Essays on Dynamic Discrete Choice Models

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Abstract

In the first chapter, “A Structural Approach to Opioid Misuse: Health, Labor, Policies, and Misperception of Opioid Misuse Risk,” I highlight the heterogeneous opioid misuse opioid behavior in health and employment statuses and the role of misperception of the risk of opioid misuse in evaluating policy interventions to reduce opioid misuse. Three aggregate changes that characterize the opioid epidemic during 2015-2019 are considered: the increased probability of death from opioid misuse, the expansion of state-level policies on opioid prescribing, and the fluctuating illegally traded opioid prices. A dynamic model of opioid misuse and labor decisions with two-dimensional latent health with a stochastic misperception of the risk of misusing opioids is developed, where the misperception bias induces agents to discount the probability of dying from opioid misuse more than the rational agent. The model estimates show that separation from the labor market is just as important as poor health conditions in determining opioid misuse. Moreover, I find that people who experience a misperception of opioid misuse risk significantly discount the probability of death from opioid misuse. The decomposition exercise using the 2015 population as a benchmark shows that the observed secular trend in the decrease in opioid misuse rate is almost entirely attributed to the increased statistical probability of death from opioid use. State-level policies on opioid prescribing decrease the opioid misuse rate for the population who are not displaced from the labor market or in good physical and mental health, but its effect is offset by those who are separated from the labor market or people in poor health. Although I find reasonable signs for the price elasticity in illegally traded opioid misuse across health and labor statuses, I find no effect of opioid price changes on opioid misuse rates. Lastly, I find that shutting down the misperception of the risk of opioid misuse can significantly decrease opioid misuse, shedding light on a new channel to decrease opioid misuse.

In the second chapter, “Identification and Estimation of Dynamic Discrete Choice Models with a Terminal State,” I show that setting the terminal value to zero in a dynamic discrete choice model is not an innocuous assumption. I apply the observational equivalence theorem from Arcidiacono and Miller (2020) to this class of models to show the terminal value appears nonlinearly in the choice-specific conditional value function. I then provide a simple numerical

example to illustrate how the utility parameter estimates can be biased even with the correct specification for the flow utility if the terminal value is set to zero. This exercise thus suggests that econometricians should leave the value of the terminal state to be estimated along with the flow utility of our choice, especially since we often make a strong parametric assumption on the flow utility than what is necessary for identification. Alternatively, a researcher may modify the flow utility to take the role of the value of the terminal state.

In the third chapter, "Estimation of Dynamic Discrete Choice Models with Subjective Beliefs under Finite Dependence Property," I propose a novel estimation strategy for estimating a dynamic discrete choice model whose transition probabilities exhibit 1-period finite dependence and the economic agents' perceived transition probabilities deviate from rational expectations. Estimating dynamic discrete choice models where the perceived transition probabilities differ from rational expectations is challenging because the transition probabilities are now a function of structural parameters that need to be estimated along with utility parameters. I extend the two-step estimation strategy in Arcidiacono and Miller (2011) to overcome this challenge by iterating between finding the finite dependence paths for the conditional value function contrasts and estimating the structural parameters given the set of conditional value function differences. By deploying a parsimonious infinite horizon dynamic discrete choice model with a terminal state with stochastic perception bias, I show numerically that the method works well.

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Chapter 1

A Structural Approach to Opioid Misuse: Health, Labor, Policies, and Misperception of Opioid Misuse Risk

1.1 Introduction

There are two seemingly opposing trends in opioid misuse[1] and mortality rates from 2015 to 2019. Figures 1.1 and 1.2 show that the opioid misuse rate has been *decreasing* while mortality rates from opioid overdose have been *increasing*. These opposing trends raise several questions: What aggregate changes have contributed most to the observed trends in opioid misuse and deaths? Is there heterogeneity in opioid misuse in response to these aggregate changes? If so, how do people respond differently to these aggregate changes across health and labor status? Through which channels can policymakers intervene to decrease opioid misuse effectively?

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

[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.

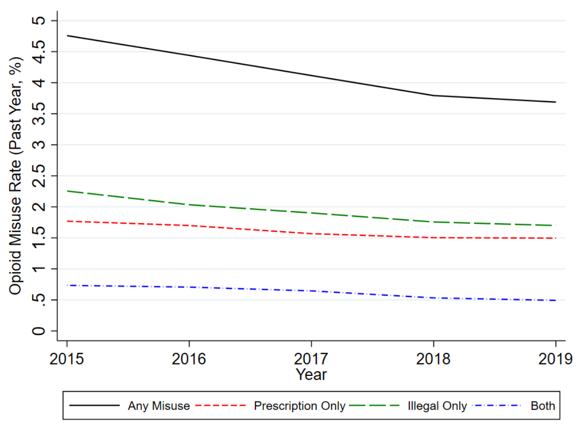


Figure 1.1: Opioid Misuse Rate 2015-2019, PUF NSDUH

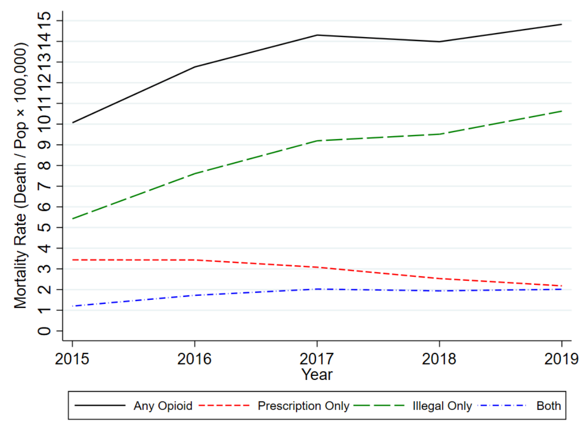


Figure 1.2: Mortality Rate by Opioid Overdose 2015-2019, RUF NVSS

own prescribed opioids. Although it simplifies opioid misuse on the intensive margin, this classification can capture the substitutability between prescription opioids and illegally traded opioids, which is of interest when designing policies to decrease opioid misuse and deaths.

I evaluate how three aggregate changes during 2015-2019 affected opioid misuse differently across health and labor status. First, state-level policies aimed at controlling opioid prescribing have been widely implemented during this period. Second, the probability of dying from opioid misuse has been increasing as illegal opioids become more risky. Third, prices of illegally traded opioids at the state level have fluctuated over time. Since all of these changes occurred simultaneously, the individual effect of each change is ambiguous.

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

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

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

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

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

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

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

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

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

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

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

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

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

1.2 Data Patterns

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

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

1.2.1 Health and Opioid Misuse

The main motivation for restricting opioid prescription is that excessive opioid prescription facilitates prescription opioid misuse. If this is true, then groups with higher opioid prescription rates would be associated with higher opioid misuse in the data. This pattern is observed in Table 1.1. It shows that people in worse health tend to be positively associated with receiving prescription opioids and misusing opioids. In the NSDUH, about 20% of respondents who answered that they were in excellent health received opioids and used them as directed by a doctor in the past 12 months. About 2.6% of the respondents with excellent health have misused opioids during this period. In contrast, about 45% of people with fair or poor health have received opioids in the past 12 months and used them as directed by a doctor, and 5.9% have misused opioids.

Although a higher prescription rate is associated with higher opioid misuse in Table 1.1, this does not show why people in worse health are misusing opioids. This could be due to having easier access to opioids, but it could also be there are other aspects associated with health. As later sections show, labor and perception bias on opioid prescribing are intertwined

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

Table 1.1: Row Percentages of Opioid Use by Health: Nonuser, Prescription User, and Opioid Misuse. PUF NSDUH, 2015-2019.

with this pattern.

1.2.2 Labor and Opioid Misuse

This paper emphasizes the role of labor status on opioid misuse. Table 1.2 shows the row percentages of opioid use across labor status. 57% of those who answered they "cannot work due to health reasons" have received prescription opioids and used as directed by a doctor. Such a high prescription rate is associated with higher opioid misuse, around 6.71%. However, the opioid misuse rate by the unemployed population is even higher, marking 8.47%, while their prescription rate is around the same as those who are working and who are not working by choice. Considering this, people might be misusing opioids out of frustration from the labor market outcome, similar to the "death of despair" hypothesis (Case and Deaton (2017)).

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

Table 1.2: Row Percentages of Opioid Use by Labor Market Displacement: Nonuser, Prescription User, and Opioid Misuse. PUF NSDUH, 2015-2019.

Table 1.2 also shows that labor status matters in studying opioid misuse. While 4.5% were unemployed during 2015-2019, they represent about 7.2% to 13% of opioid misusers.

Similarly, while 5% of the population were unable to work due to health reasons, 6% to 11% of opioid misusers were in this category.

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

Table 1.3: Column Percentages of Opioid Use by Labor Market Displacement: Nonuser, Prescription User, and Misuse by Type. PUF NSDUH, 2015-2019.

Dividing the prescription patterns and opioid misuse rates by age groups further shows that higher prescription is not the sole reason for opioid misuse. Figures 1.3 and 1.4 show opioid prescription and opioid misuse rates by age groups during 2015-2019. Although prescription rates become higher as you get older, opioid misuse is only higher among young people, and older people generally do not misuse opioids.

Figures 1.5 and 1.6 further highlight that the opioid crisis applies to the prime working age. During 2015-2019, many states began to impose restrictions on prescribing opioids. In this period, the mortality rates by opioid overdose with prescription opioids were generally steady, while opioid overdose deaths by illegal opioids (e.g., fentanyl) have sharply increased. Despite the changes, the hump-shaped curve across age groups is also persistent. Notably, most of the deaths were from the prime working age group.

