The Downward Spiral*

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Abstract

There have been more than 500,000 opioid overdose deaths since 2000. To analyze the opioid epidemic, a model is constructed where individuals, with and without pain, choose whether to misuse opioids knowing the probabilities of addiction and dying. These odds are functions of opioid use. Markov chains are estimated from the US data for the college and non-college educated that summarize the transitions into and out of opioid addiction as well as to a deadly overdose. A structural model is constructed that matches the estimated Markov chains. The epidemic's drivers, and the impact of medical interventions, are examined.

Keywords: addiction, college/non-college educated, deaths, fentanyl, Markov chain, medical interventions, opioids, OxyContin, pain, prices, structural model
JEL Nos: D11, D12, E13, I12, I14, I31, J11, J17

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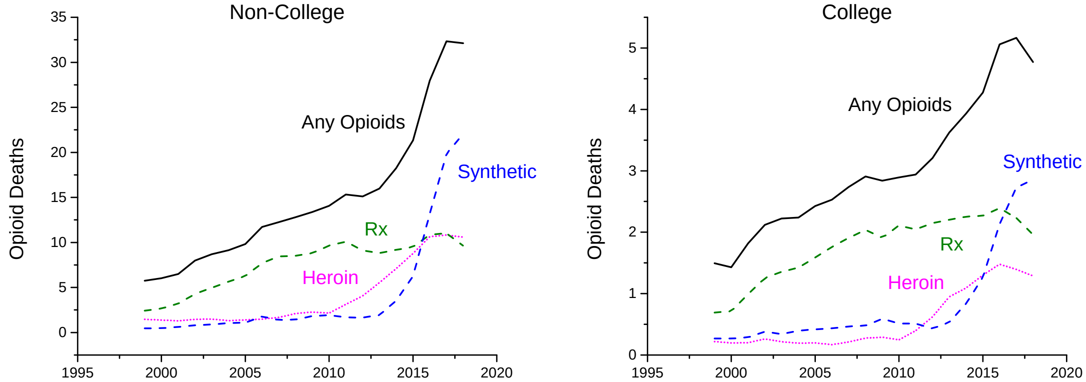

Figure 1: Opioid deaths for both the non-college and college educated as measured per 100,000 people in the respective education class.

1 Opening

1.1 Some Background

In 2019 the age-adjusted death rate from an opioid overdose was 21.6 per 100,000 people. This compares with 12.9 for kidney disease, 14.2 from suicides, 14.7 for influenza, 21.6 from diabetes, and 161.5 from heart disease (the leading cause of death in the United States). Opioid overdose deaths place in the top 10 leading causes of death in the United States. As can been from Figure 1, prior to 2015 most of these opioid deaths arose from prescription (Rx) overdoses, but after that they came from synthetic opioids; in particular, fentanyl. (The sources for all the data displayed in the figures are presented in Appendix B.) The overdose death rate was much higher for those without a college degree compared with those who had one. The rise in the death rate from synthetic opioids is particularly marked for the non-college educated population.

Surprisingly, this is not the first opioid epidemic in the United States. Morphine was distilled from opium in 1804 by the German chemist F.W.A. Sertürner.[1] Merk started selling it in 1827. In the later part of the 19th century, opium and morphine were widely available in United States. Morphine was used in the Civil War to control the pain suffered by soldiers. Based on surveys of pharmacists and physicians, maintenance records for addicts, military medical examinations, and opiate imports, Courtwright (2001) estimates that there were 0.72 addicts per 1,000 population in 1842 and perhaps as much as 4.59 in the 1890s. Table 1 reports the results of some surveys of pharmacists about the number of addicted customers visiting their dispensaries.

[1] In 1810 he issued a prophetic warning: "I consider it my duty to attract attention to the terrible effects of this new substance in order that calamity may be averted."

Table 1: Surveys of Pharmacists, 1880-1903

Year	**Place**	**Addicts/Store**	**Addicts/1,000 pop**
1880	Chicago	4.70	2.09-2.54
1885	Iowa towns	1.91	0.85-1.03
1902	Eastern cities and towns	4.00	1.78-2.16

Source: Courtwright (2001, Table 1)

The root of most morphine addictions in the late 1800s was prescriptions by physicians. The modal addict was a middle/upper-class, 37-year-old, white housewife. While morphine was routinely prescribed for a wide range of ailments, it was used for women's health issues such as dysmenorrhea and afflictions such as anxiety/depression and headaches that disproportionately affect women. Aspirin wasn't invented until 1899. Morphine might have been a substitute for alcohol since it was unfitting at the time for a woman to drink. Figure 2 displays an ad for a children's teething pain formula that contained morphine. Addiction was viewed as such a problem that the US Congress passed the Harrison Narcotics Act in 1914 to control the distribution of opioids.[2] Heroin was introduced as a cough suppressant in 1898. In the early 1900s the prototypical heroin addict was a lower-class white male in his early twenties.

What caused the recent epidemic? Protracted pain diminishes the value of life. In the 1990s physicians rethought the need to manage pain. This led to the view that doctors were under prescribing pain killers, such as morphine, epitomized by a 1990 article in *Scientific American* titled "The Tragedy of Needless Pain." Ronald Melzack, a psychology professor, wrote

> "Yet the fact is that when patients take morphine to combat pain, it is rare to see addiction-which is characterized by a psychological craving for a substance and, when the substance is suddenly removed, by the development of withdrawal symptoms (for example, sweating, aches and nausea). Addiction seems to arise only in some fraction of morphine users who take the drug for its psychological effects, such as its ability to produce euphoria and relieve tension." Melzack (1990, p. 27).

Drug companies moved onto the new landscape.

In 1996 Purdue Pharma introduced OxyContin with an aggressive marketing campaign.[3] "Oxy" came from the opioid-based painkiller oxycodine and "Contin" meant continuous.

[2] Courtwright (2001) believes that government officials and politicians exaggerated the epidemic in order to pass the legislation.

[3] Among other things, Purdue Pharma staged all-expenses-paid informational seminars at resort locations in Arizona, California, and Florida for somewhere between 2,000 and 3,000 physicians–Meier (2018, p. 78).

Figure 2: The left panel shows an 1885 ad for a children's teething syrup that contained alcohol and morphine. An ad for OxyContin is shown in the right panel.

Purdue Pharma asserted that because the drug released its effect in a prolonged slow continuous manner the rate of addiction was less than one percent.[4] The Food and Drug Administration (FDA) allowed Purdue Pharma to make the claim in its marketing campaigns that "(d)elayed absorption, as provided by OxyContin tablets, is believed to reduce the abuse liability of a drug"–Meier (2018, p. 76). Figure 2 displays an ad for OxyContin that notes the most common side effects are "constipation, nausea and somnolence." The pills were open to abuse by those with or without pain. After the slow-release coating was removed, they could be crushed and then either snorted or mixed with water and injected. When heroin came online in the early 1900s it was claimed to be: "'Safe and Reliable,''addiction scarce be possible,' and the 'absence of danger of acquiring the habit.'"–Courtwright (2001, p 91).

Starting around the year 2000 there was a dramatic increase in number of opioid prescriptions per person for both the college- and non-college-educated populations, as shown in Figure 3. The non-college educated were much more likely to have an opioid prescription than the college educated. The former often work in occupations involving physical labor. Additionally, the amount of Rx opioids consumed, conditional on a prescription, also rose. Again, this was particularly true for those without a college degree. The price of prescription opioids has fallen dramatically since 2000. Figure 4 shows that the out-of-pocket expense for prescription opioids has fallen by a factor of 3 since 2001. This has been attributed to two factors. First, the advent of generic prescription opioids. Second, the expansion of social

[4] This assertion was based upon a one paragraph letter to the *New England Journal of Medicine* in 1980 titled "Addition Rare in Patients Treated with Narcotics." The letter was based upon patients who were hospitalized mostly for short stays at the time of treatment. No supporting evidence was provided by the two correspondents.

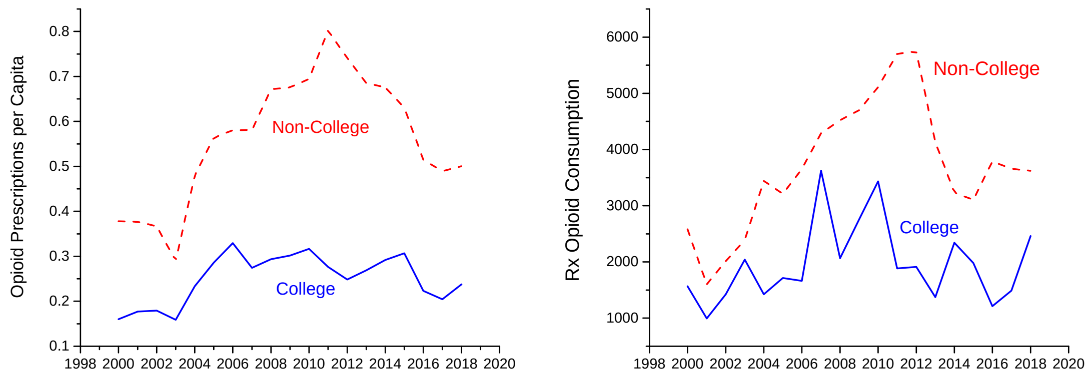

Figure 3: The left panel shows opioid prescriptions per person in an education class for both the college- and non-college-educated populations. The right panel shows Rx opioid consumption, conditional on having a prescription, measured in morphine milligram equivalents (MMEs) per person in an education class.

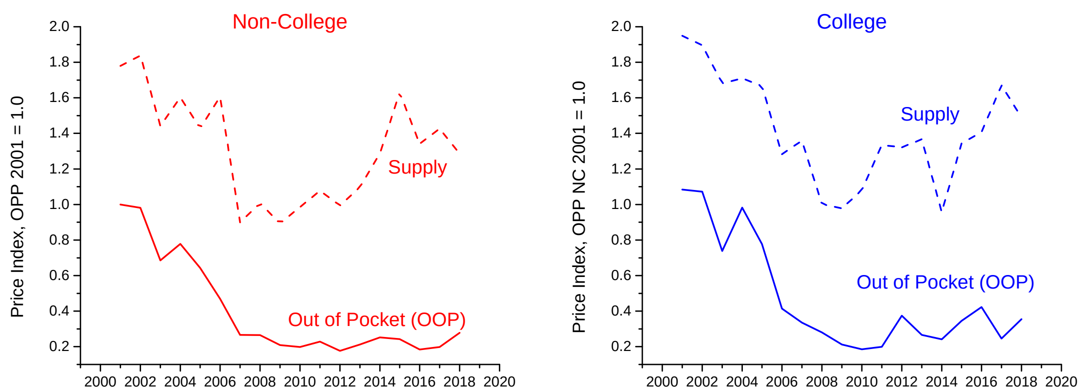

Figure 4: Price of prescription opioids for both the non-college- and college-educated populations. The series have been normalized so that the out-of-pocket price for the non-college educated is 1.0 in 2001.

programs such as Medicare and Medicaid that subsidized the purchase of opioids, as can be seen from Figure 5. For the college educated Medicaid is less important than private payers while for the non-college educated the reverse is true. The share of opioids prescriptions funded by the government grew from 17 percent in 2001 to 60 percent in 2010. The vast majority of opioids went to people who needed relief from pain caused by either disability or illness.

Over the same period the street price of opioids dropped by a factor of 3. This has been chalked up to both the illegal imports of inexpensive powerful synthetic opioids, for example fentanyl, from China and elsewhere. Additionally, the diversion of opioids from legal sources onto the black market via fraudulent prescription, family and friends giving away and/or selling their prescriptions, and theft. The rise of illegal imports is ascribed to the tightening

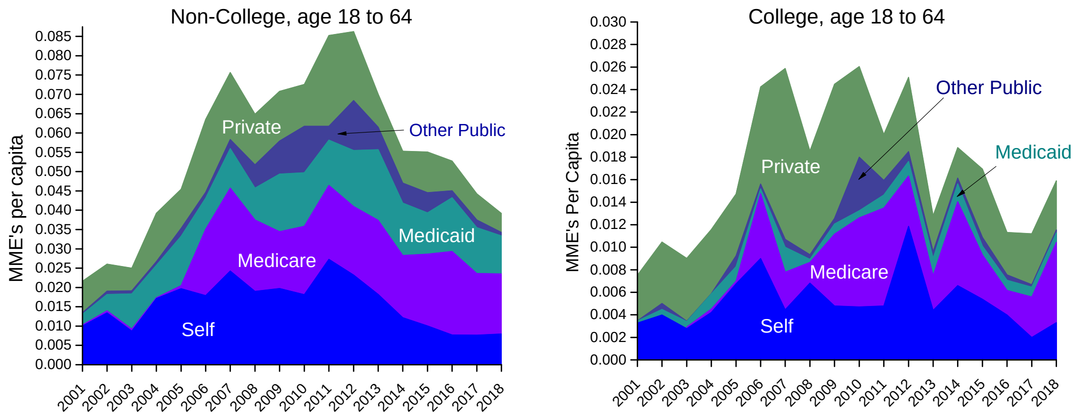

Figure 5: Primary payer by morphine milligram equivalents (MME's). The left panel is for the non-college educated while the right panel is for the college educated.

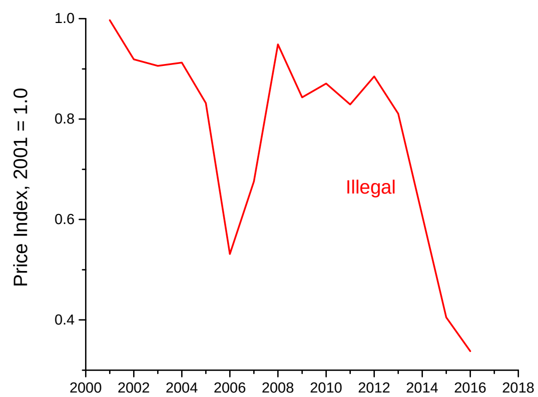

Figure 6: Price of Illegal Opioids. Source: *Economic Report of the President, 2020* (Figure 7-19).

of prescriptions and the introduction of a tamper-proof form of OxyContin. The upshot is that opioids are much less expensive now than they were in 2001. Likewise, the introduction of low-cost heroin at the beginning of the 20th century was due to the banning of smoking opioids and the increased restrictions on the use of cocaine.

1.2 What's Done Here

A model is developed where some people use opioids and others don't. There are two routes to opioid use. Individuals may experiment with opioids for enjoyment. Others start using prescription opioids to reduce pain. A fraction of the individuals experiencing pain will misuse their prescriptions. Individuals who misuse opioids, through either experimentation or as a pain killer, can end up as addicts. Addicts face the possibility of death. The probabilities of addiction and death depend upon the extent of opioid usage. The decisions to misuse opioids, in the first place, and, in the second place, how much to use, are endogenous. Opioid abusers and addicts may also choose whether to work or not. This decision is a function of how opioid use affects a person, which varies across individuals. These choices depend on idiosyncratic predilections toward opioid use, incomes, the chance of experiencing pain, the odds of how opioid use affects becoming an addict and dying, abuser's and addict's individualized inclinations to work, and the street price of opioids. A person makes their decisions fully cognizant about the chances of becoming unemployed, addicted, and dying. Stops in opioid use can occur.

