception $\boldsymbol{\theta}^\pi$, and the magnitude of discounting the probability of death, δ. The discount factor is set to $\beta = 0.96$, the value you receive upon death is set to $W = 0$, and the distribution of choice-specific idiosyncratic shocks is assumed to follow type 1 extreme value.

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

The perception bias δ is identified by the "differences in differences in choice probabilities" across the perception of the risk of misusing opioids conditional on the same state. Given the same state and proxies, the differences in the choice probabilities must be the same. The difference in the choice probability differences is attributed to the change in π, thus, δ.

Lastly, the parameters that govern the utility from misusing opioids $\boldsymbol{\theta}^o$ are identified by differences in choice probabilities across different choices compared to the baseline choice $j = 1$ at a given state variable. As an illustration, consider the differences in conditional value function between choices j and 1 at (Ω_a, s, π). The Hotz-Miller inversion theorem implies that (2) holds.

$$
\begin{aligned}
&\log \frac{P(d_j|\Omega_g, \Omega_a, s, \pi)}{P(d_1|\Omega_g, \Omega_a, s, \pi)} = v_j(\Omega_g, \Omega_a, s, \pi) - v_1(\Omega_g, \Omega_a, s, \pi) \\
&= \bar{u}_j(\Omega_a, s, \pi; \boldsymbol{\theta}^y, \boldsymbol{\theta}^w, \boldsymbol{\theta}^o) - \bar{u}_1(\Omega_a, s, \pi; \boldsymbol{\theta}^y, \boldsymbol{\theta}^w, \boldsymbol{\theta}^o) \\
&+ \beta W \begin{bmatrix} f_{d|s_0',j} + (1-\pi\delta) f_{s_1'|j} \left(f_{d|s_1',j} - f_{d|s_0',j} \right) \\ -f_{d|s_0',1} - (1-\pi\delta) f_{s_1'|1} \left(f_{d|s_1',1} - f_{d|s_0',1} \right) \end{bmatrix} \\
&+ \beta(1-\pi\delta) \sum_{\Omega_g', \Omega_a', \pi'} \mathbb{E}_{\boldsymbol{\varepsilon}} \left[[V(\Omega_g', \Omega_a', \pi', s_1', \boldsymbol{\varepsilon}')] \right] \begin{bmatrix} f_{\Omega_g', \Omega_a', \pi'|\Omega_g, \Omega_a, s_1', j} (1 - f_{d|s_1',j}) f_{s_1',j} \\ -f_{\Omega_g', \Omega_a', \pi'|\Omega_g, \Omega_a, s_1', 1} (1 - f_{d|s_1',1}) f_{s_1',1} \end{bmatrix} \\
&+ \beta \sum_{x', \pi'} \sum_{\Omega_g', \Omega_a', \pi'} \mathbb{E}_{\boldsymbol{\varepsilon}} \left[[V(\Omega_g', \Omega_a', \pi', s_0', \boldsymbol{\varepsilon}')] \right] \begin{bmatrix} f_{\Omega_g', \Omega_a', \pi'|\Omega_g, \Omega_a, s_1', j} (1 - f_{d|s_0',j}) \left(1 - (1-\pi\delta) f_{s_1',j} \right) \\ f_{\Omega_g', \Omega_a', \pi'|\Omega_g, \Omega_a, s_0', 1} (1 - f_{d|s_0',1}) \left(1 - (1-\pi\delta) f_{s_1',1} \right) \end{bmatrix}
\end{aligned} \tag{2}
$$

where $\bar{u}_j(\Omega_a, s, \pi; \boldsymbol{\theta}^y, \boldsymbol{\theta}^w, \boldsymbol{\theta}^o) := u_j(\Omega_a, s, \pi, \boldsymbol{\varepsilon}; \boldsymbol{\theta}^y, \boldsymbol{\theta}^w, \boldsymbol{\theta}^o) - \varepsilon_j$.