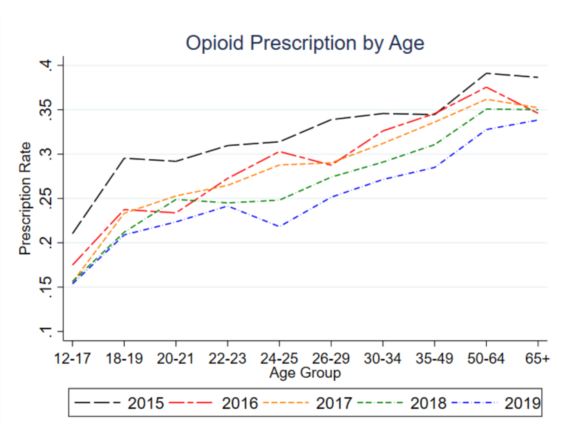


Figure 1.3: Prescription Rates across Age Groups, PUF NSDUH, 2015-2019

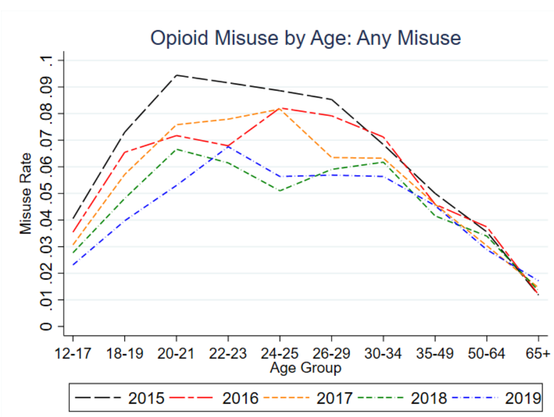


Figure 1.4: Mortality rates by prescription opioids across age groups, NVSS, 2011-2019

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

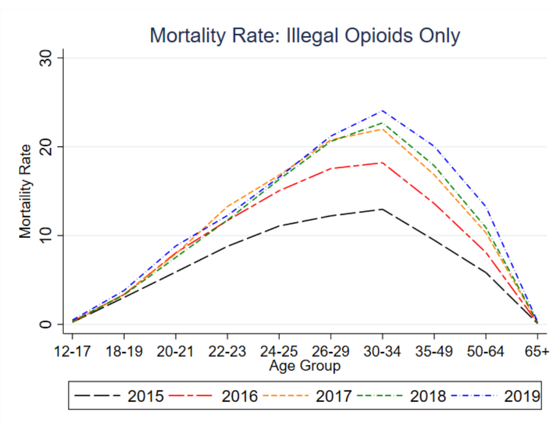


Figure 1.5: Prescription Rates across Age Groups, PUF NSDUH, 2015-2019

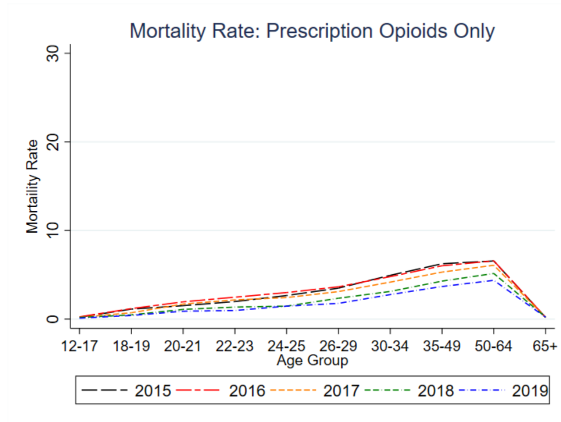


Figure 1.6: Mortality rates by prescription opioids across age groups, NVSS, 2011-2019

1.2.3 State-level Policies on Opioid Prescribing and Their Effects

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

Table 1.4 shows that the probability of dying from other causes than opioid overdose has stayed constant during this period. However, the probability of dying from opioid overdose have surged, mainly led by illegal opioids becoming more lethal.

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

Table 1.4: Probability Dying from Other Causes of Death and from Opioid Overdose, PUF NSDUH & NVSS, 2015-2019

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

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

$$\log(y_{s,t}) = \beta_1 r_{s,t}(1 - m_{s,t}) + \beta_2 m_{s,t}(1 - r_{s,t}) + \beta_3 r_{s,t} m_{s,t} + X\beta + \alpha_s + \delta_t + \varepsilon_{s,t} \tag{1.1}$$

β_1, β_2, and β_3 capture the association between the state-level restrictions and the opioid prescription rate. While state-level restrictions and must-access PDMP seem to be uncorrelated with prescription rates, states that implement two policies together have a strong negative correlation with opioid prescriptions.

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

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

$$\text{Mort}_{s,t} = \beta_1 r_{s,t}(1 - m_{s,t}) + \beta_2 m_{s,t}(1 - r_{s,t}) + \beta_3 r_{s,t} m_{s,t} + X\beta + \alpha_s + \delta_t + \varepsilon_{s,t} \tag{1.2}$$

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

Table 1.5: Two-way Fixed Effects Regression Results of the Number of Prescriptions per 100 Population and Opioids Dispensed on State-level Policies on Opioid Prescribing, CDC, ARCOS, and CPS, 2014-2019.

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

Table 1.6: Two-way Fixed Effects Regression Results of Opioid Overdose Mortality Rate on State-level Policies on Opioid Prescribing, CDC, ARCOS, and CPS, 2014-2019.

As Table 1.6 shows, state-level policies seem to have positive association with the increase in the mortality rate by synthetic opioid overdose, which are considered to be illegally traded[2]. However, it is unclear exactly who substituted reduced access to prescription opioids to illegal opioids with this reduced-form result.

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

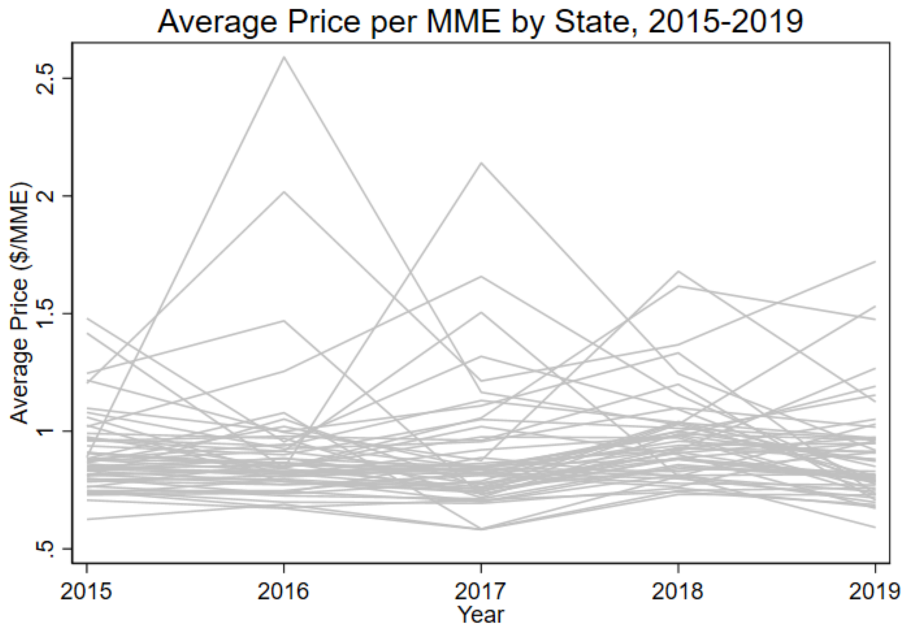


Figure 1.7: Average Illegal Opioid Prices by State, StreetRx, 2015-2019.

1.2.4 Illegal Opioid Prices

Figure 1.7 shows average prices for illegally traded opioids across states during 2015-2019 from StreetRx. While most states' prices for illegally traded opioids were below a dollar per milligram of morphine equivalent (MME), the prices fluctuated a lot during this period. I use this variation across states to see whether people changed their opioid misuse rate. I provide empirical evidence that the state-level policies do not affect prices for illegal opioids. If illegally traded opioids are derived from prescription opioids, then restricting opioid dispense via state-level policies would have a positive correlation with illegally traded opioid prices. To see this, I run a two-way fixed effects regression of the average price per MME for illegally traded opioid prices on state-level policies on opioid prescribing. Equation 1.3 is the specification for the regression:

$$\bar{p}_{s,t} = \beta_1 r_{s,t}(1 - m_{s,t}) + \beta_2 m_{s,t}(1 - r_{s,t}) + \beta_3 r_{s,t} m_{s,t} + X\beta + \alpha_s + \delta_t + \varepsilon_{s,t}. \tag{1.3}$$

β_1, β_2, and β_3 capture the association between the state-level restrictions and the average reported price for illegal trade prices. Table 1.7 shows that the policies have statistically insignificant associations with illegally traded prices, if not negative. Based on the empirical evidence, I assume that the state-level restrictions only affect opioid prescription on an extensive margin and not on the prices for illegally traded opioids. This implies that I am

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

Table 1.7: Two-way Fixed Effect Regression Result of Average Illegally Traded Opioid Price on State-level Policies, StreetRx and CPS, 2014-2019.

assuming a flat supply curve for illegal opioids. This assumption is innocuous based on the characteristics of the opioid crisis during 2015-2019. After the introduction of fentanyl in the United States in 2013, illegal opioids became widely accessible. Surveys also show that "(. . .) nearly half feel it is extremely or somewhat easy to access opioids for illicit use" in 2018.[3]

1.2.5 Perception of Opioid Misuse Risk

The rationale for state-level policies on prescribing opioids is that people are overconfident about the risk of misusing opioids. If this misperception of the risk of misusing opioids induces opioid misuse, it might seem justifiable to design a policy to correct the public's perception of opioid misuse risk. Thus, my paper highlights the perception of the risk of opioid misuse as an additional channel where labor, health, and prescription of opioids may affect opioid misuse.