The model is calibrated to the US data on opioid use. This is done for both the non-college- and college-educated segments of the population. Data taken from the Medical Expenditure Panel Survey and the National Survey of Drug Use and Health are used to tabulate the number of nonusers, prescription users, misusers, and addicts. Data are also collected on the opioid dosages used by prescription users, misusers, and addicts. The fractions of misusers and addicts who are unemployed is also calculated. Information on the prices for prescription and black market opioids is also collected. A key step in the calibration exercise is the estimation of Markov chains for the college- and non-college-educated populations. These Markov chains specify things such as the odds of a nonuser or a prescription user becoming an opioid abuser, the probability of an abuser making the transition to an addict, and the chance that an addict will die. The output from the model is then matched up with the results from the estimated Markov chains. A check on the calibration is performed by comparing the evidence on cross-state differences in prescription access to OxyContin and opioid deaths with the model's prediction on the relationship between prescription access and deaths.

The calibrated model is then used to highlight the forces underlying the recent opioid epidemic. Through the eyes of the model, there were two key forces. The first force is the decline in prices for both prescription and black market opioids. This had a big effect. The second force is the increase in the dosages per prescription meted out by doctors. This also had a significant impact. The fact that doctors kept pain suffers on prescription opioids for a longer period of time had little effect. Last, an analysis is conducted on medical interventions that reduce either the probability of becoming addicted or the odds of an addict dying from an overdose. While such interventions are valued by consumers, they increase the number of opioid users. Reducing the odds of addiction can result in even more deaths due to the rise in users.

2 Literature

There is now an extensive empirical literature on opioid epidemics. Following Case and Deaton (2017, 2020), some studies focus on demand factors, such as physical and mental pain, unemployment, and social isolation. The increase in pain has been documented by Blanchflower and Oswald (2020) and Nahin et al. (2019). In their recent review, Cutler and Glaeser (2021) suggest that the rise in pain can't explain the increase in opioid deaths. The effects of other economic factors on opioid deaths, such as import competition, unemployment, and poverty, are also estimated to be small–see, e.g., Pierce and Schott (2020) and Ruhm (2019). In contrast, Currie and Schwandt (2021), Cutler and Glaeser (2021), and Mulligan (2000) suggest that lower prices combined with easy access to opioids were the main drivers. Alpert et al. (2019) show, by exploiting cross-state variation in exposure to OxyContin, that the introduction and marketing of OxyContin can explain a substantial share of overdose deaths over the last two decades.[5]

Theoretical analyses of addiction started with Becker and Murphy (1988).[6] They developed a model of habit formation where past consumption of an addictive good increases the marginal utility from future consumption of it. Orphanides and Zervos (1995) extend the framework to a setting where individuals must learn over time, in Bayesian fashion, about how addictive a good will be for them. Strulik (2021) also extends the Becker and Murphy (1988) habit-formation framework by incorporating it into a model with health deficits. Specifically, the use of opioids to control pain creates health deficits as a person ages that increase the probability of death. He considers two settings. One where a person is completely rational and another where they do not understand how their addiction evolves by usage. For the two scenarios, he then compares numerically how addiction changes over the life cycle.

The current analysis replaces Becker and Murphy's (1988) habit-formation model with a framework of state-contingent preferences; i.e., individuals' preferences evolve randomly through various addiction stages in a manner that is a function of their opioid usage. Individuals are also allowed to have different predilections toward opioid misuse and leisure. This heterogeneity in preferences is necessary for matching facts in the US data. A person fully understands the state-contingent structure of tastes when making their consumption decisions, so as in Becker and Murphy (1988) they undertake all decisions rationally. The

[5]The impact of the opioid crisis on labor-force participation and employment is studied by Aliprantis, Fee, and Schweitzer (2019), Currie, Jin, and Schnell (2018), Harris et al. (2020), Krueger (2017), Ouimet, Simintzi, and Ye (2020), and Powell (2021).

[6]For empirical tests of rational addiction models, see, among others, Chaloupka (1991) and Becker, Grossman, and Murphy (1994). Cawley and Ruhm (2012) provide a review.

framework is matched up with US data on addiction; namely, the population fractions of nonusers, misusers, addicts, and deaths, and the transition probabilities between these states. This is done for both college- and non-college-educated individuals. All of this is something the above models do not do.

The analysis relates to a large literature on quantitative models of health and mortality. Borella, De Nardi, and Yang (2020), Hall and Jones (2007), Hosseini, Kopecky, and Zhao (2021), Margaris and Wallenius (2020), Nygaard (2021), Ozkan (2017), Scholz and Seshadri (2013), and Suen (2006) are recent examples from this literature. It also connects with economic models of epidemics, such as Bairoliya and Imrohoroglu (2020), Brotherhood, Kircher, Santos, and Tertilt (2020), Eichenbaum, Rebelo, and Trabandt (2021), Greenwood, Kircher, Santos, and Tertilt (2019), and Kremer (1996).

3 The Setup

Individuals may consume three goods; namely, regular consumption goods, c, leisure, l, and opioids, o. The prescription price of opioids is p, while the black market price is q. There are potentially 5 stages of addiction, s, with $s = n, p, b, a, d$. A person moves from addiction stage i to addiction stage j with probability σ_{ij}. These transition probabilities depend both upon chance and opioid use. A person starts out as a pain-free nonuser, n. With exogenous probability σ_{np} the individual experiences pain next period, p, which requires opioids to medicate. At that time the person may abide by their prescription or misuse opioids. Abuse, b, occurs with endogenous probability σ_{pb}. An individual who follows their prescription for pain returns to normality with exogenous probability σ_{pn}. Even when a nonuser doesn't experience pain they may decide to use opioids. A pain-free nonuser enters the abuse state with the endogenous probability σ_{nb}. An abuser, b, becomes an addict, a, with the endogenous odds, σ_{ba}. They return to pain-free normality with exogenous probability, σ_{bn}. An addict reverts through rehabilitation to a nonuser, n, with exogenous odds σ_{an}. An addict dies with endogenous probability σ_{ad}. Upon death addicts are replaced by their young doppelgangers. A schematic of the stages is shown in Figure 3.

An individual has one unit of time that they split between working and leisure. Hours worked, h, are indivisible so $h \in \{0, \mathfrak{h}\}$, where $0 < \mathfrak{h} < 1$. Leisure, l, is just given by $l = 1 - h$. A person's stage-s productivity at work is denoted by π_s for $s = n, p, b, a$. Labor productivity declines with the extent of a person's opioid use so that $\pi_a < \pi_b < \pi_p = \pi_n$. A worker earns the wage π_s, which is equal to their productivity. A nonworker receives a transfer in the amount, t. The employment decision is made *after* the opioid one. For convenience assume that a person in stages n and p always works. An individual discounts the future by the

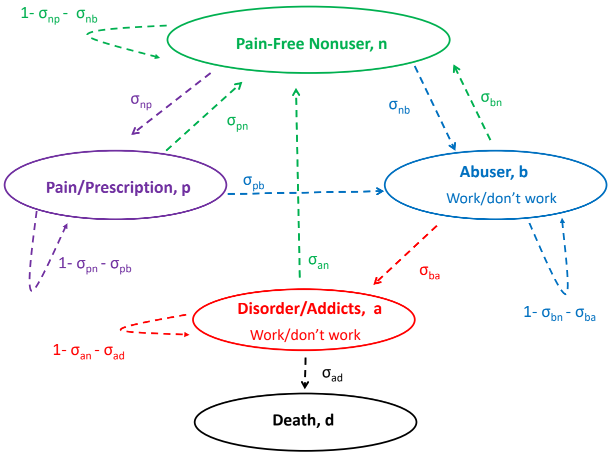

Figure 7: Stages. A person starts out as a pain-free nonuser, n. From there they may move either to an opioid abuser, b, or a prescription opioid user, p. Prescription users may also become abusers. Abusers face the chance of addiction, a. An addict can die, d. Abusers and addicts may work or not. Last, it is possible for an addict, an abuser, and a prescription user to return to the pain-free nonuser state.

factor β. The budget constraint for an opioid user in the s-th stage (for $s \neq d$) reads

$$c = \begin{cases} \pi_s \mathfrak{h}, & \text{works and doesn't use in } s = n; \\ \pi_s \mathfrak{h} - p\underline{o} - q(o - \underline{o}), & \text{works and uses in } s = n, p, b, a; \\ t - p\underline{o} - q(o - \underline{o}), & \text{doesn't work and uses in } s = b, a. \end{cases}$$

Additionally, a user can always acquire $\underline{o}$ units of opioids at the per unit legal price p. Any excess amount must be purchased on the black market at the per unit price q.

The utility function for regular goods, c, is

$$U(c) = (1 - \mu_s)(1 - \eta)(c^{1-\rho} - 1)/(1 - \rho), \text{ with } \rho \geq 0.$$

The leisure utility function is given by

$$L(l) = \begin{cases} L_s(1 - \mathfrak{h}) = (1 - \mu_s)\eta \ln(1 - \mathfrak{h}), & \text{employed in } s = n, p, b, a; \\ L_s(1) + \lambda_s = \lambda_s, & \text{unemployed in } s = b, a. \end{cases}$$

Abusers and addicts draw a leisure shock λ_s, which affects their desire to work or not. This shock is drawn after they make their opioid decision. Let λ_s come from a Gumbel distribution so that

$$\Pr[\lambda_s \leq \tilde{\lambda}_s] = \Lambda(\tilde{\lambda}_s) = \exp\left(-\exp[-(\tilde{\lambda}_s - \iota_s)/\xi_s]\right), \text{ for } s = b, a.$$

The conditional mean of the Gumbel distribution for those whose leisure shock exceeds a threshold level λ_s^*, is given by

$$\mathbf{E}[\lambda_s|\lambda_s \geq \lambda_s^*] = \lambda_s^* + \iota_s + \gamma\xi_s,$$

where γ is the Euler–Mascheroni constant.

The stage-s utility function for opioids, o, is

$$O(o - \underline{o}) = \begin{cases} O_s(o - \underline{o}) + \varepsilon_s = \mu_s[(o - \underline{o})^{1-\psi} - 1]/(1 - \psi) + \varepsilon_s, & \text{user in } s = n, p; \\ O_s(o - \underline{o}) = \mu_b[(o - \underline{o})^{1-\psi} - 1]/(1 - \psi), & \text{user in } s = b; \\ O_s(o - \underline{o}) = \mu_a[(o - \underline{o})^{1-\psi} - 1]/(1 - \psi) - \omega_a, & \text{user in } s = a; \\ 0, & \text{nonabuser in } s = n, p. \end{cases}$$

(In the above $\psi \geq 0$.) The user only realizes utility when they consume opioids in excess of the regulated amount $\underline{o}$. Here ε_s is a random variable reflecting the ecstasy that a user obtains in states n or p. This variable triggers opioid use. It is drawn from a Gumbel distribution so that

$$\Pr[\varepsilon_s \leq \tilde{\varepsilon_s}] = \Gamma(\tilde{\varepsilon_s}) = \exp\left(-\exp[-(\tilde{\varepsilon_s} - \nu_s)/\zeta_s]\right), \text{ for } s = n, p.$$

The conditional mean of the ecstasy from opioid use for those whose shock exceeds a threshold level ε_s^* is

$$\mathbf{E}[\varepsilon_s|\varepsilon_s \geq \varepsilon_s^*] = \varepsilon_s^* + \nu_s + \gamma\zeta_s.$$

This shock is realized *before* an individual decides to use opioids.

The idea here is that some types of individuals desire opioids more than others. As can be seen, the weight, μ_s, on opioids depends on the stage of a person's opioid usage, s, i.e., a person's craving for opioids depends on their stage of usage. The natural assumption is $\mu_a \geq \mu_b \geq \mu_p \geq \mu_n$. The weights on the utility functions for consumption, leisure, and opioids sum to one; i.e., $(1 - \mu_s)(1 - \eta) + (1 - \mu_s)\eta + \mu_s = 1$. Thus, differences in μ_s affect how individuals in different stages enjoy opioids relative to regular consumption and leisure, but do not influence how people fancy consumption versus leisure. Addicts also suffer a utility cost ω_a, which captures the difficulties they may face running their lives.

The probability of transiting between stage i and stage j, σ_{ij}, is given by

$$\sigma_{ij} = S_{ij}(o) = \sigma_j\sqrt{o}, \text{ for } (i \to j) = (b \to a), (a \to d).$$

The big picture is this. A nonuser or a person in pain may or may not use opioids at stages n or p depending on their draws for ε_s. If they do, they go from the abuse stage, b, to the addiction stage, a, with the probability $S_{ba}(o)$, which is increasing in their usage, o. The extent of usage depends on the stage of use. An addict craves more opioids, relative to an abuser, other things equal. Also, an opioid user's productivity at work declines in the later stages b and a and given this they may choose not to work. Ultimately, an addict may even die. The speed of the downward spiral depends both upon an individual's luck and opioid usage.

The empirical analysis is done for both the non-college and college educated populations. These two populations may differ by their underlying attributes, such as their labor productivities, the likelihood of experiencing pain, etc. To save on notation the decision problems in Section 4 below are presented for a generic person.

4 Decision Problems by Stage

Turn now to a presentation of the decision problems at each stage s, for $s = n, p, b, a$. Let N represent the expected lifetime utility for a nonuser without pain who has not yet drawn the opioid ecstasy shock; P the expected lifetime utility for a person with pain who still has to draw the opioid ecstasy shock; B the expected lifetime utility for an abuser before the leisure shock; and A the expected lifetime utility for addict who is waiting for the leisure shock. The decision problems for an individual in each of these states are formulated now. In the nonuser and prescription-user stages a person always works.