The ex-ante future value function tomorrow, $\bar{V}(\Omega_g', \Omega_a', \pi', s_1') := \mathbb{E}_{\boldsymbol{\varepsilon}} \left[V(\Omega_g', \Omega_a', \pi', s_1', \boldsymbol{\varepsilon}') \right]$, is equal to the weighted sum of the choice-specific conditional value function and the "correction term" in relevance to the conditional choice probabilities.

$$
\bar{V}(\Omega_g', \Omega_a', \pi', s') = \sum_{j \in \mathcal{J}(\mathbf{1}\{cw \neq 0\}, rx)} \begin{bmatrix} \left(v_j(\Omega_g', \Omega_a', \pi', s') + \gamma - \log P(d_{j'}|\Omega_g', \Omega_a', \pi', s') \right) \times \\ \omega(\Omega_g', \Omega_a', \pi', s_1', j'; \Omega_g, \Omega_a, \pi, s, j) \end{bmatrix} \tag{3}
$$

where $|\omega(\Omega_g', \Omega_a', \pi', s_1', j'; \Omega_g, \Omega_a, \pi, s, j)| < \infty$ for all $(\Omega_g', \Omega_a', \pi', s_1', j', \Omega_g, \Omega_a, \pi, s, j)$, and $\sum_{j \in \mathcal{J}(k, rx)} \omega(\Omega_g', \Omega_a', \pi', s_1', j'; \Omega_g, \Omega_a, \pi, s_1, j) = 1$. Plugging this into (2), the log differences in conditional choice probabilities are now equal to the sum of differences in utility functions today and tomorrow, transition probabilities, future conditional choice probabilities, weight function $\omega(\cdot)$, and two-periods-ahead value functions. When everything else is identified, $\boldsymbol{\theta}^o$ is identified by the moments from conditional value function differences.

6 Estimation

To estimate the model, I modify the two-step conditional choice probabilities estimator augmented with the Expectation-Maximization algorithm (Arcidiacono and Miller (2011)). In the first step, I estimate the distribution of the latent health state s, the probability of opioid misuse perception bias, and conditional choice probabilities. Next, I estimate per-period income and transition probabilities. The third step first the decision weight function $\omega(\Omega_g', \Omega_a', \pi', j'; \Omega_g, \Omega_a, \pi, j)$ that satisfies one-period finite dependence (Arcidiacono and Miller (2019)) for any guess for δ. Then, the utility parameters $\boldsymbol{\theta}^o$ and perception bias δ are jointly estimated from the conditional value function differences. I then update the decision weights using the new δ and update $\boldsymbol{\theta}^o$ and δ. I iterate until δ converges.

6.1 First Stage

In the first stage, I estimate the distribution of latent health state θ_u, the probability of perceiving opioid misuse as not a great risk θ_π, reduced-form CCP's $P(d_j|\Omega_g, \Omega_a, s, \pi)$. The likelihood of observing $\pi_n, d_{j,n}, y_{k,n}, s_n'$ conditional on proxy variables $\text{pxy}_{1,n}, \text{pxy}_{2,n}, \text{pxy}_{3,n}$ for an individual n is:

$$
\begin{aligned}
&l(\pi_n, \{\pi_k^*\}_{k=1}^4, d_n, y_n, s_n'|\Omega_g, \Omega_{a,n}) \\
&= \sum_{s=0,1} q(s|\Omega_g, \Omega_{a,n}) \prod_{j,\pi,y_k,s'} \begin{bmatrix} f_\pi(\pi|x_\pi, s; \boldsymbol{\theta}^\pi) \prod_{k=1}^4 f_\pi(\pi_k^*|x_\pi, s; \boldsymbol{\theta}^{\text{pxy}}) \times \\ P(j_n|\Omega_g, \Omega_{a,n}, \pi_n, s) \times \\ F_y(y_{k,n}|j_n, \Omega_g, \Omega_{a,n}, s; \boldsymbol{\theta}^y, \sigma_y) \times \\ f_s(s_n'|j_n, \Omega_g, \Omega_{a,n}, s; \boldsymbol{\theta}^s) \end{bmatrix}^{\mathbf{1}\{\pi_n, \pi_n^*, d_{jn}=1, y_{kn}, s_n'\}}
\end{aligned}
$$

I augment the two-step Expectation-Maximization algorithm in Arcidiacono and Miller (2011) to estimate structural parameters. The conditional choice probabilities are flexibly constructed to capture variation across the state space. From the first stage, I estimate $\hat{\boldsymbol{\theta}}^u$, $\hat{P}(d_j|x, \pi, s)$, $\hat{\boldsymbol{\theta}}^\pi$, and $\hat{\boldsymbol{\theta}}^s$.