Table 1.8 shows that about 14% of the population thinks that other people are not taking a great risk when using heroin, a well-known illegal opioid. Considering that the fraction of people with opioid use disorder (i.e., addiction) is less than 1%, this discrepancy in the perception of the risk of misusing opioids may initiate opioid misuse. Table 1.9 shows that the perception of the risk of opioid misuse is also associated with unfavorable labor status and poor health. With this regression, however, it is difficult to understand which one affected the other. It could be that people with perception bias began misusing opioids and ended up with worse labor and health outcomes, or vice versa. This why I develop a model where the causality runs both ways and runs a counterfactual analysis by shutting down the perception

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

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

Table 1.8: Perception of Opioid Misuse Risk, PUF NSDUH 2015-2019

bias channel.

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

Table 1.9: Average Marginal Effects of Health, Labor, and Prescription to Opioids on Perception of Opioid Misuse Risk. PUF NSDUH 2015-2019.

1.2.6 Summary

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

1.3 Model

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

1.3.1 State Variables and Choice Set

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

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

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

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

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

If the person is displaced from labor, the person cannot work during this period. If the person is not displaced from labor ($\text{cw} = 0$), the person can choose to work or not during this period.

While retirement is not an explicit endogenous choice, its transition probability depends on the previous working decision and labor market displacement. People can return to the labor force after retirement, but this is not modeled explicitly. The transition back to the labor force after retirement is captured through the transition probability.

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

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

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

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

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

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

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

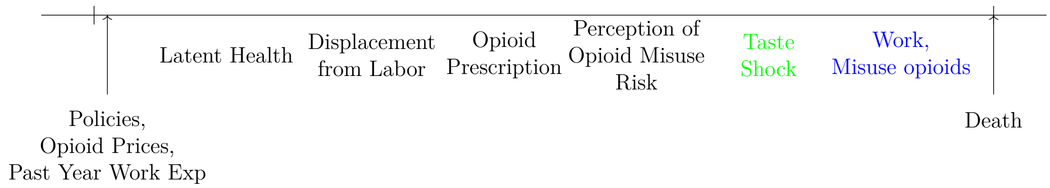


Figure 1.8: State Realization and Decision in Each Period

The individual receives a vector of idiosyncratic shocks $(\varepsilon_1, \ldots, \varepsilon_{|\mathcal{J}(\mathbf{1}\{cw \neq 0\}, rx)|})$, 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, $W = 0$.[5] Figure 1.8 summarizes each period's state realization and decision process. To simplify notation, I use $\Omega_{s,t} = (s, r_{s,t}, m_{s,t}, p^{il}_{s,t})$ to denote all state-level aggregate variables relevant to opioid prescriptions and opioid prices. $x = (e, \text{xp}, \text{cw}, \text{rx})$ to denote all individual-level state variables except for latent health $h = (h_1, h_2)$, the perception of opioid misuse risk b, and the vector of idiosyncratic shocks $\boldsymbol{\varepsilon}$. The state space is then defined by $\Omega = (\Omega_g, x, h, b, \boldsymbol{\varepsilon})$.

1.3.2 Per-period Utility

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

$$\begin{aligned} u_j(x, h, \Omega_{s,t}, \boldsymbol{\varepsilon}; \boldsymbol{\theta}^y, \boldsymbol{\theta}^u) = & \underbrace{\theta^u_1 y(x, h, d_w, d^{rx}_o, d^{il}_o; \boldsymbol{\theta}^y)}_{\text{Pecuniary Benefit from Working}} + \underbrace{u_w(x, h, d^{rx}_o, d^{il}_o; \boldsymbol{\theta}^u) d_w}_{\text{Non-pecuniary Utility from Working}} \\ & + \underbrace{u_o(x, h, p^{il}_{s,t}, d_w, d^{rx}_o, d^{il}_o; \boldsymbol{\theta}^u)}_{\text{Utility from opioid misuse}} + \varepsilon_j. \end{aligned} \tag{1.4}$$

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

In each period, the wage is a function of latent health, prescription, opioid misuse,

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

education, and past year work experience.

$$\begin{aligned}\log y = (1-d_w)\left(\theta_1^y(1-e)+\theta_2^y e\right) + d_w\Bigg(\theta_3^y + \sum_{m=2}^{4}\theta_{m+2}^y \mathbf{1}\{h=m\} \\ + \sum_{m=2}^{4}\theta_{m+5}^y \mathbf{1}\{h=m\}rx + \theta_{10}d_o^{rx} + \theta_{11}d_o^{il} + \theta_{13}e + \theta_{13}xp + \theta_{14}e\times xp\Bigg) + \nu\end{aligned} \tag{1.5}$$

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

1.3.3 Transition Probabilities

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

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

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

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

$$\begin{aligned}&\frac{P(h'=k|e,h,\text{cw},\text{rx},\text{xp},j)}{P(h'=1|e,h,\text{cw},\text{rx},\text{xp},j)} \\ &= \theta_{1,k}^h + \theta_{2,k}^h e + \sum_{m=1}^{3}\theta_{m+2}^h\mathbf{1}\{\text{cw}=m\} + \theta_{6,k}^h\text{xp} + \sum_{m=2}^{4}\theta_{m+5}^h\mathbf{1}\{h=m\} + \theta_{10,k}^h\text{rx} \\ &+ \theta_{11,k}^h d_w + \theta_{12,k}^h d_o^{rx} + \theta_{13,k}^h d_o^{il}\end{aligned} \tag{1.6}$$

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

$$\begin{aligned}\frac{P(\text{cw}'=k|e,h',\text{cw},\text{rx},\text{xp},j)}{P(\text{cw}'=0|e,h',\text{cw},\text{rx},\text{xp},j)} = \theta_{1,k}^{cw} + \theta_{2,k}^{cw}e + \sum_{m=1}^{3}\theta_{m+2,k}^{cw}\mathbf{1}\{\text{cw}=m\} + \theta_{6,k}^{cw}\text{xp} \\ + \sum_{m=2}^{4}\theta_{m+5,k}^{cw}\mathbf{1}\{h'=m\} + \theta_{10,k}^{cw}\text{rx} + \theta_{11,k}^{cw}d_w + \theta_{12,k}\mathbf{1}\{d_o^{rx}=1 \vee d_o^{il}=1\}\end{aligned} \tag{1.7}$$

for $k=1,2,3$.

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

$$\frac{P(\text{rx}=1|h,\text{cw},r_{s,t},m_{s,t},s)}{P(\text{rx}=0|h,\text{cw},r_{s,t},m_{s,t},s)} = \theta_1^{rx} + \sum_{m=1}^{3}\theta_{m+4}^{rx}\mathbf{1}\{\text{cw}=m\}+$$
$$\sum_{m=2}^{4}\theta_m^{rx}\mathbf{1}\{h=m\}+ + r_{s,t}(1-m_{s,t})\left(\theta_8^{rx}+\sum_{m=2}^{4}\theta_{m+7}^{rx}\mathbf{1}\{h=m\}\right)$$
$$+ m_{s,t}(1-r_{s,t})\left(\theta_{12}^{rx}+\sum_{m=2}^{4}\theta_{m+11}^{rx}\mathbf{1}\{h=m\}\right)$$
$$+ r_{s,t}m_{s,t}\left(\theta_{16}^{rx}+\sum_{m=2}^{4}\theta_{m+15}^{rx}\mathbf{1}\{h=m\}\right)+\alpha_s. \tag{1.8}$$

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

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

$$\frac{P(b=L|e,h,\text{cw},\text{rx})}{P(b=H|e,b,\text{cw},\text{rx})} = \theta_1^b+\theta_2^b e+\sum_{m=2}^{4}\theta_{m+1}^{b}\mathbf{1}\{h=m\}+\sum_{m=1}^{3}\theta_{m+5}^{b}\mathbf{1}\{\text{cw}=m\}+\theta_9^b\text{rx}. \tag{1.9}$$

When the individual perceives that misusing opioids has a low risk, he discounts the probability of dying from opioid misuse by δ. Equation 1.10 illustrates how the perception of the risk of misusing opioids affects the belief about the probability of dying from opioid misuse.

$$f_d(h,b,j,t;\boldsymbol{\theta}^d,\delta) = \theta_1+\theta_2^d h_1+\theta_3^d h_2+(1-\delta\mathbf{1}\{b=L\})\left(\theta_{4,t}^d d_{rx}+\theta_{5,t}^d d_{il}+\theta_{6,t}^d d_{rx}d_{il}\right). \tag{1.10}$$

1.3.4 Value Function Representation

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

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

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

$$\begin{aligned} V(\Omega_{s,t}, x, h, b, \boldsymbol{\varepsilon}) = \max_{j \in \mathcal{J}(\mathbf{1}\{\text{cw}\neq 0\}, rx)} u_j(x, h; \boldsymbol{\theta}^y, \boldsymbol{\theta}^u) + \varepsilon_j + \beta f_d(h, b, j, t; \boldsymbol{\theta}^d, \delta) W + \\ \beta \left(1 - f_d(h, b, j, t; \boldsymbol{\theta}^d, \delta)\right) \sum_{x', h', b'} \mathbb{E}_{\boldsymbol{\varepsilon}'} \left[V(\Omega_{s,t}, x', h', b', \boldsymbol{\varepsilon}')\right] f(x', h', b' | \Omega_{s,t}, x, h, j) \end{aligned} \tag{1.11}$$