4.1 Nonuser

Start with a nonuser who isn't experiencing pain. Assume that they will use opioids when ε_n exceeds some threshold value, ε_n^*, and won't otherwise. Their opioid-use decision is then

$$o = \begin{cases} 0, & \text{don't use, if } \varepsilon_n < \varepsilon_n^*; \\ o > \underline{o}, & \text{use, if } \varepsilon_n > \varepsilon_n^*. \end{cases}$$

The Bellman equation for a pain-free nonuser who has not yet drawn the opioid ecstasy shock is

$$\begin{aligned} N = {} & \Gamma(\varepsilon_n^*)\{U(\pi_n \mathfrak{h}) + L_n(1-\mathfrak{h}) + \beta[(1-\sigma_{np})N + \sigma_{np}P]\} \\ & + [1-\Gamma(\varepsilon_n^*)]\{\max_{o>\underline{o}} U\left(\pi_n \mathfrak{h} - p\underline{o} - q(o-\underline{o})\right) + O_n(o-\underline{o}) + \mathbf{E}[\varepsilon_n | \varepsilon_n \geq \varepsilon_n^*] + L_n(1-\mathfrak{h}) \\ & + \beta[(1-\sigma_{bn})B + \sigma_{bn}N]\}. \quad (1) \end{aligned}$$

The first line on the righthand side gives the expected utility for a nonuser, which occurs with probability $\Gamma(\varepsilon_n^*)$. This person experiences pain next period with chance σ_{np}, in which case their discounted expected lifetime utility is βP, or remains pain free with probability $1-\sigma_{np}$, and then realizes a discounted expected utility level of βN. The second and third lines give the expected utility when the person decides to use opioids in the current period, which occurs with the odds $1-\Gamma(\varepsilon_n^*)$. Opioids below the level $\underline{o}$ are purchased at the legal price p, while black market opioids cost q. Next period the individual will either reenter the nonuser state with probability σ_{bn}, which returns an expected utility of βN, or enter the abuser state with complementary probability $1-\sigma_{bn}$, in which case their discounted expected utility is βB. A user gets ecstasy from opioid use, which delivers $\mathbf{E}[\varepsilon_n \geq \varepsilon_n^*]$. At this stage a person always works.

The ecstasy threshold, ε_n^*, must equate the utility from nonusing and using so that

$$\begin{aligned}\varepsilon_n^* &= U(\pi_n\mathfrak{h}) + L_n(1-\mathfrak{h}) + \beta[(1-\sigma_{np})N + \sigma_{np}P \\ &\quad - \max_{o>\underline{o}}\{U\left(\pi_n\mathfrak{h} - p\underline{o} - q(o-\underline{o})\right) + L_n(1-\mathfrak{h}) + O_n(o-\underline{o}) + \beta[(1-\sigma_{bn})B + \sigma_{bn}N]\}. \qquad (2)\end{aligned}$$

As can be seen, the threshold value of the shock is simply the difference in the expected utility values from not using and using. By eyeballing the threshold equation, it appears that if q falls, then ε_n^* drops implying that there will be more users. In terms of model's stages in Figure 3, it is clear that $1-\Gamma(\varepsilon_n^*)$ will determine the endogenous transition σ_{nb}.

4.2 Prescription User

Likewise, a person experiencing pain abuses opioids in the current period when ε_p exceeds some threshold value, ε_p^* , and won't otherwise. The recursion for a person experiencing pain who has a prescription and who has not yet drawn the opioid ecstasy shock is

$$\begin{aligned}P &= \Gamma(\varepsilon_p^*)\left\{U(\pi_p\mathfrak{h} - p\underline{o}) + L_p(1-\mathfrak{h}) + \beta[(1-\sigma_{pn})P + \sigma_{pn}N]\right\} \\ &\quad + [1-\Gamma(\varepsilon_p^*)]\{\max_{o>\underline{o}} U\left(\pi_p\mathfrak{h} - p\underline{o} - q(o-\underline{o})\right) + O_p(o-\underline{o}) + \mathbf{E}[\varepsilon_p \geq \varepsilon_p^*] + L_p(1-\mathfrak{h}) \\ &\quad + \beta[(1-\sigma_{bn})B + \sigma_{bn}N]\}. \qquad (3)\end{aligned}$$

Here $\underline{o}$ denotes the level of opioids obtained from the prescription. Anything above this level is an improper use. This recursion is analogous to (1), but note that a prescription-follower experiencing pain may revert to normality with probability σ_{pn} or continue with pain with the odds $1-\sigma_{pn}$, as shown on the first line. The threshold ε_p^* is given by the equation

$$\begin{aligned}\varepsilon_p^* = {} & U(\pi_p \mathfrak{h} - p\underline{o}) + L_p(1-\mathfrak{h}) + \beta[(1-\sigma_{pn})P + \sigma_{pn}N \\ & - \max_{o>\underline{o}}\{U\left(\pi_p \mathfrak{h} - p\underline{o} - q(o-\underline{o})\right) + L_p(1-\mathfrak{h}) + O_p(o-\underline{o}) + \beta[(1-\sigma_{bn})B + \sigma_{bn}N]\}.\end{aligned} \quad (4)$$

In the nonuser and prescription-user stages the decision to misuse opioids is regulated by the generic first-order condition

$$O_s'(o-\underline{o}) = U'\left(\pi_s \mathfrak{h} - p\underline{o} - q(o-\underline{o})\right) q \text{ for } s = n, p. \quad (5)$$

The lefthand side is the marginal benefit from using opioids. The righthand side is the marginal cost; the black market price for a unit of opioids is q, which reduces the marginal utility of consumption by $U'\left(\pi_s \mathfrak{h} - p\underline{o} - q(o-\underline{o})\right)$. With respect to Figure 3, $1-\Gamma(\varepsilon_p^*)$ determines the endogenous transition σ_{pb}.

4.3 Abuser

Attention is now directed to the abuse and addition stages. In these stages a person may or may not work. Start with the abuser. An abuser will not work when λ_b exceeds some threshold value, λ_b^*, and will work otherwise. Hours worked, h, is then given by

$$h = \begin{cases} 1, & \text{work, if } \lambda_b < \lambda_b^*; \\ 0, & \text{don't work, if } \lambda_b > \lambda_b^*. \end{cases}$$

The Bellman equation for an abuser who has not yet drawn the leisure shock reads

$$\begin{aligned} B = \max_{o>\underline{o}}\{ & \Lambda(\lambda_b^*)\{U\left(\pi_b \mathfrak{h} - p\underline{o} - q(o-\underline{o})\right) + O_b(o-\underline{o}) + L_b(1-\mathfrak{h}) \\ & + [1-S_{ba}(o)]\beta[(1-\sigma_{bn})B + \sigma_{bn}N] + S_{ba}(o)\beta A\} \\ & + [1-\Lambda(\lambda_b^*)]\{U\left(t - p\underline{o} - q(o-\underline{o})\right) + O_b(o-\underline{o}) + L_b(1) + \mathbf{E}[\lambda_b \geq \lambda_b^*] \\ & + [1-S_{ba}(o)]\beta[(1-\sigma_{bn})B + \sigma_{bn}N] + S_{ba}(o)\beta A\}\}. \end{aligned} \quad (6)$$

The first and second lines pertain to an abuser who works, which happens by the chance $\Lambda(\lambda_b^*)$. As the second line shows, a working abuser may become addicted next period with probability $S_{ba}(o)$ and the discounted expected utility associated with this state is βA. The odds of addiction are increasing in current opioid use, o. If they do not become addicted, which happens with probability $1-S_{ba}(o)$, then they may either return to normality with probability σ_{bn} or remain in the abuse state with the odds $1-\sigma_{bn}$. The third and forth lines are for an unemployed abuser. An unemployed abuser enjoys the leisure shock, which has the expected value $\mathbf{E}[\lambda_b \geq \lambda_b^*]$. Last, recall that the opioid decision is made before the one to work, which explains the outer position of the single max operator in equation (6).

The leisure threshold λ_b^* equates the utility from working and not working so that

$$\lambda_b^* \quad = \quad U\left(\pi_b \mathfrak{h} - p\underline{o} - q(o-\underline{o})\right) \ + \ L_b(1 \ - \ \mathfrak{h}) \ - \ U\left(t - p\underline{o} - q(o-\underline{o})\right) \ - \ L_b(1). \quad (7)$$

So, the threshold level of the leisure shock is just the difference in utility between working or not. This decision is static, given a value for opioid usage, o.

The first-order condition for an abuser's opioid use, o, connected with (6) is

$$\begin{aligned} O_b'(o-\underline{o}) = \Lambda(\lambda_b^*)U'\left(\pi_b \mathfrak{h} - p\underline{o} - q(o-\underline{o})\right) q + [1-\Lambda(\lambda_b^*)]U'\left(t - p\underline{o} - q(o-\underline{o})\right) q \\ + S_{ba}'(o)\beta[(1-\sigma_{bn})B + \sigma_{bn}N - A]. \quad (8) \end{aligned}$$

The lefthand side is the current marginal benefit from using opioids, $O_b'(o)$. The righthand side is the expected marginal cost, which is made up of two components. First, the person must pay q for each unit of black-market opioids, which results in an expected stage-b momentary utility loss of $\Lambda(\lambda_b^*)U'\left(\pi_b \mathfrak{h} - p\underline{o} - q(o-\underline{o})\right) q + [1-\Lambda(\lambda_b^*)]U'\left(t - p\underline{o} - q(o-\underline{o})\right) q$. Second, using opioids in the current period affects the probability of becoming an addict next period through the term $S_{ba}'(o)$. This will result in a loss of discounted expected lifetime utility in the amount $\beta[(1-\sigma_{bn})B + \sigma_{bn}N - A]$. Presumably this term is positive (reflecting a cost), unless opioid use can create such ecstasy that an addict is happier than an abuser.

4.4 Addict

Finally, by analogy, the Bellman equation for an addict is

$$\begin{aligned} A = \max_{o>\underline{o}} \{ & \Lambda(\lambda_a^*)\{U\left(\pi_a \mathfrak{h} - p\underline{o} - q(o-\underline{o})\right) + O_a(o-\underline{o}) + L_a(1-\mathfrak{h}) \\ & + [1 - S_{ad}(o)]\beta[(1-\sigma_{an})A + \sigma_{an}N] + S_{ad}(o)\beta_a\delta\} \\ & + [1-\Lambda(\lambda_a^*)]\{U\left(t - p\underline{o} - q(o-\underline{o})\right) + O_a(o-\underline{o}) + L_a(1) + \mathbf{E}[\lambda_a \geq \lambda_a^*] \\ & + [1 - S_{ad}(o)]\beta[(1-\sigma_{an})A + \sigma_{an}N] + S_{ad}(o)\beta\delta\}\}, \quad (9) \end{aligned}$$

where δ is the utility associated with death. The likelihood of an addict dying next period, $S_{ad}(o)$, is an increasing function of their current opioid use, o. An addict rehabilitates with probability σ_{an}, in which case they return to the pain-free nonuser state. The leisure threshold, λ_a^*, is given by

$$\lambda_a^* = U(\pi_a \mathfrak{h} - p\underline{o} - q(o - \underline{o})) + L_a(1 - \mathfrak{h}) - U(t - p\underline{o} - q(o - \underline{o})) - L_a(1). \quad (10)$$

Last, an addict's opioid consumption decision is governed by

$$O_a'(o - \underline{o}) = \Lambda(\lambda_a^*)U'(\pi_a \mathfrak{h} - p\underline{o} - q(o - \underline{o}))\, q + [1 - \Lambda(\lambda_a^*)]U'(t - p\underline{o} - q(o - \underline{o}))\, q$$
$$+ S_{ad}'(o)\beta[(1 - \sigma_{an})A + \sigma_{an}N - \delta]. \quad (11)$$

Note that opioid use by abusers and addicts determines the endogenous transitions σ_{ba} and σ_{ad} in Figure 3 via the $S_{ba}(o)$ and $S_{ad}(o)$ functions.

5 Fitting a Markov Chain to the US Data

Markov chain representations of the schematic in Figure 3 are now fit to the US data. This is done for both the college and non-college-educated populations. At any point in time, an individual in the model is in one of five categories: a nonuser, n; a prescription opioid user for pain, p; an abuser of opioids, b; an addict, a; or dead, d. Denote the long-run fractions of the model's population in each of these categories by e_n, e_p, e_b, e_a, and e_d. These fractions represent the ergodic distribution for the model. The addiction categories in the US data are defined slightly differently. Represent these data categories by $\mathtt{n}, \mathtt{p}, \mathtt{m}, \mathtt{a}$, and $\mathtt{d}$, where $\mathtt{m}$ refers to misusers. In the data a nonuser is defined as someone who does not use opioids, while in the model this category includes first-time pain-free misusers. Likewise, prescription users in the data are defined as individuals who abide strictly by their prescription. In the model this category includes first-time prescription misusers. The misuse category in the data comprises both repeat and first-time misusers, while the abuse category in the model excludes first-time misusers. While the Markov chain will be estimated for both the non-college- and college-educated segments of the population, to save on notation the representation of the Markov chain will be cast generically. A period corresponds to one year.

5.1 Representing the Markov Chain

The first task is to construct a Markov chain representation of the US data for the model. The transition probabilities, $\{T_{ij}\}_{ij}$, across the *data* categories, $\mathtt{n}, \mathtt{p}, \mathtt{m}, \mathtt{a}$, and $\mathtt{d}$, given by the model are

$$
\begin{aligned}
T &\equiv [i \to j]_{i,j} \\
&\equiv \left[\begin{array}{ccccc}
\Gamma(\varepsilon_n^*)(1-\sigma_{np}) & \Gamma(\varepsilon_p^*)\sigma_{np} & [1-\Gamma(\varepsilon_n^*)](1-\sigma_{np})+[1-\Gamma(\varepsilon_p^*)]\sigma_{np} & 0 & 0 \\
\Gamma(\varepsilon_n^*)\sigma_{pn} & \Gamma(\varepsilon_p^*)(1-\sigma_{pn}) & [1-\Gamma(\varepsilon_n^*)]\sigma_{pn}+[1-\Gamma(\varepsilon_p^*)](1-\sigma_{pn}) & 0 & 0 \\
\{\tilde{e}_b[1-S_{ba}(o)]+\tilde{e}_n+\tilde{e}_p\}\Gamma(\varepsilon_n^*)\sigma_{bn} & 0 & T_{\texttt{mm}} & \tilde{e}_b S_{ba}(o) & 0 \\
[1-S_{ad}(o)]\sigma_{an}\Gamma(\varepsilon_n^*) & 0 & [1-S_{ad}(o)]\sigma_{an}[1-\Gamma(\varepsilon_n^*)] & [1-S_{ad}(o)](1-\sigma_{an}) & S_{ad}(o) \\
\Gamma(\varepsilon_n^*) & 0 & 1-\Gamma(\varepsilon_n^*) & 0 & 0
\end{array}\right], \qquad (12)
\end{aligned}
$$

where

$$T_{\texttt{mm}} \equiv \{\tilde{e}_b[1-S_{ba}(o)]+\tilde{e}_n+\tilde{e}_p\}\{[1-\Gamma(\varepsilon_n^*)]\sigma_{bn}+1-\sigma_{bn}\},$$

with $\tilde{e}_n$, $\tilde{e}_p$, and $\tilde{e}_b$ representing the fractions of misusers in model categories n, p, and b:

$$\tilde{e}_n \equiv \frac{[1-\Gamma(\varepsilon_n^*)]e_n}{[1-\Gamma(\varepsilon_n^*)]e_n+[1-\Gamma(\varepsilon_p^*)]e_p+e_b},$$

$$\tilde{e}_p \equiv \frac{[1-\Gamma(\varepsilon_p^*)]e_p}{[1-\Gamma(\varepsilon_n^*)]e_n+[1-\Gamma(\varepsilon_p^*)]e_p+e_b},$$

$$\tilde{e}_b \equiv \frac{e_b}{[1-\Gamma(\varepsilon_n^*)]e_n+[1-\Gamma(\varepsilon_p^*)]e_p+e_b}.$$

The ergodic distribution over the model's categories (e_n, e_p, e_b, e_a, and e_d) is defined in Appendix A.