Given the first stage estimates, I estimate $\boldsymbol{\theta}^d$, $\boldsymbol{\theta}^{cw,bh}$, $\boldsymbol{\theta}^{rx}$, γ, $\alpha_g^{cw,bh}$, α_g^{rx} in the next step. The following equality constraints estimate the probability of dying conditional on choices:

$$
\begin{aligned}
P_d^{ocd}(a,g) &= \sum_{s'} f_d(a,e,d_o^{rx},d_o^{il};\boldsymbol{\theta}_d)P(d_o^{rx}=0,d_o^{il}=0|a,g) \\
P_d^{OD:rx} &= \sum_{s',d_o^{il}} f_d(a,d_o^{rx},d_o^{il};\boldsymbol{\theta}_d)P(s',d_o^{rx}=1,d_o^{il}) \\
P_d^{OD:il} &= \sum_{s',d_o^{rx}} f_d(a,d_o^{rx},d_o^{il};\boldsymbol{\theta}_d)P(s',d_o^{rx},d_o^{il}=1) \\
P_d^{OD:bth} &= \sum_{s'} f_d(a,d_o^{rx},d_o^{il};\boldsymbol{\theta}_d)P(s',d_o^{rx}=1,d_o^{il}=1)
\end{aligned}
$$

The fractions on the left-hand side come from the restricted NVSS, and the second term in each equation comes from the restricted NSDUH. The following equality constraints estimate the rest of the joint transition probabilities:

$$
P(s'|cw,s,d_w,g) = \sum_{d_{rx},d_{il},rx,s'} \begin{bmatrix} P(d_{rx},d_{il},rx|cw,s,d_w,g)\tilde{f}_d(s,d_{rx},d_{il};\boldsymbol{\theta}_d) \\ f(s'|cw,s,rx,d_w,d_{opi},s') \end{bmatrix} \tag{4}
$$

$$
P(cw'|cw,bh,rx,d_w) = \sum_{d_{opi},s'} \begin{bmatrix} P(d_{opi},s'|cw,bh,rx,d_w)\tilde{f}_d(a,d_j;\boldsymbol{\theta}_d) \\ f(cw',bh'|cw,bh,rx,d_j,s') \\ f(rx'|cw',bh',rx,d_j,s') \end{bmatrix} \tag{5}
$$

Note that (**??**) relates the marginal transition probabilities from MEPS to the first-stage estimates from NSDUH, (**??**) relates the marginal transition probabilities from SIPP to the first-stage estimates from NSDUH, and (**??**) provides additional constraints from the year-to-year distribution changes in the NSDUH.

6.2 Second Stage

In the data, I only observe the income in categorical values y_k, $k = 1, \ldots, 23$ where each category is an interval of the income range. I assume that there is a measurement error $\eta_y\ sim\mathcal{N}(0,\sigma_y)$ that generated y_k.

In the second stage, I find the vector of weights $\omega(x', s', j'; x, s, j)$, $j = 1, \ldots, J$ that cancels out the two-period-ahead ex-ante value functions to construct a 1-period finite dependence path (Arcidiacono and Miller (2019)). This shrinks the computation problem from solving the value function for each state (including five continuous variables) to finding the set of weights and then finding the structural parameters that minimize the distance between the observed conditional choice probabilities differences and the conditional value function differences, represented by the utility parameters, future CCPs, transition probabilities, and weighting functions.

Arcidiacono and Miller (2019) discusses how to find a finite dependence path when an agent is rational. Since the belief distortion δ is in the transition probabilities, one might be concerned that the finite dependence path must be searched for each iteration of estimation. In this framework, the finite dependence path for the biased agent can be found as a function of the finite dependence weights $\omega(x', s', \pi_0'|x, s, \pi_0)$ and δ.