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

$$\begin{aligned} f(x', h', b' | \Omega_{s,t}, x, h, j) = f_b(b' | e, h', \text{cw}', \text{rx}') f_{\text{rx}}(\text{rx}' | h', \text{cw}', r_{s,t}, m_{s,t}, s) \\ \times f_{\text{cw}}(\text{cw}' | e, h', \text{cw}, \text{rx}, \text{xp}, j) f_h(h' | e, h, \text{cw}, \text{rx}, \text{xp}, j) \end{aligned} \tag{1.12}$$

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

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

$$\begin{aligned} v_j(\Omega_{s,t}, x, h, b) = u_j(x, h; \boldsymbol{\theta}^y, \boldsymbol{\theta}^u) + \beta f_d(h, j, t; \boldsymbol{\theta}^d, \delta) W \\ + \beta \left(1 - f_d(h, j, t; \boldsymbol{\theta}^d, \delta)\right) \sum_{x', h', b'} \bar{V}(\Omega_{s,t}, x', h', b') f(x', h', b' | \Omega_{s,t}, x, h, j) \end{aligned} \tag{1.13}$$

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

$$\psi(\mathbf{p}(\Omega_{s,t}, x, h, b)) = \bar{V}(\Omega_{s,t}, x, h, b) - v_j(\Omega_{s,t}, x, h, b) \tag{1.14}$$

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

$$p_j(\Omega_{s,t}, x, h, b) = \int \mathbf{1}\{v_j(\Omega_{s,t}, x, h, b) - v_k(\Omega_{s,t}, x, h, b) \geq \varepsilon_k - \varepsilon_j,\ \forall j \in \mathcal{J}\} g(\boldsymbol{\varepsilon}). \tag{1.15}$$

1.4 Identification

The model is characterized by the utility parameters $\boldsymbol{\theta}^u$, income process ($\boldsymbol{\theta}^y$,σ_y), transition probability parameters ($\boldsymbol{\theta}^d$, $\boldsymbol{\theta}^h$, $\boldsymbol{\theta}^{cw}$, $\boldsymbol{\theta}^{rx}$, α_s), stochastic process for opioid misuse perception

$\boldsymbol{\theta}^b$, terminal value upon death W, and the magnitude of discounting the probability of death, δ. The discount factor is set to $\beta = 0.98$, and the distribution of choice-specific idiosyncratic shocks is assumed to follow i.i.d. type 1 extreme value.

There are two challenges to identifying the model. First, latent health is not directly observed in the data. To address this issue, I use proxy variables to identify and estimate the probability distribution of latent health. Second, the joint transition probabilities are not observed since the NSDUH is a repeated cross-section data. Instead, I have marginal transition probabilities in SIPP and MEPS where opioid misuse is not observed. I overcome this problem by exploiting state-level variation in opioid misuse to recover the effect of opioid misuse on transition probabilities of health, labor, and prescription. wor To address the first challenge, I follow a recent work on using proxy variables for unobserved heterogeneity (Hwang (2020)). Almost all surveys collect self-reported health measures and six core disability measures. I use this information in the NSDUH to identify and estimate the probability distribution of latent health conditional on education and health measures. I recode "difficult to dress alone" and "difficult to do errands" to one variable with four values so that the number of values of the proxy variable matches the number of values in latent health. Then, the 4-level self-reported health measure and "difficult to do errands & dress alone" to proxy for the joint distribution of latent health $h = (h_1, h_2)$. I use "difficult to walk," "difficult to see" and "difficult to hear" to proxy for latent physical health h_1. Lastly, I use "difficult to think, concentrate, make decisions" to proxy for latent mental health h_2. Table 1.10 summarizes how this paper uses the proxy variables to recover the probability distribution of latent health.

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

Table 1.10: Proxy Variables for Latent Health

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

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

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

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

Lastly, the parameters that govern the utility from misusing opioids $\boldsymbol{\theta}^u$ are identified by differences in choice probabilities across different choices compared to the baseline choice $j = 1$ at a given state variable. As an example, consider the differences in conditional value function between choices j and 1 at $(\Omega_{s,t}, x, h, b)$. The Hotz-Miller inversion theorem implies that (1.16) holds if the idiosyncratic shocks follow i.i.d. type 1 extreme value.

$$
\begin{aligned}
&\log \frac{P(d_1|\Omega_{s,t}, x, h, b)}{P(d_j|\Omega_{s,t}, x, h, b)} = v_j(\Omega_{s,t}, x, h, b) - v_1(\Omega_{s,t}, x, h, b) \\
&= u_j(x, h; \boldsymbol{\theta}^y, \boldsymbol{\theta}^u) - u_1(x, h; \boldsymbol{\theta}^y, \boldsymbol{\theta}^u) + \beta W \left(f_d(h, b, j, t; \boldsymbol{\theta}^d, \delta) - f_d(h, b, 1, t; \boldsymbol{\theta}^d, \delta) \right) \\
&+ \beta \sum_{x', h', b'} \bar{V}(\Omega_{s,t}, x', h', b') \begin{bmatrix} f(x', h', b'|\Omega_{s,t}, x, h, j) \left(1 - f_d(h, b, j, t; \boldsymbol{\theta}^d, \delta)\right) - \\ f(x', h', b'|\Omega_{s,t}, x, h, 1) \left(1 - f_d(h, b, 1, t; \boldsymbol{\theta}^d, \delta)\right) \end{bmatrix}
\end{aligned} \tag{1.16}
$$

By equation (1.14), equation (1.17) holds for any vector of decision weights $\boldsymbol{\omega}(x', h', b'|\Omega_{s,t}, x, h, b, j) = (\omega_1(x', h', b'|\Omega_{s,t}, x, h, b, j), \ldots, \omega_{j'}(x', h', b'|\Omega_{s,t}, x, h, b, j))^\top$ such that $|\omega_{j'}(x', h', b'|\Omega_{s,t}, x, h, b, j)| <$

∞ and $\sum_{j'\in\mathcal{J}} \omega_{j'}(x', h', b'|\Omega_{s,t}, x, h, b, j) = 1$.

$$\begin{aligned}&\bar{V}(\Omega_{s,t}, x', h', b') = \\ &\sum_{j'\in\mathcal{J}} (v_{j'}(\Omega_{s,t}, x', h', b') + \gamma - \log P(d_{j'}|\Omega_{s,t}, x', h', b'))\, \omega_{j'}(x', h', b'|\Omega_{s,t}, x, h, b, j).\end{aligned} \tag{1.17}$$

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

$$\begin{aligned}&\sum_{x',h',b'}\sum_{j'\in\mathcal{J}} \begin{bmatrix} f(x'', h'', b''|\Omega_{s,t}, x', h', b', j')\times \\ (1 - f_d(h', b', j', t; \boldsymbol{\theta}^d, \delta)) \end{bmatrix} \omega_{j'}(x', h', b'|\Omega_{s,t}, x, h, b, j) \begin{bmatrix} f(x', h', b'|\Omega_{s,t}, x, h, b, j)\times \\ (1 - f_d(h, b, j, t; \boldsymbol{\theta}^d, \delta)) \end{bmatrix} \\ = &\sum_{x',h',b'}\sum_{j'\in\mathcal{J}} \begin{bmatrix} f(x'', h'', b''|\Omega_{s,t}, x', h', b', j')\times \\ (1 - f_d(h', b', j', t; \boldsymbol{\theta}^d, \delta)) \end{bmatrix} \omega_{j'}(x', h', b'|\Omega_{s,t}, x, h, b, 1) \begin{bmatrix} f(x', h', b'|\Omega_{s,t}, x, h, b, 1)\times \\ (1 - f_d(h, b, 1, t; \boldsymbol{\theta}^d, \delta)) \end{bmatrix}\end{aligned} \tag{1.18}$$

for all $(\Omega_{s,t}, x'', h'', b'') \in \Omega$. Then, (1.19) holds under the 1-period finite dependence after replacing $v_{j'}(\Omega_{s,t}, x', h', b')$ forward as the sum of flow utility $u_{j'}(x', h')$ and ex-ante value function $\bar{V}(\Omega_{s,t}, x'', h'', b'')$.

$$\begin{aligned}&\log \frac{P(d_1|\Omega_{s,t}, x, h, b)}{P(d_j|\Omega_{s,t}, x, h, b)} \\ &= u_j(x, h) - u_1(x, h) + \beta W \left(f_d(h, 1, t; \boldsymbol{\theta}^d, \delta) - f_d(h, 1, t; \boldsymbol{\theta}^d, \delta)\right) \\ &+ \beta(1 - f_d(h, j, t; \boldsymbol{\theta}^d, \delta)) \sum_{x',h',b'}\sum_{j'\in\mathcal{J}} \begin{bmatrix} u_{j'}(x', h')+ \\ \psi_{j'}(\mathbf{p}(x', h', b')) \end{bmatrix} \begin{bmatrix} \omega_{j'}(x', h', b'|\Omega_{s,t}x, h, b, j)\times \\ f(x', h', b'|\Omega_{s,t}, x, h, b, j) \end{bmatrix} \\ &- \beta(1 - f_d(h, 1, t; \boldsymbol{\theta}^d, \delta)) \sum_{x',h',b'}\sum_{j'\in\mathcal{J}} \begin{bmatrix} u_{j'}(x', h')+ \\ \psi_{j'}(\mathbf{p}(x', h', b')) \end{bmatrix} \begin{bmatrix} \omega_{j'}(x', h', b'|\Omega_{s,t}x, h, b, 1)\times \\ f(x', h', b'|\Omega_{s,t}, x, h, b, 1) \end{bmatrix} \\ &+ \beta^2(1 - f_d(h, j, t; \boldsymbol{\theta}^d, \delta)) \sum_{x',h',b'}\sum_{j'\in\mathcal{J}} W f_d(h', j', t; \boldsymbol{\theta}^d, \delta) \begin{bmatrix} \omega_{j'}(x', h', b'|\Omega_{s,t}x, h, b, j)\times \\ f(x', h', b'|\Omega_{s,t}, x, h, b, j) \end{bmatrix} \\ &- \beta^2(1 - f_d(h, 1, t; \boldsymbol{\theta}^d, \delta)) \sum_{x',h',b'}\sum_{j'\in\mathcal{J}} W f_d(h', j', t; \boldsymbol{\theta}^d, \delta) \begin{bmatrix} \omega_{j'}(x', h', b'|\Omega_{s,t}x, h, b, 1)\times \\ f(x', h', b'|\Omega_{s,t}, x, h, b, 1). \end{bmatrix}\end{aligned} \tag{1.19}$$

Stacking (1.19) for all state space and choices for all (t, s, e), I have $(400 - 128) \times 5 \times 51 \times 2 = 138,720$ equations. The utility parameters are identified as long as the system equations have a full column rank. By the exclusion restriction, δ only appears in the transition probabilities. Thus, the average difference-in-differences of choice probabilities across b for all (x, h) identifies δ.