To understand the above transition matrix, take the first element $T_{\texttt{nn}} = \Gamma(\varepsilon_n^*)(1-\sigma_{np})$. This represents the fraction of current nonusers, in the data category `n`, who will remain nonusers, or in `n`, next period. For this to occur in the model, a nonuser must remain pain free, which occurs with probability $1-\sigma_{np}$ and then decide not to use, which happens with chance $\Gamma(\varepsilon_n^*)$. As another example, consider the transition probability from the data category `p` to category `m` or $T_{\texttt{pm}}$= $[1-\Gamma(\varepsilon_n^*)]\sigma_{pn}+[1-\Gamma(\varepsilon_p^*)](1-\sigma_{pn})$. There are two ways that a prescription user can become a misuser next period in the model. First, they may revert to a pain-free nonuser but then decide to use opioids. This occurs with probability $[1-\Gamma(\varepsilon_n^*)]\sigma_{pn}$. Second, they could remain in pain and misuse their prescription, which happens with odds $[1-\Gamma(\varepsilon_p^*)](1-\sigma_{pn})$. Last, take the cell $T_{\texttt{ma}} = \tilde{e}_b S_{ba}(o)$, which is the transition from being a misuser, $\mathtt{m}$, into an addict, $\mathtt{a}$. A misuser who is in category b in the model can become an addict with chance $S_{ba}(o)$. But, first-time misusers cannot immediately become addicts. Only the fraction $\tilde{e}_b$ of misusers in the data can become addicts in the model. So, when mapping the model into the data the probability $S_{ba}(o)$ must be adjusted downward by $\tilde{e}_b$ to account for this fact. The other elements of T can be interpreted in a similar fashion.

5.2 Estimation, Preliminaries

Turn now to the US data. A Markov transition matrix is estimated separately for those with and without a college degree. Let $\mathtt{T}_{ij}$ be the fraction of individuals, as estimated from the US data, who move from state i to state j, for $i, j = \mathtt{n}, \mathtt{p}, \mathtt{m}, \mathtt{a}, \mathtt{d}$. The generic Markov transition matrix for the data estimation is

$$\begin{aligned} &\mathtt{T} \equiv [i \to j]_{i,j} \\ &\equiv \begin{bmatrix} \mathtt{T_{nn}} = 1 - \mathtt{T_{np}} - \mathtt{T_{nm}} & \mathtt{T_{np}} & \mathtt{T_{nm}} & 0 & 0 \\ \mathtt{T_{pn}} & \mathtt{T_{pp}} = 1 - \mathtt{T_{pn}} - \mathtt{T_{pm}} & \mathtt{T_{pm}} & 0 & 0 \\ \mathtt{T_{mn}} & 0 & \mathtt{T_{mm}} = 1 - \mathtt{T_{mn}} - \mathtt{T_{ma}} & \mathtt{T_{ma}} & 0 \\ \mathtt{T_{an}} & 0 & \mathtt{T_{am}} = \mathtt{T_{an}}(1 - \mathtt{T_{dn}})/\mathtt{T_{dn}} & \mathtt{T_{aa}} = 1 - \mathtt{T_{an}} - \mathtt{T_{ad}} & \mathtt{T_{ad}} \\ \mathtt{T_{dn}} = (\mathtt{T_{nn}}\mathtt{T_{pp}} - \mathtt{T_{np}}\mathtt{T_{pn}})/(\mathtt{T_{pp}} - \mathtt{T_{np}}) & 0 & 1 - \mathtt{T_{dn}} & 0 & 0 \end{bmatrix}. \end{aligned} \quad (13)$$

Each cell in generic matrix (13) is a function of model parameters as is shown in matrix (12). The model imposes cross-parameter restrictions on the values of $\mathtt{T_{am}}$ and $\mathtt{T_{dn}}$ that can be derived from matrix (12).[7]

Estimated values of the elements of $\mathtt{T}$ can be used to determine the values of model parameters. Start with the US population who are in data categories $\mathtt{n}, \mathtt{p}, \mathtt{m}, \mathtt{a}$, and $\mathtt{d}$, and let $\mathtt{t_n}, \mathtt{t_p}, \mathtt{t_m}, \mathtt{t_a}$, and $\mathtt{t_d}$ represent the fractions of the US population who are nonusers, prescription users, misusers, addicts, and those that die. Assume that these fractions are invariant over time; i.e., they represent the long-run distribution of the estimated Markov chain. That is, $\mathtt{t} \equiv [\mathtt{t_n}, \mathtt{t_p}, \mathtt{t_m}, \mathtt{t_a}, \mathtt{t_d}]$, must solve

$$\mathtt{t} = \mathtt{t}\mathtt{T}.$$

Some of the cells in the Markov chain can be filled in directly from the data. Others are estimated by requiring that the long-run distribution $\mathtt{t}$ is consistent with the empirical estimate of the fractions of the US population in each of the five addiction states.

[7] For instance, the restriction on $\mathtt{T_{am}}$ is due to the fact that cell (4,3) in matrix (12), which contains the element $[1 - S_{ad}(o)]\sigma_{an}[1 - \Gamma(\varepsilon_n^*)]$ can be written as cell (4,1), or $[1 - S_{ad}(o)]\sigma_{an}\Gamma(\varepsilon_n^*)$, multiplied by 1 minus cell (5,1), or $1 - \Gamma(\varepsilon_n^*)$, and divided by cell (5,1), or $\Gamma(\varepsilon_n^*)$. Similar manipulations imply the restriction on $\mathtt{T_{dn}}$.

US Population by Addiction State

Take the population between ages 18 and 64, about 200 million individuals in 2017. Start with those who are either misusing opioids or are addicted to them. The most comprehensive data on illicit drugs (including the non-medical use of prescription drugs) is provided by the National Survey of Drug Use and Health (NSDUH). The NSDUH interviews about 70,000 individuals, ages 12 and older, and provides information on their use of alcohol, tobacco, and a wide range of illicit drugs. The survey also contains information on employment, health, and income. The NSDUH classifies individuals as misusers if they use any opioids without a prescription, use them for reasons other than directed by a physician, or use them in greater amounts or more often than prescribed during the past 12 months. Heroin users are classified as misusers by default. Misusers are then asked follow-up questions to determine whether they have an opioid disorder (referred to as addicts here). To be labeled as an addict, opioids must interfere with a person's daily life. Hence, in the NSDUH, the addicts are a subset of misusers. Given the model's structure, for the analysis below, someone who is misusing but is not an addict is labeled as a misuser. Details on all data definitions and sources are provided in Data Appendix B.

The 2015-2018 surveys are used for the analysis, where 33.25 percent of respondents are college graduates or about 66.5 million individuals (when extrapolated to the entire population), and the rest, about 133.5 million, do not have a college degree. Among non-college individuals between the ages 18 and 64, 4.48 percent, about 5.9 million people, are classified as misusers, and an additional 1.33 percent, roughly 1.8 million people, are labeled as addicts. Shares of misusers and addicts are lower for college graduates; 3.04 percent (2.0 million) and 0.43 percent (0.29 million).

To determine the number of individuals who use prescription opioids for pain, the Medical Expenditure Panel Survey (MEPS) is used. MEPS surveys individuals and families, their medical providers, and employers in the United States. The household component, which is used here, provides information on demographic characteristics, health conditions, health status, and the use of medical services. Between 2015 and 2018, about 13.5 percent of the US non-college-educated population between the ages 18 and 64 used prescription opioids for pain. The number for college graduates was 9.2 percent. Finally, according to the CDC's Vital Statistics, there were 40,641 deaths related to opioid overdoses during the 2015-2018 period among those ages 18 to 64. Of those 37,596 or about 92.5 percent, were people without college degrees. All these pieces are put together in Table 2, which shows for both education groups the fractions of the population in each of the five data categories; viz, $\mathtt{t_n}, \mathtt{t_p}, \mathtt{t_m}, \mathtt{t_a}$, and $\mathtt{t_d}$. Nonusers, $\mathtt{n}$, are the residual group. The table can be thought of as giving the long-run probabilities of being in particular states. The shares of college and non-college

Table 2: US Population by Opioid Use, Fractions

	Nonuser	***Prescription***	***Misuser***	***Addict***	***Dead***
	$\mathtt{t}_{\mathtt{n}}$	$\mathtt{t}_{\mathtt{p}}$	$\mathtt{t}_{\mathtt{m}}$	$\mathtt{t}_{\mathtt{a}}$	$\mathtt{t}_{\mathtt{d}}$
Non-College	0.80688	0.13477	0.04479	0.01327	0.00028
College	0.87342	0.09182	0.03040	0.00432	0.00005

Table 3: Opioid Users by Education, Fractions

	Nonuser	***Misuser***	***Addict***
	$\mathtt{t}_{\mathtt{n}}$	$\mathtt{t}_{\mathtt{m}}$	$\mathtt{t}_{\mathtt{a}}$
Non-College	0.6848	0.7474	0.8604
College	0.3152	0.2526	0.1396

graduates in the nonuser, misuser, and addict categories are reported in Table 3.

Filling in the Transition Probabilities

The elements of the estimated transition matrix, $\mathtt{T}$, are now filled in starting with the easy ones.

Transition Probabilities Directly Assigned. According to the NSDUH, about 15.8 percent of non-college and 18.9 percent of college misusers started misusing opioids during the last year. The data does not speak on how they arrive in the misuse state, $\mathtt{m}$. They can arrive from either the nonuser, $\mathtt{n}$, or prescription user, $\mathtt{p}$, states. In the NSDUH, 64.7 percent of non-college misusers and 46.0 percent of addicts report pain as their primary motivation for opioid use. The fractions for college graduates are 68.5 and 48.1 percent. In a qualitative study on a small sample of patients with an opioid disorder, Stumbo et al. (2017) report that 41 percent of patients develop a disorder from taking prescription opioids. Taking 50 percent as the fraction of misusers that come from each state for both education groups yields (numbers in italics in the brackets refer to college graduates)

$$\mathtt{T}_{\mathtt{nm}}\mathtt{t}_{\mathtt{n}} = 0.5 \times 0.1581[\mathit{0.1889}] \times \mathtt{t}_{\mathtt{m}} \quad \text{and} \quad \mathtt{T}_{\mathtt{pm}}\mathtt{t}_{\mathtt{p}} = 0.5 \times 0.1581[\mathit{0.1889}] \times \mathtt{t}_{\mathtt{m}},$$

delivering $\mathtt{T}_{\mathtt{nm}}$ and $\mathtt{T}_{\mathtt{pm}}$.[8]

Dividing the number of deaths by the number of addicts, yields a value for $\mathtt{T}_{\mathtt{ad}}$. To determine $\mathtt{T}_{\mathtt{an}}$, two pieces of information are used. First, Weiss and Rao (2017) report a recovery rate of about 15 percent for addicts who are treated. But, the fraction of addicts who seek treatment is not large. In the NSDUH, only 29.6 percent of non-college addicts and

[8]Summing the above two conditions gives $\mathtt{T}_{\mathtt{nm}}\mathtt{t}_{\mathtt{n}} + \mathtt{T}_{\mathtt{pm}}\mathtt{t}_{\mathtt{p}} = 0.1581[\mathit{0.1889}] \times \mathtt{t}_{\mathtt{m}}$; i.e., 15.81 percent of misusers without a college degree and 18.89 of those with one are new arrivals from the nonuser and prescription user states.

19.1 percent of college addicts do so. Set $\mathtt{T}_{\mathtt{an}}$ to be the product of the recovery and treatment rates. The transitions for each education class chosen based on available information are reported in Table 4.

Table 4: Transitions, US Population

	Source	**Non-College**	**College**
$\mathtt{T}_{\mathtt{nm}}$	NSDUH	0.0044	0.0033
$\mathtt{T}_{\mathtt{pm}}$	NSDUH	0.0263	0.0313
$\mathtt{T}_{\mathtt{ad}}$	NSDUH, CDC	0.0212	0.0106
$\mathtt{T}_{\mathtt{an}}$	NSDUH, Medical Studies	0.0444	0.0287

Estimated Transition Probabilities. There are four transition probabilities left to determine; namely, $\mathtt{T}_{\mathtt{np}}$, $\mathtt{T}_{\mathtt{pn}}$, $\mathtt{T}_{\mathtt{mn}}$ and $\mathtt{T}_{\mathtt{ma}}$. These are treated as free parameters. They are chosen to minimize the distance between the fractions of the US population in each state and their analogues implied by the Markov chain. The minimization procedure gives $\mathtt{T}_{\mathtt{np}}= 0.0337$, $\mathtt{T}_{\mathtt{pn}} = 0.1752$, $\mathtt{T}_{\mathtt{mn}}=0.1386$ and $\mathtt{T}_{\mathtt{ma}}=0.0195$ for the non-college population and $\mathtt{T}_{\mathtt{np}}= 0.0427$, $\mathtt{T}_{\mathtt{pn}} = 0.3699$, $\mathtt{T}_{\mathtt{mn}}=0.1842$ and $\mathtt{T}_{\mathtt{ma}}=0.0056$ for the college population.[9]

5.3 Estimation, Results

The upshot of the above discussion is the following estimates of the Markov transition matrices for the non-college and college (in italics) populations:

$$\mathtt{T} = \begin{bmatrix} 0.9620,\ \mathit{0.9541} & 0.0337,\ \mathit{0.0427} & 0.0044,\ \mathit{0.0033} & 0 & 0 \\ 0.1752,\ \mathit{0.3699} & 0.7985,\ \mathit{0.5989} & 0.0263,\ \mathit{0.0313} & 0 & 0 \\ 0.1386,\ \mathit{0.1842} & 0 & 0.8419,\ \mathit{0.8102} & 0.0195,\ \mathit{0.0056} & 0 \\ 0.0444,\ \mathit{0.0287} & 0 & 0.0002,\ \mathit{0.0000} & 0.9342,\ \mathit{0.9607} & 0.0212,\ \mathit{0.0106} \\ 0.9966,\ \mathit{0.9989} & 0 & 0.0034,\ \mathit{0.0011} & 0 & 0 \end{bmatrix}.$$

The long-run transition probabilities, $\mathtt{t}$, connected with these Markov chains are reported in Table 5.