Remark 1 *Suppose that a pair of choices (i, j) in a given state (x_t, s_t, π_t) exhibits a one-period finite dependence path with weights that only involves a rational state $(\omega_{i'}(x', s', \pi_0'; x_t, \pi_t, i))_{i' \in \mathcal{J}}$ and $(\omega_{j'}(x', s', \pi_0'; x_t, \pi_t, j))_{j' \in \mathcal{J}}$. i.e.,*

$$\kappa(x_{t+2}, \pi_{t+2}|x_t, \pi_t, i; \pi_{0,t+1}) = \kappa(x_{t+2}, \pi_{t+2}|x_t, \pi_t, j; \pi_{0,t+1}) \text{ for all } (x_{t+2}, \pi_{t+2})$$

where

$$\begin{aligned}
&\kappa(x_{t+2}, \pi_{t+2}|x_t, \pi_t, i; \pi_{0,t+1}) \\
&= \sum_{x_{t+1}} \sum_{i' \in \mathcal{J}} f(x_{t+2}, \pi_{t+2}|x_{t+1}, \pi_{0,t+1}; i') \omega_{j'}(x_{t+1}, \pi_{0,t+1}; x_t, \pi_t, i) f(x_{t+1}, \pi_{0,t+1}|x_t, \pi_t; i) \\
&\kappa(x_{t+2}, \pi_{t+2}|x_t, \pi_t, j; \pi_{0,t+1}) \\
&= \sum_{x_{t+1}} \sum_{j' \in \mathcal{J}} f(x_{t+2}, \pi_{t+2}|x_{t+1}, \pi_{0,t+1}; j') \omega_{j'}(x_{t+1}, \pi_{0,t+1}; x_t, \pi_t, j) f(x_{t+1}, \pi_{0,t+1}|x_t, \pi_t; j)
\end{aligned}$$

Then, one-period finite dependence is achieved;

$$\kappa(x_{t+2}, \pi_{t+2}|x_t, \pi_t, i) = \kappa(x_{t+2}, \pi_{t+2}|x_t, \pi_t, j) \textit{ for all } (x_{t+2}, \pi_{t+2})$$

6.3 Third Stage

Once the finite dependence weights are found, I use the weights to generate the moments using the Hotz-Miller inversion and finite dependence to identify δ, W, and $\boldsymbol{\theta}^o$. The estimation of the rest of the structural parameters, $\boldsymbol{\theta}^o, W, \delta$, is performed by a minimum distance estimator:

where x_k, $k = 1, \ldots, M$ denote the state that generates the moments.

7 Potential Counterfactuals

I consider three counterfactual predictions based on the model. First, I change the state-level policies and prices, r_{gt} and $p^{il}_{g,t}$, in a given state to evaluate how that would change the behavior of individuals.

Second, I consider how raising the perception of the risk of misusing opioids changes the behavior of individuals. This is done by changing the parameters in $\boldsymbol{\theta}^{\pi}$.

Third, I consider changing the labor market environment. One exercise I plan is changing the probability of getting out of layoff. There are two potential results. The individual might misuse opioids more if they believe that they can still be employed later even when they misuse opioids today, or the individual may not misuse opioids today because waiting one period being unemployed is not going to be as painful as before. Another exercise is changing the unemployment benefits to a subset of people, say, people with opioid use disorder. The same argument for the potential results of this exercise applies.

8 Conclusion

This paper studies how people misuse opioids, which interacts with three channels of interest: labor, health, and prescription. Modeling opioid misuse as a choice between today's pain relief or euphoria and tomorrow's negative outcomes, this paper quantifies the substitution to illegal opioids when prescription opioids are not given. As this substitution pattern is heterogeneous across socioeconomic status, state-level restrictions on opioid prescribing can have different results in those groups. The paper will include counterfactual policy experiments based on the model estimates in the future.

9 Appendix

9.1 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 contains valuable information on substance use, it is repeated cross-sections, which hinders inference on the dynamic decision process of individuals. For details of how each variable in this paper's model is measured, see section 9.1.1.

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. The drawback of the MEPS is that it does not have information about opioid use not as directed by a doctor (with or without prescriptions). Thus, the data set provides state transitions in which using opioids not as directed by a doctor (with or without prescriptions) are integrated out.

Additionally, I use the Survey of Income and Program Participation (SIPP) 2015-2019. The SIPP captures the state-level variation in SES, including age, education, working status, and bad health. The MEPS and the SIPP jointly provide the marginal transition probabilities for the dynamic model.