W is identified by the choice probability differences in $(x, h, b = L)$ where the choices affect the transition probability of arriving (h_1, h_2) next period. This is because the baseline mortality differs by latent health. Thus, the information about the preference of arriving across latent health status in the choice probabilities identifies W. For economic interpretability, I set $W = 0$ and instead allow the baseline utility 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 terminal state.

1.5 Estimation

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

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

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

1.5.1 First Stage: CCP-EM

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

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

I use flexible multinomial logistic functions to estimate the reduced-form conditional choice probabilities. I utilize the EM algorithm to estimate the parameters. Table 1.11 shows the estimation result for unconditional latent health using public NSDUH. The proxy measurement

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

Table 1.11: First Stage Estimates: Unconditional Latent Health Distribution. PUF NSDUH, 2015-2019.

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

Given the latent health distribution, I estimate the log income process for the NSDUH sample. The NSDUH asks the respondents to report their aggregate income in intervals. I take the sample in the NSDUH who are working this period for estimation. The latent log income has the following functional form:

$$\begin{aligned}\log w_{n,t} &= \theta_1^y + \sum_{m=1}^{3} \theta_{m+1}^y \mathbf{1}\{h = m\} + \sum_{m=1}^{3} \theta_{m+4} \mathbf{1}\{h = m\}\text{rx} \\ &+ \theta_8 d_o^{rx} + \theta_9 d_o^{il} + \theta_{10}^y e + \theta_{11}^y \text{xp} + \theta_{12}^y \text{xp} \times e + \nu_n \\ &:= x_y^\top \boldsymbol{\theta}^y + \nu_n\end{aligned}$$

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

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

I estimate $\boldsymbol{\theta}^y$ via MLE. Table 1.12 shows the estimates for log income process. People lose productivity when they are in worse health and also when they misuse opioids. Prescription to opioids when people are in worse health recovers some productivity. Education and past year work experience both have positive effects on productivity and they are complementary.

1.5.2 Second Stage: Transition Probabilities

Given the first stage estimates, I estimate parameters for transition probability of death $\boldsymbol{\theta}^d$, health $\boldsymbol{\theta}^h$, labor market displacement $\boldsymbol{\theta}^{cw}$, and prescription $\boldsymbol{\theta}^{rx}$ and α_s^{rx} by sequentially

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

Table 1.12: Estimates for Log Income, PUF NSDUH 2015-2019.

applying minimum distance estimators. First, the following equations are used to estimate the probability of dying conditional on latent health and opioid misuse for each state location s and year t:

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

The fractions on the left-hand side come from the restricted NVSS and the state-level population estimates from the Census. The distribution of opioid misuse and the predicted distribution of latent health come from the NSDUH. The identification of the probability of death conditional on health comes from the state-level variation in latent health. Likewise, the identification of the probability of death conditional on opioid misuse comes from the state-level variation in opioid misuse rate and mortality rates. The probability of death from other causes of death besides opioid misuse varies only by latent health status, not by year or state. Table 1.13 shows that people generally die in about 0.6 percent probability. Having bad physical health increases the probability of dying by 2.35 percent point. Having bad mental health also increases the probability of dying by 1.28 percent point. Opioid misuse also increases the probability of dying from opioid overdose, and this varies by year. In 2015, using illegal opioids increased the probability of death by 0.25 percent point, whereas it increased to 0.64 percent point in 2019. The probability of dying from misusing prescription opioids was stable during this period. Next, I estimate the transition probability of latent

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

Table 1.13: Estimates for Probability of Death (Percent), Public NSDUH and Restricted NVSS, 2015-2019.

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

$$P(h'|h, \text{cw}, \text{xp}, d_w, s, t, e) = \sum_{\text{rx}, d_o^{rx}, d_o^{il}} f_h(h'|e, h, \text{cw}, \text{rx}, \text{xp}, d_w, d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^h) \times \\ (1 - \hat{f}_d(h, b = H, j, t; \boldsymbol{\theta}^d, \delta = 0)) \times \\ \hat{P}(\text{rx}, d_o^{rx}, d_o^{il}|h, \text{cw}, \text{xp}, d_w, s, t, e) \tag{1.20}$$

$$P(h'|h, \text{cw}, \text{rx}, \text{xp}, d_w, t, e) = \sum_{\text{rx}, d_o^{rx}, d_o^{il}} f_h(h'|e, h, \text{cw}, \text{rx}, \text{xp}, d_w, d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^h) \times \\ (1 - \hat{f}_d(h, b = H, j, t; \boldsymbol{\theta}^d, \delta = 0)) \times \\ \hat{P}(\text{rx}, d_o^{rx}, d_o^{il}|h, \text{cw}, \text{rx}, \text{xp}, d_w, t, e) \tag{1.21}$$

where $\hat{f}_d$ is the fitted objective probability of death. Equation 1.20 helps identify the transition probability of the latent health state by opioid misuse by using the state-level variation in opioid misuse and marginal transition probabilities from SIPP. Equations 1.20 and 1.21 identify the transition probability of the latent health state conditional on being prescribed with opioids from MEPS.

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

$$\hat{P}(\text{cw}'|h', \text{cw}, \text{xp}, d_w, s, t, e) = \sum_{h, \text{rx}, d_o^{rx}, d_o^{il}} f_{cw}(\text{cw}'|e, h', \text{cw}, \text{rx}, \text{xp}, d_w, d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^{cw}) \\ \hat{f}_h \tilde{f}_d \hat{P}(\text{rx}, d_o^{rx}, d_o^{il}|h, \text{cw}, \text{xp}, d_w, s, t, e) \tag{1.22}$$

$$\hat{P}(\text{cw}'|e, h', \text{cw}, \text{rx}, \text{xp}, d_w, t, e) = \sum_{h, \text{rx}, d_o^{rx}, d_o^{il}} f_{cw}(\text{cw}'|e, h', \text{cw}, \text{rx}, \text{xp}, d_w, d_o^{rx}, d_o^{il}; \boldsymbol{\theta}^{cw}) \\ \hat{f}_h \tilde{f}_d \hat{P}(\text{rx}, d_o^{rx}, d_o^{il}|h, \text{cw}, \text{rx}, \text{xp}, d_w, t, e) \tag{1.23}$$

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

1.5.3 Third Stage: Iterated Minimum Distance Estimator

In the final stage, I use the system of equations constructed by stacking (1.19) for all states and choices to estimate the structural parameters. I start with $\delta = 0.25$ and iterate until convergence. I suspect the utility parameters align with data patterns observed in the public NSDUH.

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

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

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

1.6 Counterfactuals

I use the 2015 population as the reference and impose aggregate changes observed in 2019 to see how much each aggregate change has contributed to the observed change in the opioid misuse rate. Taking the 2015 population as a benchmark and imposing the 2019 environment altogether, the model predicts the overall opioid misuse rate would have decreased by [number not disclosed yet]%. This is larger than the actual decrease in opioid misuse rate from 2015 to 2019, but considering that the population in 2015 and 2019 are different and that the model's predicted opioid misuse rate for the 2019 sample not too different from the data, I think the model's predicted change in opioid misuse rate by aggregate variable changes is reasonable.

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.

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. This indicates that, considering the size of the target population, the policymakers may be able to design a cost-effective policy to decrease the opioid misuse rate.

1.7 Conclusion

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

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

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

1.8 Appendix

1.8.1 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 1.8.1.

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

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

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

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

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

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

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

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. 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.

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.

1.8.2 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

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

Table 1.14: Summary Statistics of the NSDUH Samples 22 or older. NSDUH Public Use Files, 2015-2019

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.

1.8.3 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[8], a conversion chart from Utah Department of Health and Human Services[9], Washington Health Care Authority's conversion table[10]. One milligram of Diamorphine, or heroin, is converted to 3 MME according to the UK National Health Services[11].

In StreetRx, 63.96% of fentanyl transaction records do not have a milligram dosage for each unit even though the records have a dosage for microgram (mcg) per hour. This is because fentanyl patches differ by effective duration. According to the latest available version of the MME conversion chart from the Utah Department of Health and Human Services, one patch typically lasts for three days. I impute the milligram dosage data for fentanyl patches by $\texttt{dosage/mcg} \times 0.001 \times 24 \times 3 \times \texttt{MME}$. 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 opioids is

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

1.8.4 Estimates

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

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

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

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

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

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

Table 1.15: Proxy Measurement Structure Matrix: 4-level Health Measure, Difficult to do Errands & Dressing, PUF NSDUH, 2015-2019.

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

Table 1.16: Proxy Measurement Structure Matrix: Difficult to Think, PUF NSDUH, 2015-2019.