[9]It is possible to compute the transitions $\mathtt{T}_{\mathtt{np}}$ and $\mathtt{T}_{\mathtt{pn}}$ directly using data from MEPS. The results of an alternative estimation strategy, where only $\mathtt{T}_{\mathtt{mn}}$ and $\mathtt{T}_{\mathtt{ma}}$ are estimated, are presented in Appendix C. The fit is worse than the one obtained in Table 5.

Table 5: Opioid Use, Fractions–Data and Markov Chain

	Nonuser	***Prescription***	***Misuser***	***Addict***	***Dead***
	$\texttt{t}_{\texttt{n}}$	$\texttt{t}_{\texttt{p}}$	$\texttt{t}_{\texttt{m}}$	$\texttt{t}_{\texttt{a}}$	$\texttt{t}_{\texttt{d}}$
Non-College					
Data	0.8069	0.1348	0.0448	0.0133	0.0003
Markov Chain	0.8069	0.1348	0.0448	0.0133	0.0003
College					
Data	0.8734	0.0918	0.0304	0.0043	0.0000
Markov Chain	0.8725	0.0928	0.0304	0.0043	0.0000

The fit is very good. Now that the entries in matrix (13) are filled, the parameters in the model's matrix representation of the data (12) can be recovered. First note that $\sigma_{pn} = \texttt{T}_{\texttt{pn}}/\Gamma(\varepsilon_n^*)$, $\sigma_{np} = \texttt{T}_{\texttt{np}}/\Gamma(\varepsilon_p^*)$, and $\sigma_{an} = \texttt{T}_{\texttt{an}}/[\texttt{T}_{\texttt{dn}}(1 - \texttt{T}_{\texttt{ad}})]$. These three equations, together with $\Gamma(\varepsilon_n^*) = \texttt{T}_{\texttt{dn}}$ and $\Gamma(\varepsilon_p^*) = \texttt{T}_{\texttt{pp}}/(1 - \sigma_{pn})$, determine three exogenous transitions in the model; i.e., σ_{pn}, σ_{np}, and σ_{an}. They also determine $\Gamma(\varepsilon_n^*)$ and $\Gamma(\varepsilon_p^*)$, which are the fractions of nonusers and prescription users who do not misuse opioids. A value for $S_{ad}(o) = \texttt{T}_{\texttt{ad}}$, the endogenous transition rate from addiction to death, is also determined. Last, two other items can also be determined from matrix (13); viz, $S_{ba}(o)$, another endogenous model transition, and σ_{bn}, an exogenous transition. Recovering these items involves solving two nonlinear equations in two unknowns,

$$\tilde{e}_b S_{ba}(o) = T_{\texttt{ma}},$$

and

$$T_{\texttt{mm}} \equiv \{\tilde{e}_b[1 - S_{ba}(o)] + \tilde{e}_n + \tilde{e}_p\}\{[1 - \Gamma(\varepsilon_n^*)]\sigma_{bn} + 1 - \sigma_{bn}\},$$

with $\tilde{e}_n$, $\tilde{e}_p$, and $\tilde{e}_b$ as defined above. The outcome of the mapping between the model's transition matrix (12) and the estimated Markov chain (13) is presented in Table 6.

6 Calibration

To simulate the model, values must be assigned to the model's various parameters. A few parameters are standard in the literature. Some parameter values can be selected directly from the US data. These parameters govern the incomes of individuals, prescription and street prices of opioids, the prescription consumption of opioids, and the exogenous transition probabilities. Other parameters are chosen by maximizing the model's fit with respect to data targets. Examples of such parameters are the utility weights that individuals attach to opioid consumption, the location and scale parameters for the Gumbel distributions governing the ecstasy and leisure shocks, the parameters controlling the endogenous transitions from misuse

Table 6: Parameters for the Model´s Markov Chain Representations

Parameter	Explanation	Non-College	College
σ_{np}	Prob[$n \to p$]	0.0347	0.0449
σ_{pn}	Prob[$p \to n$]	0.1759	0.3703
σ_{bn}	Prob[$b \to n$]	0.1419	0.1854
σ_{an}	Prob[$a \to n$]	0.0455	0.0290
$\Gamma(\varepsilon_n^*)$	Non-misusers ÷ Nonusers	0.9966	0.9989
$\Gamma(\varepsilon_p^*)$	Non-misusers ÷ Prescription users	0.9689	0.9510
$S_{ba}(o)$	Prob[$b \to a$]	0.0232	0.0069
$S_{ad}(o)$	Prob[$a \to d$]	0.0212	0.0106

to addiction and addiction to death, and the utility associated with death. Again, the model period is one year.

6.1 Parameter Values Chosen from the Literature

Three parameters are set to standard values in the literature. The coefficient of relative risk aversion, ρ, is assumed to be 2. Following Cooley and Prescott (1995), the share of leisure in the utility function, η, takes a value of 0.64 and the annual discount factor, β, is 0.96.

6.2 Parameter Values Chosen Directly From the US Data

Several parameters are set directly to their data counterparts. These parameters are now discussed.

Exogenous Transition Probabilities

The exogenous transition probabilities between different stages, σ_{np}, σ_{pn}, σ_{bn}, and σ_{an} are read from Table 6.

Nonuser's Incomes

In the 2016 Current Population Survey (CPS), the annual hours worked by non-college and college graduates are 1,893 and 2,061, respectively. These represent 38 and 41 percent of the 5,000 available hours in a year; these fractions pin down the values for $\mathfrak{h}$. Next, normalize, the productivity of a nonuser, π_n, without a college degree to 1. The annual income of an employed, nonuser without a college degree, $\pi_n\mathfrak{h}$, was about \$41,920 in the NSDUH for the 2015-2018 period. Hence, π_n corresponds to $\$41,920/0.38 = \$110,725$. For an employed college nonuser, $\pi_n \mathfrak{h}$ was about \$68,108, so π_n is roughly $\$68,108/0.41 = \$165,231$, or with the productivity for the non-college educated normalized to one, 1.49. For those who are not employed their total non-labor income in the CPS is used for t. The non-labor incomes for non-college and college graduates are \$8,697 and \$14,333, respectively, which implies $t = 0.079$ ($\$8,697/\$110,725$) [*0.129* (*\$14, 333/\$110, 725*)] relative to a non-college, nonuser's average productivity.

Prescription and Street Prices, and Prescription Consumption of Opioids

Next turn to the cost of opioids. Start with street prices. Table 7 shows the street prices per milligram (mg) of different opioids obtained from different sources—Dasgupta et al. (2013).[10] While individuals use different types of opioids, each type has a certain morphine milligram equivalence (MME), which can be used to calculate a price per MME.[11] As a rough measure of q, the street price of Oxycodone, a popular opioid sold under the brand name OxyContin, was \$1 per mg or about \$0.67 per MME—see also Surrat et al. (2013) and Lebin et al. (2017).

Table 7: Street Price in Dollars per mg of Different Opioids by Source

Opioid	Street Rx	Drug Diversion Survey	Silk Road	MME
Hydromorphone	3.29	4.47	3.55	4
Oxymorphone	1.57	1.65	1.58	3
Methadone	0.96	1.16	0.93	3
Oxycodone	0.97	0.86	0.99	1.5
Hydrocodone	0.81	0.9	0.97	1

The cost of opioids for prescription patients is much lower. Based on MEPS, the average out-of-pocket expenses per person for all outpatient opioid prescriptions among adults with one or more prescription drug opioid purchases was about \$48.38 for those without a college degree and \$37.10 for college graduates over the 2015-2018 period. MEPS can also be used to calculate how much prescription opioids patients take. During 2015-2018, the average yearly opioid usage for non-college prescription patients was about 3,543.75 MME (about 9.84 MME per day) and the average usage for college ones was about 1,785.00 MME (about

[10]StreetRx is a website that gathers, organizes, and displays street price data on diverted pharmaceutical controlled substances. The site allows for the anonymous submission of street prices that are paid for specific prescription and illicit drugs. The Researched Abuse, Diversion and Addiction-Related Surveillance (RADARS®) System collects product- and geographically-specific data on abuse, misuse, and the diversion of prescription drugs. The Drug Diversion Program of RADARS is composed of approximately 250 prescription drug diversion investigators and regulatory agencies across the United States who are surveyed quarterly and asked to report the number of new instances of pharmaceutical diversion investigated. Silk Road is an anonymous online marketplace.

[11]The MME for an opioid drug indicates how many milligrams of morphine produces the same effect as one milligram of the drug.

4.96 MME per day).[12] Hence, set $\underline{o}$ to 3,543.75 and p to \$0.0137 per MME (=\$48.38/3,543.75 MME) for those without a college degree. For college graduates, $\underline{o}$ is 1,785.00 and p is \$0.0208 per MME (=\$37.10/1,785.00 MME).

Given the large gap between prescription and street prices, and the other costs associated with obtaining opioids through non-medical channels, it is not surprising that misusers and addicts try to obtain opioids through doctors, friends, and relatives. In the NSDUH, close to 80 percent of misusers and addicts obtain opioids either from prescriptions or as gifts from friends and family. The share is about 73 percent for those without a college degree and 86 percent for those who are college graduates (Table 8). This suggests that the effective cost of opioids for misusers and addicts is lower than the street price. Since in the model everyone can obtain $\underline{o}$ at p, focus on non-prescription sources. For misusers and addicts as a whole, 64.9 percent of the non-college educated and 81.4 percent of college graduates obtain opioids from friends or steal them, at an assumed cost of zero. The remaining 35.1 percent of those without a college degree and 18.6 percent of college graduates obtain opioids from the street, at a cost of \$0.67/MME.[13] Then, the effective price for misusers and addicts is $q = 0.3512 \times \$0.67/\text{MME} = \$0.235/\text{MME}$ for the non-college population, and $q = 0.1862 \times \$0.67/\text{MME} = \$0.125/\text{MME}$ for the college one. As a fraction of a non-college, nonuser's average productivity, p and q are then obtained by dividing them by \$110,725.

Table 9 lists the parameters chosen based on outside information, either the literature or the US data.

[12] To put this in context, 9.84 MME per day would be equal to 6.6 (= 9.84/1.5) OxyContin 10 mg pills per day (the lowest dosage), while 4.96 MME per day corresponds to 3.3 pills.

[13] To obtain 64.9% *[81.4%]*, sum 40.43% *[41.75%]* and 3.43% *[3.33%]* (friends/relative and stolen) and divide by 67.6% *[55.4%]* (the sum of all non-prescription sources).

Table 8: Source of Opioids for Misusers and Addicts, %

Source	**Misusers**	**Addicts**	**Total**
Non-College			
Prescribed by one or more doctor	31.92	34.42	32.40
Given from friends/relatives	44.49	23.31	40.43
Bought from friends/relatives	10.06	17.43	11.47
Stolen (hospitals, friends/relatives)	3.57	2.82	3.43
Bought from dealer	5.29	18.47	7.82
Other	4.67	3.54	4.45
College			
Prescribed by one or more doctor	43.09	57.24	44.60
Given from friends/relatives	44.89	15.55	41.75
Bought from friends/relatives	4.56	17.79	5.97
Stolen (hospitals, friends/relatives)	3.50	1.93	3.33
Bought from dealer	0.88	6.04	1.43
Other	3.09	1.46	2.91

Table 9: Parameters, Chosen Directly from Outside Information

Parameter	**Explanation**	**Non-College**	**College**	**Comment**
		From the Literature		
ρ	Relative risk aversion	2		Standard
η	Weight on leisure	0.64		C.&P. (1995)
β	Discount factors, nonaddicts	0.96		Standard
		From the US Data		
Transitions				
σ_{np}	Prob[$n \rightarrow p$]	0.0347	0.0449	Table 6
σ_{pn}	Prob[$p \rightarrow n$]	0.1759	0.3703	Table 6
σ_{bn}	Prob[$b \rightarrow n$]	0.1419	0.1854	Table 6
σ_{an}	Prob[$a \rightarrow n$]	0.0455	0.0290	Table 6
Employment				
$\mathfrak{h}$	Hours worked	0.38	0.41	CPS
π_n	Productivity, nonusers	1	1.49	normalization
t	Income, non-employed	0.079	0.129	CPS
Opioids				
$\underline{o}$	Rx usage, MME	3,543.75	1,785.00	MEPS
p	Rx price/1,000 MME	0.000123	0.000188	MEPS
q	Street price/1,000 MME	0.00213	0.00113	MEPS and NSDUH

6.3 Parameters Values Chosen by Matching the Model with the Data

The remaining model parameters specify preferences, the relative labor market productivity of abusers and addicts, and how opioid use maps into the transitions from abuse to addiction and addiction to death. These parameters are chosen so that the model is consistent with the data on the fractions of the US population that are misusers and addicts, their opioid consumption, employment, and incomes, and their transitions from misuse to addiction and addiction to death. Furthermore, parameters are disciplined to make sure that the model-implied elasticity of opioid consumption with respect to opioid prices and the statistical value of life for non-college and college individuals are in line with the available evidence. Start with the easy ones.

Leisure Shock Parameters

In the NSDUH, 70.5 percent of non-college nonusers between ages 18 and 64 are employed. Employment declines to 66.6 percent for misusers and to 51.2 percent for addicts. As all nonusers and prescription users work in the model, the employment rates of non-college misusers and addicts relative to nonusers, 94 and 73 percent, are targeted in the calibration. For college graduates, the employment rates of misusers and addicts, relative to nonusers, are 99 and 85 percent. These employment targets are used to determine the parameters of the Gumbel distributions for leisure shocks and the relative labor productivities of abusers and addicts.[14] The scale parameter for each leisure-shock Gumbel distribution, ξ_s, for $s = b, a$, is chosen to generate the observed fraction of misusers or addicts who work in each education group. Given ξ_s, the mode parameter, ι_s, is selected so that the mean of the leisure shock distribution is normalized to 0.

Productivities–misusers and addicts

The employment patterns are mirrored in relative incomes; for the non-college educated, misusers have about 10 percent lower income than nonusers, while addicts' incomes are only 67 percent of nonusers. For college graduates the incomes of misusers and addicts are 91 and 87 percent of nonusers. Given the fraction of workers among abusers and addicts, their relative labor productivity levels, π_s for $s = b, a$, are calibrated such that the observed relative income levels of misusers and addicts match those in the data for each education group.

[14] The model's statistics for the employment rates and labor productivities of misusers are constructed to be consistent with their data counterparts. In particular, the employment rates and labor productivities for misusers include both abusers in category b and first-time misusers in categories n and p.

Recall that π_n is normalized to 1 for non-college nonusers and 1.49 for college nonusers. It is assumed that prescription users have the same productivity as nonusers, so, in each education group, $\pi_n = \pi_p$.