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[12]. ARCOS posts opioids dispensed by pharmacies in each county and state in terms of Milligrams of Morphine Equivalent (MME)[13]. 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

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

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

received prescriptions for opioids, it is difficult to see whether the amount of opioids per capita given prescription has changed over time. Balestra et al. (2023) argues that PDMP affected the extensive margin on the number of prescriptions but not on the intensive margin, the amount of opioids dispensed given prescription.

Transactions in the secondary market are difficult to observe because they are illegal. The best available data, to my knowledge, is the crowd-sourced StreetRx program 2013-2021 collected by Rocky Mountain Poison & Drug Safety under Denver Health. The data contains information on the location, time, drug classification, product name, active ingredient, total cost, dosage form (e.g., capsule, patch, spray), price per milligram, dose per unit, and whether the recorded transaction is a bulk purchase or not. The data set is used to see how prices change to state-level restrictions[14]. 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.

9.1.1 National Survey of Drug Use and Health

Opioid use in the NSDUH is characterized by two measures: whether the person used opioids with or without her prescription (Rx) and whether the person suffered from Opioid Use Disorder. The first criterion is used to retrieve the person's choice on opioid use not as directed by a doctor and the second criterion is used to observe the consequences of opioid use not as directed by a doctor.

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.

[14] System to Retrieve Information from Drug Evidence (STRIDE) also collects data on seized drugs by law enforcement; the Freedom of Information Act (FOIA) pending.

	2015	2016	2017	2018	2019
Opioid Use					
Prescribed Opioids	0.357	0.335	0.329	0.313	0.294
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Misused Opioids	0.048	0.045	0.042	0.039	0.038
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
-Prescribed Opioids Only	0.017	0.016	0.015	0.014	0.014
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
-Illegally Purchased Opioids Only	0.023	0.021	0.020	0.018	0.018
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
-Both	0.008	0.007	0.007	0.006	0.005
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Misused Opioids, experiences SUD	0.009	0.009	0.008	0.008	0.006
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ever Misused Opioids	0.109	0.106	0.107	0.102	0.103
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Perceives Low Misuse Risk:					
Heroin	0.148	0.143	0.137	0.135	0.146
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Cocaine	0.283	0.283	0.287	0.286	0.302
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
LSD	0.303	0.309	0.324	0.336	0.358
	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
Employment					
Working	0.622	0.623	0.628	0.626	0.627
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Not Working	0.378	0.377	0.372	0.374	0.373
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Displacement from Labor					
Not Displacement	0.759	0.757	0.763	0.764	0.760
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Laid Off	0.056	0.054	0.051	0.048	0.049
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Unable to Work	0.052	0.051	0.047	0.047	0.047
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Retired	0.133	0.138	0.139	0.141	0.145
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Income					
≤ $10,000	0.231	0.228	0.216	0.211	0.203
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$10,000-$19,999	0.189	0.182	0.179	0.178	0.169
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
$20,000-$29,999	0.132	0.133	0.131	0.133	0.131
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
$30,000-$39,999	0.104	0.104	0.109	0.105	0.112
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
$40,000-$49,999	0.091	0.091	0.087	0.089	0.093
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$50,000-$74,999	0.119	0.121	0.126	0.130	0.133
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
≥ $75,000	0.133	0.141	0.152	0.153	0.160
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Age Category					
18-25	0.144	0.141	0.139	0.137	0.135
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
26-34	0.158	0.159	0.160	0.161	0.161
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
35-49	0.249	0.248	0.247	0.246	0.243
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
50-64	0.257	0.255	0.253	0.249	0.250
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
≥ 65	0.192	0.197	0.201	0.207	0.211
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Bad Health	0.140	0.139	0.139	0.138	0.140
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Weighted N	242360450	244031068	246762003	248437606	249665764

Table 1: Summary Statistics in the NSDUH Public Use Files, 2015-2019

	No OUD	OUD	Total
Ever Misused	88.673%	11.327%	100%
Never Misused	95.874%	4.1261%	100%
Total	95.135%	4.8652%	100%

Table 2: Percent of Population Experiencing Opioid Use Disorder after using prescription opioids as directed by a doctor, NSDUH PUF 2021

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.

9.2 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.

9.3 StreetRx

Each opioid has different strength, so Morphine Milligram Equivalents (MME) is used for comparison. I convert MME for each opioid using three references: CDC's guidance in prescribing opioids[15], a conversion chart from Utah Department of Health and Human Services[16], Washington Health Care Authority's conversion table[17]. One milligram of Diamorphine, or heroin, is converted to 3 MME according to the UK National Health Services[18].