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

Table 1.17: Proxy Measurement Structure Matrix: Difficult to Walk, Difficult to See and Difficult to Hear, PUF NSDUH, 2015-2019.

Chapter 2

Identification and Estimation of Dynamic Discrete Choice Models with a Terminal State

2.1 Introduction

In this chapter, I discuss the identification of a dynamic discrete choice model with a terminal state.

The under-identification result in dynamic discrete choice models implies that the parameterization of the utility function is critical in the application. More often than not, parametrization on the utility function implies much more restrictions on the set of equations that identify the structural parameters of the dynamic model. As such, a searcher should be comfortable in relaxing one parameter—the value of terminal state—when estimating the model. The set of Monte Carlo simulations in this chapter includes a case where the true value of the terminal state is zero, and show that the estimate of the estimator is not significantly different from zero.

The literature on identifying dynamic discrete choice models has a long history dating back to Rust (1987). It is well known in the literature that dynamic discrete choice models are under-identified nonparametrically (Magnac and Thesmar (2002)). The latest known result is Arcidiacono and Miller (2020), where the authors show that at least one value for the utility of the normalization choice for each state must be known to identify deep parameters nonparametrically.

This paper directly applies the result in Arcidiacono and Miller (2020) with a terminal state. Note that the terminal *state* is not a terminal *choice* unlike sterilization considered in

Hotz and Miller (1993) or retirement decisions, the class of models I consider in this paper includes choices that change the probability of transition to the absorbing state, but not deterministically.

I show that putting a zero value in the terminal state is not an innocuous assumption, just as misleading as assuming a zero value on the utility for the baseline choice for each state.

The underidentification result in dynamic discrete choice models implies that the parameterization of the utility function is critical in the application. More often than not, parametrization on the utility function implies much more restrictions on the set of equations that identify the structural parameters of the dynamic model. As such, a searcher should be comfortable in relaxing one parameter—the value of terminal state—when estimating the model. The set of Monte Carlo simulations in this chapter includes a case where the true value of the terminal state is zero and shows that the estimator's estimate is not significantly different from zero.

2.2 Model

2.2.1 Dynamic Discrete Choice Model with Terminal State

In this section, I define the class of models that I consider in this paper. The specification closely follows Arcidiacono and Miller (2020) for consistency with the literature.

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

The flow utility $x \in \mathcal{X}$ given $j \in \mathcal{J}$ is

$$u_j(x, \varepsilon) = u_j(x) + \varepsilon_j \tag{2.1}$$

The representative individual is rational and makes optimal choices for each period given the observed transition probabilities.

$$V_t(x_t, \boldsymbol{\varepsilon}_t) = \max_{j \in \mathcal{J}} u_{j,t}(x_t) + \varepsilon_{j,t} + \sum_{\tau=t}^{T} \sum_{x_\tau \in \mathcal{X}} \sum_{j \in \mathcal{J}} \bar{V}(x_\tau)(1 - f^d(x,j)) f(x'|x,j) \tag{2.2}$$

2.2.2 Identification

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

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

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

$$\kappa^*_\tau(x_{\tau+1}|x_t, j) = \begin{cases} (1 - f_W(x_t, j)) f_\tau(x_{\tau+1}|x_t, j) & \text{if } \tau = t \\ \sum_{x=1}^{X} \kappa^*_{\tau-1}(x|x_t, j)(1 - f_W(x_\tau, l(x,\tau))) f_\tau(x_{\tau+1}|x, l(x,\tau)) & \text{if } \tau > t \end{cases} \tag{2.3}$$

$$\kappa^W_\tau(x_t, j) = \begin{cases} f_W(x_t, j) & \text{if } \tau = t \\ \kappa^*_{\tau-1}(x|x_t, j) f_W(x, l(x,\tau)) & \text{if } \tau > t \end{cases} \tag{2.4}$$

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

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

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

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

$j \in \mathcal{J}$ and $t = 1, 2, \ldots, R$:

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

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

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

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

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

2.3 Illustration

I provide an example using a simple infinite-horizon dynamic discrete choice model to illustrate the importance of leaving the value of the terminal state to be estimated.

The state space is $(x_1, x_2, \boldsymbol{\varepsilon})$ where $x_1 = 1, 2, 3, 4$, $x_2 = 1, 2, 3, 4$, and $\boldsymbol{\varepsilon} = (\varepsilon_1, \ldots, \varepsilon_4)$ is a vector of idiosyncratic errors whose distribution is independently and identically distributed with type 1 extreme value distribution.

The flow utility is defined as:

$$u(x_1, x_2, j, \boldsymbol{\varepsilon}; \boldsymbol{\theta}) = d_1(x_1\theta_1 + x_2\theta_2) + d_2(x_1\theta_3 + x_2\theta_4) + d_1 d_2(x_1\theta_5 + x_2\theta_6) + \varepsilon_j. \tag{2.5}$$

The parameters for the flow utility function and the value for the terminal state are set as below:

	Values
θ_1	0.22
θ_2	0.09
θ_3	0.36
θ_4	0.11
θ_5	-0.38
θ_6	-0.17
W	-35

Table 2.1: The parameters for the flow utility

The transition probability for entering the terminal state is specified as a logit form:

$$\log \frac{f_W(x_1, x_2, d_1, d_2; \boldsymbol{\theta}_w)}{1 - f_W(x_1, x_2, d_1, d_2; \boldsymbol{\theta}_w)} = \theta_1^d + x_1\theta_2^d + x_2\theta_3^d + d_1\theta_4^d + d_2\theta_5^d. \tag{2.6}$$

The transition probability for (x_1, x_2) conditional on not reaching the terminal state is defined as a multinomial logit form:

$$\log \frac{f_x(x' = k | x, j; \boldsymbol{\theta}^s)}{f_x(x' = 1 | x, j; \boldsymbol{\theta}^x)} = \theta_{1,k}^x + x_1\theta_{2,k}^x + x_2\theta_{3,k}^x + d_1\theta_{4,k}^x + d_2\theta_{5,k}^x. \tag{2.7}$$

for $k = 2, \ldots, 16$.

I show five cases to illustrate i) that setting $W = 0$ is essentially solving for a different problem and that the parameter estimates will be widely off from the DGP and ii) that the researcher can recover the DGP's flow utility parameters by adding a few additional

	Values
Constant	-1.50
x_1	0.25
x_2	0.45
d_1	0.15
d_2	0.10

Table 2.2: The parameters for transition probability of entering the terminal state

parameters on the flow utility that can represent the effect of the omitted terminal value.

In the first case, I set $W = 0$ while keeping the specification of the flow utility the same. This results in forcing the flow utility parameters to reflect the effect of the terminal value in the DGP, which leads to forcing the utility parameters to be off from the DGP. Column 1 in Table 2.3 shows that the parameter found using the criterion function is off by at most 17% in this example. The predicted choice probability based on the model estimates also significantly differs from the DGP.

In the second case, I allow for W to be estimated along with the flow utility parameters. The parameter estimate for W in this case is -34.9996, which is very close to the DGP. While W is not a flow utility per se, this is a part of the structure of the model and is easily calculated. While the value for the terminal state is not nonparametrically identifiable, sufficient parametrization on the utility parameters allows for identification.

From the third case to the fifth, I add additional terms in the flow utility to take into account setting $W = 0$. The third column adds $\theta_1^u + f_W(x_1, x_2, j; \theta_d)\theta_2^u$. The third column in Table 2.3 shows that the two terms play together to mimic the role of W. In words, θ_1^u works as the constant value of being in the non-terminal state, and θ_2^u works as the disutility of being exposed to the probability of entering the terminal state given state x and choice j. The predicted choice probabilities are almost the same as the second case.

In this specification, one can still recover the flow utility parameters by adding either one of the two terms. Case 4 adds only θ_1^u and Case 5 adds only $f_W(x_1, x_2, j; \theta_d)\theta_2^u$. The latter is uninteresting as it should be equal to $\frac{1}{\beta} f_W(x_1, x_2, j; \theta_d)$. The former is more interesting as it only adds a constant term to the utility function. Nevertheless, both work well to take into account the role of parameterizing the value to the terminal state to zero. The predicted choice probabilities are almost the same as the second case as well.

2.4 Conclusion

Although most dynamic discrete choice models assume zero values whose states are uninteresting, this assumption can have non-trivial implications for identifying other parameters. This chapter illustrates the special case of the terminal state, although its value is often unobserved and is assumed to be zero in application. I apply the observational equivalence theorem in Arcidiacono and Miller (2020) to this case to prove that the terminal value shows up in the conditional value function nonlinearly so that setting its value to zero is not an innocuous assumption. In numerical illustration, I deploy a simple infinite-horizon dynamic discrete choice model with 1-period finite dependence to make this point in detail. I show that parametrizing the terminal state to zero is essentially fitting a different model, whose

	Case 1	Case 2	Case 3	Case 4	Case 5
Difference in parameter values (in percent)					
θ_1	0.78	-0.0001	0.0003	0.0003	-0.0002
θ_2	17.02	0.0001	-0.0020	-0.0011	-0.0000
θ_3	5.25	-0.0004	-0.0009	-0.0009	-0.0001
θ_4	-4.02	0.0002	0.0024	0.0015	-0.0005
θ_5	-1.55	-0.0004	-0.0004	-0.0006	-0.0000
θ_6	12.16	0.0002	0.0005	0.0009	-0.0003
Fitted parameter values					
W	-	-34.9996	-	-	-
θ_1^u	-	-	1.1726	1.4000	-
θ_2^u	-	-	-5.4580	-	-33.5994
Difference in predicted choice probabilities					
L2	0.03246	3.3e-06	4.613e-06	3.406-06	3.007-06
L0	0.01359	1.173e-06	2.658e-06	1.196e-06	1.087e-06

Table 2.3: Summary of Results in Cases 1 to 5

flow utility is asked to take a role of terminal state's value in choice probabilities. This problem is resolved either by i) directly fitting the terminal value or ii) modifying the utility function to take into account the terminal state's role in the dynamic model.