Ecstasy Shock Parameters

Next, turn attention to the population fractions of misusers and addicts, and the transitions from misuse to addiction and addiction to death. The opioid ecstasy shocks, ε_s for $s = n, p$, like the leisure shocks, are distributed according to Gumbel distributions. Recall that in the data, for the non-college population, $\Gamma(\varepsilon_n^*) = 0.9966$ of nonusers and $\Gamma(\varepsilon_p^*) = 0.9689$ of prescription users do not misuse opioids, while the rest are misusers each period (Table 6). The fractions of non-misusers among nonusers and prescription users for college graduates are 0.9989 and 0.9510. Given the optimal decisions for ε_n^* and ε_p^*, the shapes of the Gumbel distributions determine these fractions. So, each scale parameter, ζ_s, is chosen to match the population fractions. Then, given ζ_s, the mode of each distribution, ν_s, is set such that the mean of the ecstasy shock is normalized to 0.

Transitions to Addiction and Death

According to the data, each period 2.32 percent of non-college and 0.69 percent of college misusers become addicts, while 2.12 percent of non-college addicts and 1.06 percent of college addicts die (Table 6). The parameters σ_s, for $s = a, d$, which determine how opioid use affects these transitions, are chosen so that the model transitions match the data.

Preferences

The preference parameters remain to be determined, i.e. the curvature, ψ, and weights, μ_s for $s = n, p, b, a$, of the utility function for opioids, the utility cost of addiction, ω_a, and the utility associated to death, δ. Three sets of targets are used to discipline these parameters: opioid use, the statistical value of life, and the price elasticity of opioid demand.

(1) Opioid Consumption. The first set of targets is opioid consumption by misusers and addicts. Unfortunately, consumption data limited (mainly available for prescription patients), so some bold assumptions have to be made to arrive at numbers that can be used for calibration. Glanz et al. (2017) study 14,898 patients with opioid therapy who were part of a large Colorado health care provider between 2006 and 2018. Among these patients, some 288 of them experienced opioid overdoses. A control group was created by matching these patients to similar patents who did not develop overdose problems. Table 10 shows the daily opioid use in MMEs during the 90 days prior to an overdose event. For the entire

sample, the average daily opioid usage was 44.4 MME. For patients with overdose problems, the average daily usage was much higher, 80.5 MME.

According to Dowell, Tamara, and Chou (2016), in a national sample of Veterans Health Administration patients with chronic pain receiving opioids from 2004 to 2009, patients who died from opioid overdoses had been prescribed an average of 98 MME per day, while other patients had been prescribed an average of 48 MME per day. These numbers are in line with those reported by Glanz et al. (2017). Dowell, Tamara, and Chou (2016) also indicate that "Clinicians should use caution when prescribing opioids at any dosage, should carefully reassess evidence of individual benefits and risks when considering increasing dosage to ≥50 morphine milligram equivalents (MME)/day, and should avoid increasing dosage to ≥90 MME/day or carefully justify a decision to titrate dosage to ≥90 MME/day." For the model, daily usages of 50 MME for misusers and 90 MME for addicts are chosen as targets.

Table 10: Daily Opioid Use, Patients with Prescriptions–distribution %

MME	**Assigned Value**	**All (N=14,898)**	**Overdose (N=14,898)**	**Control (N=3,547)**
0-20	10	33.3	17.1	30.6
21-50	35	40.5	23.7	29.4
51-100	75	16.4	24.6	19.1
100+	150	9.7	34.7	20.8
AVERAGE		44.4	80.5	58.9

Since the model period is a year, an adjustment has to be made to arrive at yearly opioid consumption. As noted above, the average yearly opioid consumption of prescription patients in MEPS is about 3,543.75 MME for the non-college educated and 1,789.00 MME for the college educated. In Galant et al. (2017) patients who did not develop overdose problems used about 44.4 MME per day or 16,190 MME per year if they were using opioids everyday, which seems to be much higher than the MEPS numbers. The average amount in MEPS, however, reflects the fact that prescription patients do not necessarily use opioids all year long.

In the NSDUH, misusers and addicts are also asked how many times they misused opioids during the last month—Table 11. For non-college educated, opioids are misused 6.52 times per month by misusers and 13.13 times per month by addicts (21.74 and 43.75 percent of the time). Thus, for the non-college educated, the annual levels of opioid misuse are $0.2174 \times 365 \times 50$ MME $= 3,967.8$ MME for misusers and $0.4375 \times 365 \times 90$ MME $= 14,372.5$ MME for addicts. For the college educated, misuse of opioids occurs 4.76 times per month for misusers and 12.58 times per month for addicts (15.85 and 41.92 percent of the time). So, for the college educated, annual opioid consumption is $0.1585 \times 365 \times 50$ MME $= 2,893.2$ MME for misusers and $0.4192 \times 365 \times 90$ MME $= 13,772.0$ MME for addicts.

To summarize, in the model, the targeted level of opioid consumption for non-college misusers, whether they are first-time misusers in stages n or p or experienced misusers in stage b, is 3,967.8 MME. The number for college misusers is 2,893.2 MME, or about 27 percent less. For addicts, the gap between college and non-college opioid consumption is smaller, $13,772.0$ MME$\div 14,372.5$ MME $= 0.96$.

Table 11: Frequency Distribution of Opioid Misuse Last Month, %

Times Misused	**Assigned Value**	**Misuser, %**	**Addicts, %**
Non-College			
Less than 5	2.5	62.63	24.94
5-9	7	16.24	18.55
10-14	12	8.97	13.61
15-19	167	3.70	14.44
20-30	25	8.46	28.46
AVERAGE		6.52	13.13
Non-College			
Less than 5	2.5	77.52	23.02
5-9	7	11.23	25.27
10-14	12	4.94	16.95
15-19	167	1.73	6.14
20-30	25	4.58	28.62
AVERAGE		4.76	12.58

In the model, the opioid consumption of first-time users in stages n and p is determined by the generic static first-order condition (5),

$$\mu_s(o - \underline{o})^{-\psi} = (1 - \mu_s)(1 - \eta)\left(\pi_s \mathfrak{h} - p\underline{o} - q(o - \underline{o})\right)^{-\rho} q \text{ , for } s = n, p.$$

There are two unknowns in this equation: the elasticity parameter for opioid utility, ψ, and the weights on utility for opioids, $\mu_n = \mu_p$. They are chosen so that first-time non-college and college misusers in the n and p stages consume 3,967.8 MME and 2,893.2 MME, respectively. The generic first-order conditions (8) and (11) that determine the consumptions of abusers and addicts are more involved. But the same logic dictates that the levels of opioid consumption of abusers and addicts can be used to determine μ_b and μ_a.

(2) Statistical Value of Life. The second set of targets pertain to the statistical value of life. These are useful for determining the utility value of death, δ. The value of a statistical life (VSL) is a measure of the amount individuals are willing to pay to reduce their mortality

risk by 100 percent. That is, according to the U.S. Department of Transportation, "when an individual is willing to pay \$1,000 to reduce the annual risk of death by one in 10,000, she is said to have a VSL of \$10 million."[15] The VSL prorates the willingness to pay (WTP) for a reduction in risk in a linear fashion. "The assumption of a linear relationship between risk and willingness to pay (WTP) breaks down when the annual WTP becomes a substantial portion of annual income, so the assumption of a constant VSL is not appropriate for substantially larger risks." Moreover, this calculation does *not* give a dollar estimate of the value of life as "(w)hat is involved is not the valuation of life as such, but the valuation of reductions in risks."

In the model, the interesting sources of risk are the transitions from abuse to addiction and from addiction to death. The probability of transiting between stage i and stage j, σ_{ij}, is given by

$$\sigma_{ij} = S_{ij}(o) = \sigma_j \sqrt{o}, \text{ for } (i, j) = (b, a), (a, d).$$

Focus on the risk of death,

$$\sigma_{ad} = \sigma_d \sqrt{o}.$$

Now, consider a small change in this risk. Since it is endogenous, hold o fixed at the benchmark value and let σ_d change to obtain some desired change in $\sigma_d \sqrt{o}$. How much would a person be willing to pay out of current consumption to obtain this decline in risk? The amount they are willing to pay is informative about the utility obtained in death, δ, relative to utility while alive. This exercise could be done in any of the four stages, $s = n, p, b, a$. Focus on the nonuser stage n. Denote a nonuser's expected lifetime utility before and after the decline in risk by N and N'. After the reduction in σ_d, the nonuser will change the level of their opioid consumption in the events where they use opioids. Presumably they would increase it because the risk of death has fallen. So, N' results from the optimization problem with the lower level of risk. A prime ($'$) superscript is added to variables to denote their values in the setting with reduced risk.

Let α be the fraction of current income that a nonuser is willing to pay to reduce the probability of dying while being addicted. The compensating variation, α, must solve the

[15]See Trottenberg and Rivkin (2013).

nonlinear equation

$$\Gamma(\varepsilon_n^{*\prime})\{U((1-\alpha)\pi_n\mathfrak{h}) + L_n(1-\mathfrak{h}) + \beta[(1-\sigma_{np})N' + \sigma_{np}P']\}$$
$$+ [1-\Gamma(\varepsilon_n^{*\prime})]\{U\left((1-\alpha)\pi_n\mathfrak{h} - p\underline{o} - q(o' - \underline{o})\right) + O_n(o' - \underline{o}) + \mathbf{E}[\varepsilon_n|\varepsilon_n \geq \varepsilon_n^{*\prime}] + L_n(1-\mathfrak{h})$$
$$+ \beta[(1-\sigma_{bn})B' + \sigma_{bn}N']\} = N,$$

where the terms on the lefthand side are all evaluated at the values that obtain in the setting with the reduced risk without the compensating differential; i.e., no re-optimization is involved on the lefthand side due to the lower level of income. For the beginning stage the value of α is likely to be small. Addiction is an unlikely event and it is off in the future. The equations that determine compensating variations for stages p, b, and n are presented in Appendix D.

To calculate the VSL, the average WTP of alive individuals in the baseline economy is calculated for a small (4 percent) decline in death. Then, the VSL is given by the average WTP divided by the decline in the unconditional death probability. This is done separately for each education group. VSL's of \$9 million and \$11.8 million are targeted for non-college and college graduates, respectively. The targets are consistent with a mean VSL of \$10 million and an income elasticity of the VSL of 0.5, which are inline with estimates in the literature; see Viscusi and Aldy (2003).

(3) Price Elasticity of Opioid Use. The final set of targets that are used to determine the preference parameters are the estimates of the price elasticity of opioid use. The price elasticity, in particular, helps to determine the utility cost of addiction, ω_a. An excellent summary of the available evidence on this price elasticity is provided in the 2020 *Economic Report of the President*. The available estimates range from -0.40 to -1.5. The calibration targets the midpoint of this range or a price elasticity of -0.95.

The calibrated parameters are presented in Table 12. The match between the model and data targets is provided in Table 13. The fit of the model to the data targets is excellent. The opioid price elasticity in the model at -1.03 is close to the midpoint of the range estimated in the literature.

Table 12: Parameters, Calibrated

Parameter	**Explanation**	**Non-College**	**College**
ψ	elasticity of opioid use	1.652	
μ_a=μ_p,	utility weight on opioids	0.00129	
μ_b	utility weight on opioids	0.00893	0.00542
μ_a	utility weight on opioids	0.82215	0.318
ζ_n,ν_n	ecstasy shock, nonusers	0.1205, -0.0695	0.0442, -0.0255
ζ_p, ν_p	ecstasy shock, Rx users	0.2192, -0.1265	0.1169, -0.0675
ξ_b,ι_b	leisure shock, abusers	1.630, -0.9409	0.471, -0.2719
ξ_a,ι_a	leisure shock, addicts	1.575, -0.9091	1.180, -0.6811
π_b	relative productivity, abusers	0.934	0.900
π_a	relative productivity, addicts	0.840	0.984
σ_a	Prob[b→a]	0.01165	0.00406
σ_d	Prob[a→d]	0.00559	0.00286
δ	utility associated with death	-34.41	-20.958
ω_a	utility cost of addiction	2.777	0.8886

Table 13: Targets

Targets	**Model**	**Data**	**Model**	**Data**
	Non-College		*College*	
Opioid Consumption				
Usage, first-time misusers, MME	3,967.8	3,967.8	2,893.2	2,893.2
Usage, abusers, MME	3,967.8	3,967.8	2,893.2	2,893.2
Usage, addicts, MME	14,372.3	14,372.5	13,7713.1	13,772.0
Fraction non-misusers in n	0.9966	0.9966	0.9989	0.9989
Fraction non-misusers in p	0.9689	0.9689	0.9510	0.9510
Transitions				
Prob[b→a]	0.0232	0.0232	0.0069	0.0069
Prob[a→d]	0.0212	0.0212	0.0106	0.0106
Employment (fraction)				
All misusers/Nonusers	0.94	0.94	0.99	0.99
Addicts/Nonusers	0.73	0.73	0.85	0.85
Income				
All misusers/Nonusers	0.90	0.90	0.91	0.91
Addicts/Nonusers	0.67	0.67	0.87	0.87
VSL (millions of 2018 dollars)	9.0	9.0	11.8	11.8
	All			
Opioid price elasticity	-1.03	-1.5 to -0.4		

6.4 Cross-State Validation Check: Evidence on OxyContin Access

In a recent paper, Alpert et al. (2019) exploit cross-state variation in the exposure to OxyContin's introduction due to differences in drug monitoring programs. When OxyContin was introduced to the market in 1996, some US states (California, Idaho, Illinois, New York, and Texas) had existing drug monitoring programs, called Triplicate Prescription Programs, while others did not. These programs reduced OxyContin sales significantly and OxyContin distribution was about 50 percent lower in triplicate states in the years after its launch. Alpert et al.'s (2019) comparison between triplicate and non-triplicate states implies that a state without such a program could reduce opioid deaths by 44 percent by implementing one. The number of individuals misusing opioids would also decline by 50 percent. Is the model-implied relationship between access to opioid prescriptions, on the one hand, and opioid misuse and deaths, on the other, consistent with this evidence? In the model, the amount of prescription opioids distributed is given by the number of opioid prescription users times the level of opioids prescribed to them. A 50 percent lower distribution of prescription opioids can be implemented by reducing the number of prescription users, or the transition rate from the nonuser state to the pain state, σ_{np}, by 50 percent. Alternatively, it can be implemented by a 50 percent reduction in prescription opioid strength, $\underline{o}$. The first approach assumes that all of the decline in opioid prescription distribution is due to a reduction in the fraction of individuals who are prescribed opioids while the second assumes it is all due to a reduction in the amount of opioids each prescription-user is prescribed. The decline could also be due to some combination of the two, such as a 29 ($\simeq 1 - \sqrt{0.5}$) percent decline in opioid prescription users and a 29 percent reduction in the amount of opioids each user is prescribed.