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.

The formula for computing the amount of opioid is

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

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

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

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

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

9.4 Derivation

The conditional value function of an individual choosing action j at state (x, s, π) is

$$v_j(s, cw, rx, \pi) = u_j(s, cw, rx) + \beta(1 - \pi\delta)f_d(s, cw, rx, j)W$$
$$+ \beta\left(1 - (1 - \pi\delta)f_d(x, s, j)\right) \sum_{x', s', \pi'} \bar{V}(s', cw', rx', \pi')f_{rx}(s', cw', rx, j)f_{cw}(s', cw, rx, j)f_s(s, cw, rx, j)$$

If a pair of choices $(1, j)$ at (x, s, π) exhibit a 1-finite dependence, then:

$$\psi_1(\mathbf{p}(x, s, \pi)) - \psi_j(\mathbf{p}(x, s, \pi)) = v_j(x, s, \pi) - v_1(x, s, \pi)$$
$$= u_j(x, s; \boldsymbol{\theta}^y, \boldsymbol{\theta}^o) - u_1(x, s; \boldsymbol{\theta}^y, \boldsymbol{\theta}^o)$$
$$+ \beta\left[W(1 - \pi\delta)f_{s'_1|s,j}f_{d'|x,s'_1,j} + W(1 - (1 - \pi\delta)f_{s'_1|s,j})f_{d'|x,s'_0,j}\right]$$
$$- \beta\left[W(1 - \pi\delta)f_{s'_1|s,1}f_{d'|x,s'_1,j} + W(1 - (1 - \pi\delta)f_{s'_1|s,1})f_{d'|x,s'_0,1}\right]$$
$$+ \beta \sum_{x',\pi'} \sum_{k \in \mathcal{J}(x')} \begin{bmatrix} u_k(x', s'_1; \boldsymbol{\theta}^y, \boldsymbol{\theta}^o) + \\ \psi_k(\mathbf{p}(x', s'_1, \pi')) \end{bmatrix} \boldsymbol{\omega}_{k,s'_1,j} f_{x',\pi'|x,s'_1,j}(1 - \pi\delta)f_{s'_1|x,s,j}\tilde{f}_{d'|x,s',j}$$
$$- \beta \sum_{x',\pi'} \sum_{k \in \mathcal{J}(x')} \begin{bmatrix} u_k(x', s'_1; \boldsymbol{\theta}^y, \boldsymbol{\theta}^o) + \\ \psi_k(\mathbf{p}(x', s'_1, \pi')) \end{bmatrix} \boldsymbol{\omega}_{k,s'_1,1} f_{x',\pi'|x,s'_1,j}(1 - \pi\delta)f_{s'_1|x,s,1}\tilde{f}_{d'|x,s',1}$$
$$+ \beta \sum_{x',\pi'} \sum_{k \in \mathcal{J}(x')} \begin{bmatrix} u_k(x', s'_0; \boldsymbol{\theta}^y, \boldsymbol{\theta}^o) + \\ \psi_k(\mathbf{p}(x', s'_0, \pi')) \end{bmatrix} \boldsymbol{\omega}_{k,s'_0,j} f_{x',\pi'|x,s'_0,j}(1 - (1 - \pi\delta)f_{s'_1|x,s,j})\tilde{f}_{d'|x,s',j}$$
$$- \beta \sum_{x',\pi'} \sum_{k \in \mathcal{J}(x')} \begin{bmatrix} u_k(x', s'_0; \boldsymbol{\theta}^y, \boldsymbol{\theta}^o) + \\ \psi_k(\mathbf{p}(x', s'_0, \pi')) \end{bmatrix} \boldsymbol{\omega}_{k,s'_0,1} f_{x',\pi'|x,s'_0,1}(1 - (1 - \pi\delta)f_{s'_1|x,s,1})\tilde{f}_{d'|x,s',1}$$

where $\boldsymbol{\omega}_{k,s',j} = \omega_k(x', s', \pi', x, s, \pi, j; \delta)$. This forms a moment for estimating $W, \delta, \boldsymbol{\theta}^o$ in equation (**??**).

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