(x_1', x_2')	$(1,2)$	$(1,3)$	$(1,4)$	$(2,1)$	$(2,2)$	$(2,3)$	$(2,4)$	$(3,1)$	$(3,2)$	$(3,3)$	$(3,4)$	$(4,1)$	$(4,2)$	$(4,3)$	$(4,4)$
Constant	-0.97	-0.86	-1.28	0.25	-0.41	-1.58	1.91	1.39	0.91	-0.52	-0.84	0.30	-0.41	0.65	1.22
x_1	1.77	-0.84	1.20	-2.95	0.91	-0.63	0.10	-0.74	-0.80	-1.76	-0.04	0.64	-2.79	0.63	-0.49
x_2	-1.14	0.27	-2.26	-1.91	2.67	2.10	0.68	2.7	-0.23	-1.03	-2.21	-1.91	0.06	1.95	-1.82
d_1	-1.66	-0.30	1.31	1.76	2.66	-2.05	-0.48	0.89	0.92	1.39	0.39	-0.73	0.42	-1.57	1.67
d_2	-1.27	0.88	-0.36	3.04	-2.80	-0.44	1.18	-0.95	-1.57	-2.22	-3.03	0.89	0.10	-2.68	-0.76

Table 2.4: The parameters for transition probability of the next period's state conditional on not entering the terminal state

Chapter 3

Estimation of Dynamic Discrete Choice Models with Subjective Beliefs under Finite Dependence Property

3.1 Introduction

The two-step conditional choice probabilities estimator with finite dependence property proposed by Arcidiacono and Miller (2011) and Arcidiacono and Miller (2019) has advantages in its speed compared to other well-known estimation strategies such as the full solution method Rust (1987) and the pseudo-maximum likelihood method Aguirregabiria and Mira (2010).

The literature discusses identifying dynamic discrete choice models based on rational expectations models, where the transition probabilities observed in the data are what the agents expected upon decision-making. However, when the perceived transition probabilities differ from the observed transition probabilities, estimating the structural parameters with ease of computation is an open question.

I propose a novel estimation strategy in a setting where a state variable does not enter the flow utility and represents the deviation from rational expectations. In this setting, the identification argument for the subjective belief parameter is straightforward; the difference in the choice probability differences across different values of the state variable identifies the belief parameter. Leaving identification aside, the estimation strategy iterates between i) solving for decision weights that cancel out the ex-ante value function in a few periods ahead for each conditional value function differences and ii) fitting the structural parameters given the decision weights. As long as the subjective belief parameter is uniquely identified, the estimation method will converge to the true parameter value in the data generating process.

3.2 Model

I consider a class of models where the transition probabilities exhibit a one-period finite dependence, and that the deviation from a rational expectation agent occurs randomly every period. The agent knows this misperception occurs, and that the agent knows its realization process. In this way, the model is similar to the present-bias model O'Donoghue and Rabin (2015)

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

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

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

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

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

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

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

3.3 Estimation Steps

The estimation procedure extends Arcidiacono and Miller (2011) by iterating between computing the finite dependence paths for a given parameter for the perception bias size and computing the structural parameters.

3.4 Illustration

For illustration, let us consider an infinite horizon dynamic discrete choice model. The observable state space is the two-dimensional tuple (x_1,x_2) where $x_1\in\{1,2,3,4\}$ and $x_2\in\{1,2,3\}$. The state is indexed by $x=4(x_1-1)+x_2$. There are four choices in total: $d_1=0,1$ and $d_2=0,1$. The choices are indexed by $j=1+d_1+2d_2$.

Algorithm 1 Estimation Procedure

```
Input: Initial parameters δ_0, θ_0^u, tolerance ϵ
Initialization: Set iteration counter i ← 0
repeat
    Compute finite dependence paths given δ_i for each conditional value function contrast
    Minimize the criterion function generated by the finite dependence paths
        Check if ‖δ_{i+1} − δ_i‖ < ϵ
    Update iteration counter: i ← i + 1
until convergence criterion is met
Output: Estimated parameters δ̂, θ̂^u
```

The flow utility is defined as

$$\begin{aligned} u(x, j; \boldsymbol{\theta}) =& d_1(\mathbf{1}\{x_1 = 1\}\theta_1 + x_1\theta_2 + \mathbf{1}\{x_2 = 1\}\theta_3 + x_2\theta_4) + \\ & d_2(\mathbf{1}\{x_1 = 1\}\theta_5 + x_1\theta_6 + \mathbf{1}\{x_2 = 1\}\theta_7 + x_2\theta_8) + \\ & d_1 d_2(x_1\theta_9 + x_2\theta_{10}). \end{aligned} \tag{3.1}$$

The transition probabilities are defined in three stages. First, there is a transition probability to the terminal state D. It is defined by

$$\log \frac{f_d(D = 1|x, j; \boldsymbol{\theta}^d)}{f_d(D = 0|x, j; \boldsymbol{\theta}^d)} = \theta_1^d + x_1\theta_2^d + x_2\theta_3^d + d_1\theta_4^d + d_2\theta_5^d. \tag{3.2}$$

Next, there is transition probability for (x_1, x_2) conditional on not reaching the terminal state:

$$\log \frac{f_x(x' = k|x, j; \boldsymbol{\theta}^s)}{f_x(x' = 1|x, j; \boldsymbol{\theta}^x)} = \theta_{1,k}^x + x_1\theta_{2,k}^x + x_2\theta_{3,k}^x + d_1\theta_{4,k}^x + d_2\theta_{5,k}^x \tag{3.3}$$

for $k = 2, \ldots, 12$.

Lastly, the perception bias s to the transition probability to the terminal state is realized every period given (x_1, x_2):

$$\log \frac{f_s(s = 1|x; \boldsymbol{\theta}^s)}{f_s(s = 0|x; \boldsymbol{\theta}^s)} = \theta^s + x_1\theta_1^s + x_2\theta_2^s. \tag{3.4}$$

The discount factor β is set to 0.96, and the magnitude of the perception bias is set to $\delta = 0.27$. I assume that the idiosyncratic preference shocks have an i.i.d. type 1 extreme value distribution. The parameters for the transition probabilities are in the Appendix.

I show five cases to illustrate that i) the proposed estimation procedure works well, ii) assuming that $W = 0$ is not an innocuous assumption, and iii) a researcher can parameterize the flow utility function to account for $W = 0$ at the expense of extra computation burden.

As in the first case, the estimation strategy that I propose in this chapter is implemented with the correct specification for the flow utility and leaving the value at the terminal state to be estimated. The structural parameters are computed almost perfectly, with a slight deviation in the value in the terminal state.

In the second case, I implement the same strategy while setting the terminal value to zero. Unsurprisingly, the utility parameters are off from the data generating process. More importantly, the predicted choice probabilities are off by up to 4 percentage point, which raises concern whether the model specification captures the variation in the data well.

While the first two cases illustrate that estimating the value for the terminal state is desirable, its interpretation is left debatable, especially in labor or health economics. For example, when the flow utility is measured in terms of income, the terminal value can be interpreted as the net present value of income that individuals can feel indifferent to accepting death with certainty. This is why many economists tend to put a zero value on the terminal state, to signify that the optimization problem becomes moot when the individual dies. The second case, however, shows that its parameterization does have a significant effect on estimates. Essentially, this means that we are fitting a different model using the data.

Case numbers 3, 4, and 5 show that a researcher may circumvent this problem by imposing alternative specifications on the flow utility to find an observational equivalent model to the data generating process. In these cases, I add the baseline utility for "not being in the terminal state," and the utility for being exposed to the transition probabilities to arrive at the terminal state.

$$\begin{aligned} u(x, j; \boldsymbol{\theta}) =& d_1(\mathbf{1}\{x_1 = 1\}\theta_1 + x_1\theta_2 + \mathbf{1}\{x_2 = 1\}\theta_3 + x_2\theta_4) + \\ & d_2(\mathbf{1}\{x_1 = 1\}\theta_5 + x_1\theta_6 + \mathbf{1}\{x_2 = 1\}\theta_7 + x_2\theta_8) + \\ & d_1 d_2(x_1\theta_9 + x_2\theta_{10}) + \\ & \theta_1^b + f_d(x_1, x_2, d_1, d_2; \boldsymbol{\theta}^d)\theta_2^b. \end{aligned} \tag{3.5}$$

Case 3 shows the successful incidence when the alternative specification to the utility function recovers the structural parameters for the data generating process and its predicted choice probabilities are close to observational equivalence. This essentially means that the value assigned to the terminal value is a combination of the two elements. Finding the alternative utility function, however, needs some carpentry; cases 4 and 5 show that at least only using one of the two is not sufficient to capture the value assigned to the terminal value. Notably, the perception bias to the transition probability to death is not estimated and the predicted choice probabilities are off from the second case. Case 4 also shows that adding more terms in the utility function does not guarantee improvement in fitting the data.