Table 14 shows the results from reducing prescription opioid distribution in these different ways. The total number of deaths declines anywhere between 24 to 59 percent depending on the way in which opioid prescriptions are reduced. The 44 percent decline estimated by Alpert et al. (2019) is in the middle of the range. The reduced availability of opioid prescriptions in triplicate states is likely due to a combination of fewer individuals obtaining opioid prescriptions and lower Rx dosages. Consistently, when σ_{np} and $\underline{o}$ are both reduced, there is a 50 percent decline in the fraction of opioid users (misusers and addicts) in the model, again in line with the data. As a non-targeted moment that exploits a very different source of variation in the data, these results provide further support for the calibrated model.

Table 14: Results

Outcomes	**Benchmark**	**Rx Availability**	**Rx Dosage**	**Both**
		$\sigma_{np}\downarrow$	$\underline{o}\downarrow$	
	(1)	(2)	(3)	(4)
Non-College				
Deaths	*37,569*	28,855	14,357	18,392
Decline (%)		23.25	61.81	51.08
College				
Deaths	*3,045*	1,913	2,385	2,090
Decline (%)		37.16	21.67	31.36
All				
Deaths	40.641	30,768	16,742	20,482
Decline (%)		24.29	58.80	49.60

7 Understanding the Downward Spiral

Every year between 2015 and 2018 an average of 40,641 individuals between ages 18 and 64 died of opioid overdoses. A large majority of them, 37,596, did not have a college degree. The rest, 3,045 of them, were college graduates. The benchmark economy matches these statistics exactly. The downward spiral from opioid use is portrayed in Figure 8. It shows how the college- and non-college-educateds' expected utilities steadily decline as they move through the stages of opioid addiction. The descent appears fairly gradual until one hits the addiction stage and, of course, the loss in utility associated with death is large. While utility is always higher for college graduates, the relative utility values of death to nonuse are roughly the sames for both types of individuals.

Back in 2000, the number of opioid-related deaths was only 8,179 (7,549 deaths among non-college and 629 among college graduates). Between 2000 and 2018, more than 400,000 individuals between the ages of 18 and 64 died from opioid overdoses.[16] What can account for the dramatic rise in opioid use and overdose deaths during the last two decades? The model is now used as a quantitative laboratory to answer this question. Three candidates are entertained; namely, the fall in opioid prices, more powerful prescriptions, and longer length prescriptions.

[16]Opioid-overdose deaths are calculated using medical codes reported in death certificates. Glei and Preston (2020) estimate that drug-related deaths are about 2.2 times higher than drug-coded deaths, reflecting excess mortality from other causes affected by drug use.

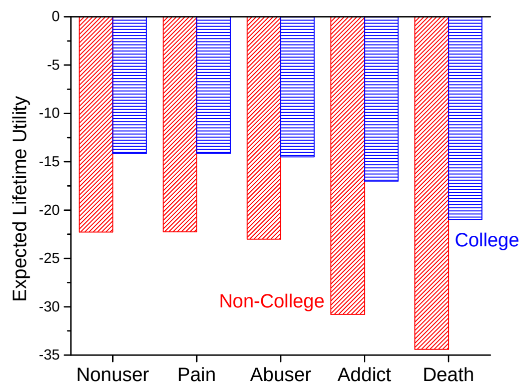

Figure 8: The Downward Spiral. A person's expected lifetime utility sinks into the abyss as they advance through the various stages of opioid addiction.

7.1 Decline in Opioid Prices

Start with the price of opioids. There has been a huge decline in the price of opioids since the turn of the century. Between 2001 and 2013, the decline in the street price was about 60 percent (Figure 6), while the prescription prices had fallen by a factor of 5 (Figure 4). As a thought experiment for the model, imagine going back to 2000, when both the prescription prices, q, and the street prices, p, were higher. The high-opioid-price economy is summarized in column 2 of Table 15. Focus on non-college graduates. With higher prices, the average opioid use declines significantly from 0.3676 to 0.0893 MGEs (or 1,000 MMEs), a fall of about 76 percent. The fall in average usage is partly driven by a drop in the number of misusers and addicts, the extensive margin of opioid use—the share of misusers declines from 4.46 percent to 1.32 percent and the share of addicts from 1.32 percent to 0.41 percent. While opioid use by misusers does not react much to higher prices, the use by addicts declines by about 35 percent. The employment rates of misusers and addicts also increase. The rise in their employment rates together with the decline in the number of misusers and addicts leads to a drop in the fraction of non-college graduates who are non-employed by a factor of nearly four, from 0.63 to 0.17 percent. Finally, there are now only 9,426 deaths, in contrast to 37,569 in the benchmark economy. Hence, lower opioid prices can account for about 94 percent of the increase in overdose deaths among non-college graduates during this period. The picture for college graduates is similar, with significant declines in the numbers of misusers and addicts. College graduates are less responsive to changes in prices, so lower opioid prices account for a smaller share, 49 percent, of their increase in overdose deaths.

7.2 More Powerful Prescriptions

Next, turn to the role of medical practices. In the benchmark economy, the opioid content of prescriptions, $\underline{o}$, is 3,543 MME for the non-college educated and 1,785 for the college educated. Since 2000, while prices were falling, the average opioid prescription also became more potent; it increased by 72 percent, from 2,066 to 3,543 MME, for non-college graduates and by a factor of 34 percent, from 1,329 to 1,785, for college graduates.[17] The effects of a lower $\underline{o}$ are shown in column 3 of Table 15. Opioid usage declines significantly, in particular, among non-college graduates. For misusers the decline is mainly due to lower consumption, the intensive margin. Reducing the opioid content of prescriptions effectively raises the price of opioids because now more of the drug has to be purchased on the black market where the price is higher (i.e., $q > p$). For addicts the extensive margin is more important. The transitions to becoming an addict and subsequently dying depend on total usage, prescription plus illicit. This falls when the opioid content of prescriptions is lowered. For non-college graduates, a higher $\underline{o}$ is a powerful driver of the increase in their overdose deaths, accounting for about 63 percent of the rise during this period.

7.3 Longer Prescription Lengths

Finally, the changes in the transitions between the nonuser and prescription states, σ_{np} and σ_{pn}, are investigated. These reflect the changing views of the medical profession on opioid prescriptions and their possible side effects. To calculate the changes in these transitions, turn again to MEPS. The transitions from being a nonuser to a prescription user have been fairly stable since 2000. Thus, there was no real change in σ_{np}. In contrast, there has been a consistent decline in p-to-n transitions. While doctors were not more likely to write opioid prescriptions for nonusers, they became more likely to keep patients on opioids once they started using them. The decline in σ_{pn} was about 16 percent for the non-college educated and 12 percent for college educated.[18] The effects, documented in column 4 of Table 15, are small.

The last column of Table 15 shows the outcome of implementing all three changes together. Through the eyes of the model, the combined effect of lower prices and changing medical practices accounts for the entire increase in deaths among the non-college population and 66 percent of the rise in deaths among college graduates. Figure 9 summarizes the

[17] The changes are based on the average MME content of prescriptions in the first three survey years, 2000-2003, versus the benchmark values for the 2015-18 period in MEPS. See Nahin et al. (2019) for a similar analysis using MEPS.

[18] The calculations are again based on a comparison between the first three survey years, 2000-2003, and the benchmark years, 2015-18, from MEPS.

decomposition of the increases in opioid deaths resulting from the fall in opioid prices, more powerful prescriptions, and longer length prescriptions.

According to the model, the combination of all three factors generates a significant rise in non-employment. Non-employment among those without a college degree increases by a factor of 20 from 0.03 to 0.63 percent and the number of college graduates not working nearly doubles. Recall that in the model, nonusers and prescription users always work. Thus, the increase in non-employment in the model is due entirely to a mixture of increases in the number of abusers and addicts and decreases in their labor supply. Taking college and non-college graduates together, the total fraction non-employed ratchets up by 0.42 percentage points from 0.04 to 0.45 percent. In other words, according to the model, the impact of the changes in opioid prices and prescribing behavior since 2000 on the number and labor supply of abusers and addicts led to a 0.42 percentage point increase in the non-employment rate.[19]

[19] There may be additional labor supply effects of the opioid crisis, such as the effects on the labor supply of prescription users, which the model is silent about. In this sense, the impact of the opioid crisis on aggregate employment in the model can be thought of as a lower bound. Consistent with this view, the model's predicted effect is on the lower end of the estimated effects in the literature that range from findings of a very small positive effect to a rise in opioid use over this period reducing labor-force participation by 2.6 percentage points (see Aliprantis, Fee, and Schweitzer (2019), who summarize the literature, and Powell (2021)).

Table 15: Results

Outcomes	**Benchmark**	**Prices** p and q ↑	**Rx Dosage** $\underline{o}$ ↓	**Rx Length** σ_{pn} ↑	**All**
	(1)	(2)	(3)	(4)	(5)
Non-College					
Opioid Cons., all	*0.3676*	0.0893	0.1483	0.3504	0.0138
Opioid Cons., Misusers & Addicts	*6.3499*	5.1579	4.5767	6.3499	3.4693
Opioid Cons., Misusers	*3.9678*	3.8383	2.5108	3.9678	2.3753
Opioid Cons., Addicts	*14.3725*	9.4037	13.1725	14.3723	7.8172
Misusers	*0.0446*	0.0132	0.0261	0.0425	0.0032
Addicts	*0.0132*	0.0041	0.0063	0.0126	0.0008
Misusers working	*0.9392*	0.9442	0.94489	0.9392	0.9574
Addicts working	*0.7256*	0.7594	0.7329	0.7256	0.7802
Non-employed	*0.0063*	0.0017	0.0031	0.0060	0.0003
Deaths	*37,569*	9,426	17,056	35,839	1,674
Deaths, accounted (%)		93.75	63.36	5.85	119.55
College					
Opioid Cons., all	*0.1468*	0.0879	0.1244	0.1377	0.0647
Opioid Cons., Misusers & Addicts	*4.2481*	3.3857	3.7333	4.2481	2.8852
Opioid Cons., Misusers	*2.8932*	2.5436	2.4510	2.8932	2.0962
Opioid Cons., Addicts	*13.7731*	9.3729	13.4982	13.7731	9.0284
Misusers	*0.0303*	0.0228	0.0294	0.0284	0.0199
Addicts	*0.0043*	0.0032	0.0039	0.0040	0.0026
Misusers working	*0.9905*	0.9915	0.9907	0.9905	0.9918
Addicts working	*0.8524*	0.8717	0.8533	0.8524	0.8736
Non-employed	*0.0009*	0.0006	0.0008	0.0009	0.0005
Deaths	*3,045*	1,869	2,708	2,855	1,461
Deaths, accounted (%)		48.68	13.94	7.87	65.53

8 Medical Advances through the Lens of the Model

How would opioid consumption and, as a result, the number of deaths change if individuals face a lower probability of addiction or death? Recall that the transitions in the model from abuse to addiction and addiction to death are given by, $\sigma_{ba} = \sigma_a \sqrt{o}$ and $\sigma_{ad} = \sigma_d \sqrt{o}$. Both of these transitions are endogenous, depending on current usage, o. To undertake these experiments, the constants σ_a and σ_d will be lowered in turn. The experiments will focus on the non-college population.

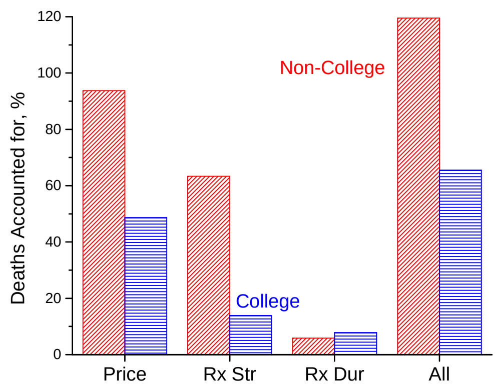

Figure 9: Accounting for the Increase in Deaths.

8.1 Probability of Death

Start with the probability of death for addicts. In the benchmark economy, σ_d is 0.00559 for the non-college educated. Suppose σ_d is lower, i.e., for a given level of o, individuals are less likely to die. This can represent, for example, the introduction of naloxone, an opioid antagonist that can reverse an opioid overdose. Naloxone was patented in 1961 and approved for opioid overdose in the United States in 1971. There are two forms of naloxone: a nasal spray (known as Narcan that was approved in 2015, with a generic version arriving in 2019) and an auto-injector. Between 2010 and 2014, naloxone access increased significantly in the US. People can use it without medical training or authorization–NIDA (2021). In a landmark study, Walley et al. (2013) compare the implementation of overdose education and nasal naloxone distribution programs in different communities in Massachusetts, comparing high and low implementation communities with those with no implementation. They show that opioid overdose death rates are 27 to 46 percent lower in communities with a naloxone program. Albert et al. (2011), based on data from a rural county in North Carolina, also find that the overdose death rate fell by about 38 percent following the introduction of an overdose-prevention program that included the distribution of naloxone.

Figure 10 shows how the number of non-college deaths (upper panel) declines with σ_d. The plot also displays how much a non-college-educated person would be willing to pay (as measured by the average compensating variation across states, CV) to reduce the probability of dying from opioid use. While the number of deaths declines as σ_d falls, the number of opioid users (misusers and addicts) and their opioid consumption increases. Hence, the monotone decline in deaths with a drop in σ_d is not a forgone conclusion. A 50 percent decline in the probability of death, for example, increases users by about 30 percent, and the

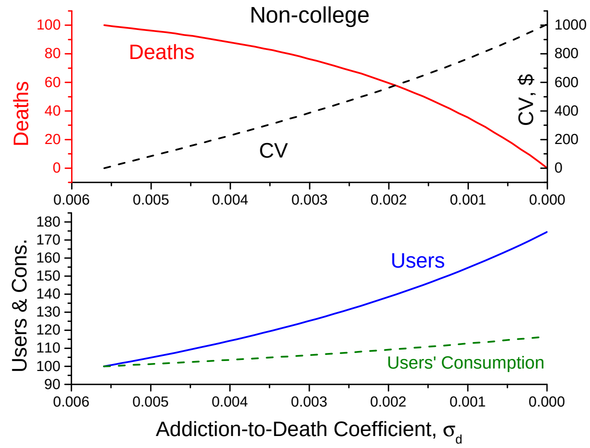

Figure 10: Changes in the probability of dying as regulated by σ_d. For deaths, users (misusers and addicts), and opioid consumption, the values for the benchmark equilibrium are set to 100.

amount of use conditional on usage by 6 percent. The number of deaths is lower by about 29 percent. When the probability of death is zero, the number of users increases by 74 percent. Yet, this is still only 10 percent of the non-college population, instead of 6 percent as in the benchmark economy. Even absent the risk of death, abusing opioids is not costless in the world of the model because addicts have lower labor market income and suffer a utility cost, ω_a.