Parameters	DGP	Case 1	Case 2	Case 3	Case 4	Case 5
θ_1	0.15	0.1500	0.0687	0.1500	0.1405	0.1330
θ_2	0.32	0.3200	0.2770	0.3200	0.4802	0.3125
θ_3	-0.95	-0.9500	-0.9356	-0.9500	-1.2058	-0.9538
θ_4^u	-0.36	-0.3600	-0.3636	-0.3600	-0.3299	-0.3644
θ_5^u	1.04	1.0400	0.7823	1.0400	1.1676	0.9378
θ_6^u	0.62	0.6200	0.5171	0.6200	0.7155	0.5820
θ_7^u	0.07	0.0700	-0.4018	0.0700	0.8979	-0.0066
θ_8^u	0.80	0.8000	0.5641	0.8000	1.3220	0.7774
θ_9^u	-0.30	-0.3000	-0.2752	-0.3000	-0.4368	-0.2977
θ_{10}^u	-0.30	-0.3000	-0.3148	-0.3000	-0.2126	-0.2919
δ	0.27	0.2700	0.3199	0.2701	0.0000	1.0000
W	-20	-20.0000	Set to 0	-	-	-
θ_1^b	-	-	-	0.7999	-1.0405	-
θ_2^b	-	-	-	-0.0032	-	-9.8964
CCP Difference						
L2	-	1.899e-07	0.14802	1.051e-06	0.8294	0.05718
L0	-	5.485e-08	0.04342	4.163e-07	0.2163	0.01488
Iterations	-	9	12	1000	15	5

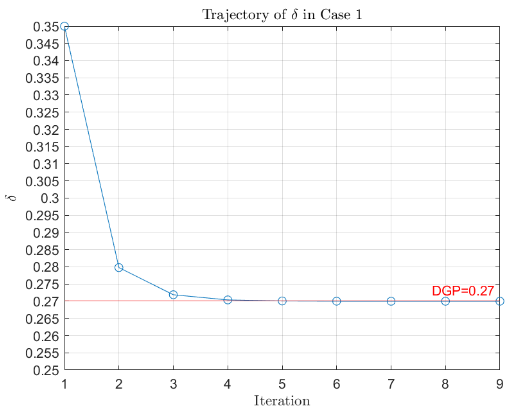
Table 3.1: Simulation Result

Compared to case 2, while I included one more term in the utility function to capture the terminal value via flow utility, its predicted choice probabilities are more off than the second case.

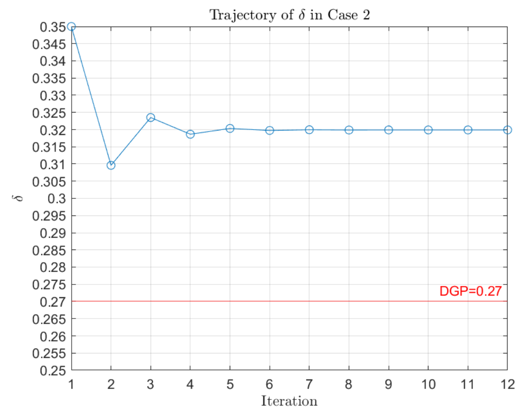
I advocate estimating the terminal value as specified in the model as opposed to case 4 because of its computation ease. While cases 2 and 4 recover the flow utility parameters and perception bias term equally well and the only difference is decomposing the terminal value into the baseline flow utility, the number of iterations they take to converge are vastly different. While case 1 took 10 iterations to converge, case 3 took 777 iterations to converge. This indicates that it might be easier to estimate the terminal value directly and interpret it as an aggregate value on arriving at the terminal state or the negative net present value of some combination of staying outside of the terminal state and the utility of being exposed to different transition probability of arriving at the terminal state.

3.5 Conclusion

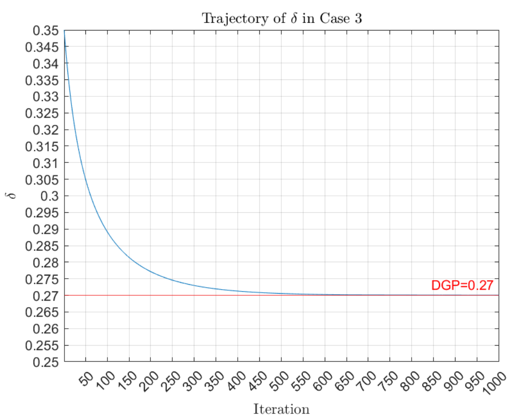
In this chapter, I discuss the new estimation procedure for dynamic discrete choice models when the individual's expectation deviates from rational expectation. The methodology works when there exists one parameter that represents the magnitude of deviation from the rational expectation. The proposed estimation iterates between i) finding the finite dependence paths for each conditional value function contrast for a given parameter of the deviation and ii) estimating the structural parameters along with the parameter of the deviation. The procedure iterates between the two and repeats until convergence. I show that this procedure works well in a parsimonious infinite-horizon dynamic discrete model with a terminal state, and the magnitude of deviation from the rational expectation is applied to the transition probability of entering the terminal state. The numerical illustration shows that the method works well and that reformulating the flow utility to recover the data generating process's utility parameters requires more work than when there is no perception bias. Even when a researcher finds such a utility functional form, the number of iterations needed for convergence increases significantly.



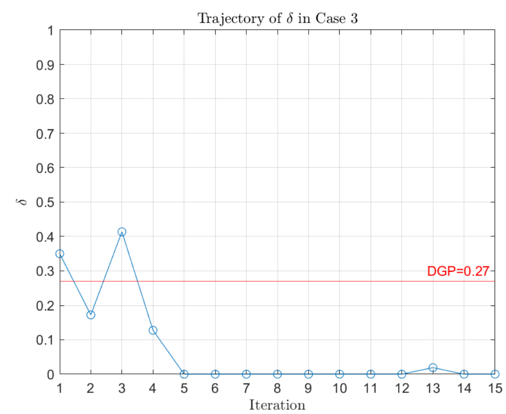
(a) Trajectory of δ in Case 1



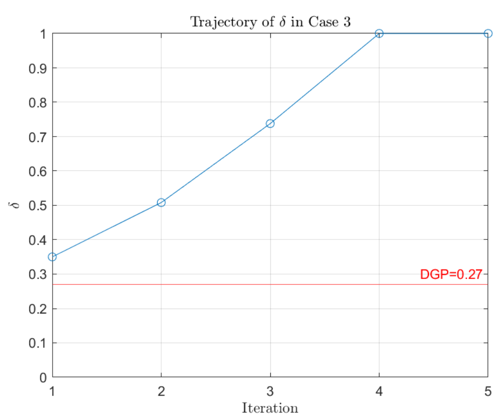
(b) Trajectory of δ in Case 2



(c) Trajectory of δ in Case 3



(d) Trajectory of δ in Case 4



(e) Trajectory of δ in Case 5

Figure 3.1: Trajectories for δ in Cases 1 to Case 5

Bibliography

Abbring, J. H. and Ø. Daljord (2020). A comment on "estimating dynamic discrete choice models with hyperbolic discounting" by hanming fang and yang wang. *International Economic Review 61*, 565–571.

Aguirregabiria, V. and P. Mira (2010). Dynamic discrete choice structural models: A survey. *Journal of Econometrics 156*, 38–67.

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.

Arcidiacono, P. and R. A. Miller (2020). Identifying dynamic discrete choice models off short panels. *Journal of Econometrics 215*, 473–485.

Balestra, S., H. Liebert, N. Maestas, and T. Sherry (2023). 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*.

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.

Gladden, R. M., P. Martinez, and P. Seth (2016). Fentanyl law enforcement submissions and increases in synthetic opioid–involved overdose deaths — 27 states, 2013–2014. *MMWR. Morbidity and Mortality Weekly Report 65*, 837–843.

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.

Hotz, V. J. and R. A. Miller (1993). Conditional choice probabilities and the estimation of dynamic models. *The Review of Economic Studies 60*, 497–529.

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.

Magnac, T. and D. Thesmar (2002). Identifying dynamic discrete decision processes. *Econometrica 70*, 801–816.

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

Mulligan, C. B. (2024). Prices and policies in opioid markets. *Journal of Political Economy*, 000–000.

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.

Peterson, A. B., R. M. Gladden, C. Delcher, E. Spies, A. Garcia-Williams, Y. Wang, J. Halpin, J. Zibbell, C. L. McCarty, J. DeFiore-Hyrmer, M. DiOrio, and B. A. Goldberger (2016). Increases in fentanyl-related overdose deaths — florida and ohio, 2013–2015. *MMWR. Morbidity and Mortality Weekly Report 65*, 844–849.

Rust, J. (1987). Optimal replacement of gmc bus engines; an empirical model of harold zurcher. *Econometrica*.

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.

Appendix A

Additional Tables and Figures

Appendix B

Data Sources

Appendix C

Appendix for Chapter 3

C.0.1 Data Generating Process

Constant	-3.50
x_1	0.15
x_2	0.35
d_1	0.05
d_2	0.35

Table C.1: Parameters for transition probability to terminal state

Constant	-2.50
x_1	0.15
x_2	0.55

Table C.2: Parameters for the perception bias

	$x' = 2$	$x' = 3$	$x' = 4$	$x' = 5$	$x' = 6$	$x' = 7$	$x' = 8$	$x' = 9$	$x' = 10$	$x' = 11$	$x' = 12$
Constant	-0.65	-0.57	-0.85	0.17	-0.28	-1.05	1.27	0.93	0.60	-0.35	-0.56
x_1	1.18	-0.56	0.80	-1.97	0.60	-0.42	0.07	-0.49	-0.54	-1.17	-0.03
x_2	-0.76	0.18	-1.51	-1.27	1.78	1.40	0.45	1.80	-0.16	-0.69	-1.48
d_1	-1.11	-0.20	0.88	1.18	1.77	-1.37	-0.32	0.57	0.61	0.93	0.26
d_2	-0.85	0.59	-0.24	2.03	-1.87	-0.29	0.79	-0.64	-1.04	-1.48	-2.02

Table C.3: Parameters for transition probabilities conditional on not arriving at the terminal state