8.2 Probability of Addiction

Next, turn to σ_a, which determines the probability of addiction for abusers. The benchmark value for this parameter is 0.01165 for the non-college population. A reduction in σ_a to zero corresponds to a world of non-addictive opioids, as if Purdue Pharmacy's claims about OxyContin were indeed true. The results of the experiment are shown in Figure 11. As the odds of addiction fall, the number of users (misusers and addicts) increases dramatically (upper panel). When the probability of addiction declines by 50 percent, the number of users increases by more than five fold from 6 percent to about 35 percent of the non-college population. Yet, users consume lower amounts of opioids. This transpires because there are less addicts, who are relatively heavy users. The increase in users and decrease in usage conditional on using have opposite effects on death rates. Consequently, the number of deaths shows a $\cap$-shaped response to a decline in σ_a. With a 50 percent decline in the risk of addiction, the number of deaths more than triples. This occurs because of the dramatic increase in users. Eventually, as the risk of addiction declines further, the lower number of

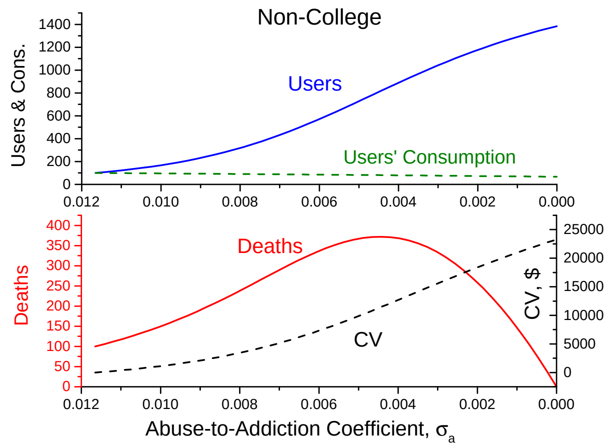

Figure 11: Changes in the probability of addiction as regulated by σ_a. For deaths, users (misusers and addicts), and opioid consumption, the values for the benchmark equilibrium are set to 100.

addicts dominates the rise in usage, and the number of deaths starts declining. The figure also shows that a reduction in the addictive nature of opioids would be highly valued by the non-college educated. This transpires because they enjoy consuming opioids, just like alcohol.

9 Closing

There have always been opiate users in America. The elderly Benjamin Franklin is said to have been an addict. At the start of the 20th century there were medical addicts using opium and morphine, and nonmedical addicts who smoked opium. Smoking opium was banned in 1909 by the Smoking Opium Exclusion Act. Additionally, at the turn of the century physicians were becoming aware of the addictive nature of morphine and became less inclined to prescribe it. Alternative therapeutics came online that reduced the need for catch-all opioids. The 1914 Harrison Narcotics Act regulated and taxed the legal dispensation of narcotics. The Act resulted in about 25,000 doctors being arrested for prescribing narcotics to addicts. All of this led to the importation of heroin, which was relatively inexpensive and stronger. The government tried to circumvent this by passing the Anti-Heroin Act in 1924.

The 1960s and 70s saw a heroin epidemic. In response the Drug Enforcement Agency (DEA) was established in 1973. There might have been as many as 634,000 heroin addicts at the end of the 1970s, which translates to 3.09 addicts per 1,000 population. This is in the (upper-end) range of the 4.59 morphine addicts per 1,000 populace at the beginning of the century. The epidemic subsided as tastes switched to cocaine and marijuana. The price of cocaine fell rapidly during the 1980s. It cost 1/6th as much in 1987 as it did in 1980. In the 1990s physicians began to prescribe opioid-based drugs, such as OxyContin, to control pain. It soon became apparent that OxyContin was addictive. Controls were placed on prescribing opioid-based painkillers such as OxyContin. This led to illegal imports of fentanyl, again cheap and powerful.

There are some parallels between the opioid epidemic and Prohibition.[20] The 18th Amendment to the Constitution prohibited "the manufacture, sale, or transportation of intoxicating liquors." It took affect in January 1920 and was rescinded by the 21st Amendment in December 1933. Upon enactment alcohol consumption dropped to somewhere between 20 to 40 percent of its pre-Prohibition levels–see Figure 12, left panel. By the end of Prohibition it had grown back to about 60 to 70 percent of the pre-Prohibition levels as a black market for alcohol emerged. This is similar to the emergence of black markets for heroin after opium was banned and for synthetic heroin after the crackdown on prescription opioids. During Prohibition the underground economy moved to more potent forms of alcohol, such as spirits, because this maximized profits–again, see Figure 12, left panel. The potency of bootlegged alcohol is estimated to be have been 150 percent stronger than when it was legal. Many of the spirits came from industrial alcohol. The government mandated that industrial alcohol be denatured by adding ingredients to it, such as poisonous methyl alcohol. While bootleggers hired chemists to neutralize these ingredients, the alcohol still contained many contaminants. Dr Charles Norris, who was New York City's first medical examiner, wrote in 1926:

> The government knows it is not stopping drinking by putting poison in alcohol. It knows what bootleggers are doing with it and yet it continues its poisoning processes, heedless of the fact that people determined to drink are daily absorbing that poison. Knowing this to be true, the United States Government must be charged with the moral responsibility for the deaths that poisoned liquor causes, although it cannot be held legally responsible. Source: Blum (2011, p. 155).

Deaths from alcoholism rose throughout Prohibition and greatly exceeded the post-Prohibition levels. There were 2.2 deaths per 100,000 people between 1918 and 1919 and this rose to 3.9 deaths between 1927 and 1929. The increased potency of alcohol as well as contaminated products contributed to this, similar to today's blackmarket opioids. The homicide rate rose during the Prohibition era and fell immediately afterwards–Figure 12, right panel–and rose again with the War on Drugs.

[20] This discussion is based on Blum (2011), Miron and Zwiebel (1991), Thornton (1991), and Warburton (1932).

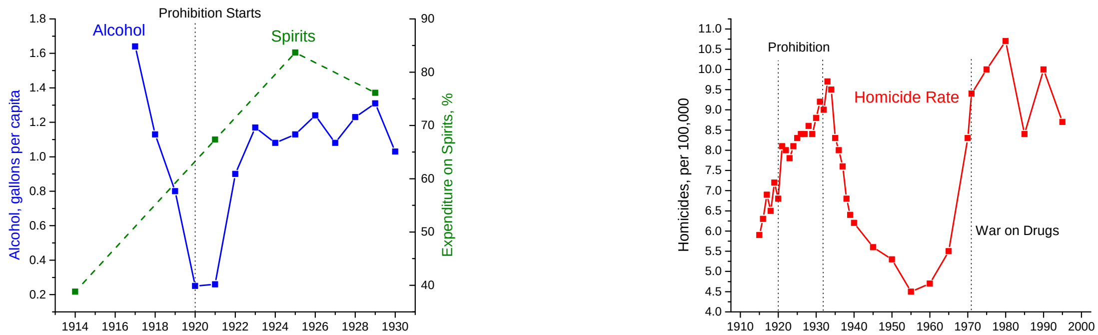

Figure 12: Prohibition, 1920-1933. The left panel illustrates the rise in alcohol consumption throughout the Prohibition era. Also shown is the shift in expenditure away from beer and wine toward spirits. After prohibition expenditure reverted back to the pre-Prohibition pattern (somewhere between 40 and 50 percent). The rise in homicide rate during prohibition is displayed in the right panel. Sources: Warburton (1932, Tables 1, 30, and 86) and Carter et al. (2006, Series Ab951)

To analyze the opioid epidemic, a model is constructed where there are two routes to opioid misuse. Some people just take opioids for enjoyment. Others start opioids because they are suffering pain and end up abusing them. Abuse leads to addiction with some odds. There is a chance that addiction results in death. The probabilities of addiction and death are increasing functions of the extent of opioid use, a choice variable. The decisions to misuse opioids in the first place, and how much to use in the second, depend upon the price of opioids. Abusers and addicts also choose whether they want to work or not.

The developed framework is taken to the US data for both the college- and non-college-educated populations. The quantitative analysis has three key steps. The first step is the estimation of Markov chains characterizing the movements in and out of misuse and addiction. Death is an absorbing state. The model is calibrated in the second step to match the estimated transitions from the Markov chains for both the college- and non-college educated. The framework fits the US data well. A check is performed on the calibration, by examining whether the model's prediction on the relationship between prescription opioid access and opioid deaths is consistent with the cross-state evidence about this. The calibrated framework is then used to decompose the rise in opioid usage. The analysis suggests that drops in the price of both Rx and illicit opioids combined with increases in Rx dosages were the primary drivers of the opioid epidemic. Keeping people who experience pain on opioid prescriptions longer had a minimal impact. Last, the impact of medical interventions that reduce either the odds of becoming addicted or the probability of an addict dying are examined. Both types of interventions increase the number of opioid users, because the risk of using opioids is lower. Lowering the odds of becoming addicted can increase the number of deaths because number of users rises dramatically. Despite this, both types of interventions are valued by consumers.

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A Appendix: The Transition Matrix across Model Categories

A Markov chain representation of the schematic in Figure 3 for the model is presented here. This differs from the model's Markov chain representation of the US data because the classifications of nonuser, prescription user, abuser/misuser, addict, and death states are different. The transition probabilities across the model states n, p, b, a, and d are

$$E \equiv [i \to j]_{i,j}$$
$$\equiv \begin{bmatrix} \Gamma(\varepsilon_n^*)(1-\sigma_{np}) + [1-\Gamma(\varepsilon_n^*)]\sigma_{bn} & \Gamma(\varepsilon_n^*)\sigma_{np} & [1-\Gamma(\varepsilon_n^*)](1-\sigma_{bn}) & 0 & 0 \\ \Gamma(\varepsilon_p^*)\sigma_{pn} + [1-\Gamma(\varepsilon_p^*)]\sigma_{bn} & \Gamma(\varepsilon_p^*)(1-\sigma_{pn}) & [1-\Gamma(\varepsilon_p^*)](1-\sigma_{bn}) & 0 & 0 \\ [1-S_{ba}(o)]\sigma_{bn} & 0 & [1-S_{ba}(o)](1-\sigma_{bn}) & S_{ba}(o) & 0 \\ [1-S_{ad}(o)]\sigma_{an} & 0 & 0 & [1-S_{ad}(o)](1-\sigma_{an}) & S_{ad}(o) \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}. \quad (14)$$

The ergodic steady state, $e = [e_n, e_p, e_b, e_a, e_d]$, associated with this Markov chain solves

$$e = eE.$$

B Appendix: Data

B.1 The National Survey on Drug Use and Health

The National Survey on Drug Use and Health (NSDUH) is an annual nationwide survey that provides national and state-level data on the use of tobacco, alcohol, illicit drugs (including the non-medical use of prescription drugs), and mental health in the United States. The survey is representative of the age 12 and over civilian non-institutionalized population of the United States for each state and the District of Columbia (D.C.). Every year approximately 70,000 individuals are randomly selected from all over the United States and asked to participate. The survey collects information from households and non-institutionalized group quarters (e.g., shelters, rooming houses, dormitories), and civilians living on military bases. The NSDUH is directed by the Substance Abuse and Mental Health Services Administration (SAMHSA), an agency in the U.S. Department of Health and Human Services (HHS).

In the NSDUH, based on opioid usage during the previous 12 months, an individual can be a user or a nonuser of an opioid prescription pain reliever (PPR) or heroin. The PPR users are then classified as legal users or misusers, while all heroin users are misusers by default. Some misusers develop use disorder, while others are just casual misusers. The misuse of prescription drugs is defined as use in any way that is not directed by a doctor during the last 12 months; i.e., without a prescription, use in greater amounts than prescribed, more often than prescribed, longer than prescribed, or in any other non-directed way. If a respondent is identified as a misuser, then they are asked further questions to determine whether they developed a substance use disorder (SUD). SUDs are impairments caused by recurrent use, such as health problems, disability, and failure to meet major responsibilities at work, school, or home. A person with a SUD can be a dependent or an abuser, following the criteria specified in the *Diagnostic and Statistical Manual of Mental Disorders* (DSM–5) by the American Psychiatric Association. There are seven dependence criteria based on activities during the 12 months prior to the interview, and if someone fulfills more than three, they are classified as a dependent:

1. Spent a lot of time engaging in activities related to use of the drug.
2. Used the drug in greater quantities or for a longer time than intended.
3. Developed tolerance to the drug.
4. Made unsuccessful attempts to cut down on the use of drug.
5. Continued to use the drug despite physical health or emotional problems associated with use.
6. Reduced or eliminated participation in other activities because of use of the drug.
7. Experienced withdrawal symptoms when respondents cut back or stopped using the drug.

Furthermore, people who did not meet the dependence criteria, are classified as having developed an abuse for that drug if they report one or more of the following:

1. Problems at work, home, or school because of use of the drug.
2. Regularly using the drug and then doing something physically dangerous.
3. Repeated trouble with the law because of use of the drug.
4. Continued use of the drug despite problems with family or friends.

In the empirical analysis, anyone who has dependence or abuse for prescription opioids or heroin are labeled as *addicts*. If someone is misusing a prescription opioid or heroin, but is not an addict, they are simply labeled as *misusers*. To obtain a larger sample size, four surveys, from 2015 to 2018 are used. The sample is restricted to individuals between ages 18 and 64, who are not students.

Table 16 shows the shares of males and employed people conditional on their opioid usage category and education (the top two panels). It also gives the shares of the non-college- and college-educated in the total population conditional on their opioid usage category (the bottom panel). The income distribution, again conditional on usage, is shown in Table 17. To calculate the average incomes for calibration purposes, the values \$5,000, \$15,0000, \$25,000, and \$44,000 are assigned to the first four income brackets. The value for the last bracket, \$91,500, is chosen so that the average income for the sample is equal to the average value for individual income in the 2016 Current Population Survey (around \$43,500).

Table 16: NSDUH, Population Characteristics, 18-64

	Non-College	**College**
Gender (% male)		
Non-users	53.22	48.53
Misusers	57.67	44.19
Addicts	61.65	54.86
Total Population	50.77	46.64
Employed (%)		
Non-users	70.54	86.23
Misusers	66.62	85.45
Addicts	51.21	73.49
Total Population	67.22	85.25
Education (%)		
Non-users	63.78	36.22
Misusers	74.74	25.26
Addicts	86.04	13.96
Total Population	66.75	33.25

Table 17: NSDUH, Income

	< \$10,000	**\$10,000 -\$19,999**	**\$20,000 -\$29,999**	**\$30,000 -\$49,000**	**\$50,000+**
Non-College					
Non-users	24.94	19.88	15.28	21.63	18.27
Misusers	26.94	24.61	14.97	18.28	15.20
Addicts	39.15	26.55	12.76	12.50	9.04
Total Population	23.53	20.82	14.92	20.84	17.88
College					
Non-users	10.79	6.68	7.13	18.80	56.42
Misusers	9.03	10.03	11.23	22.87	46.84
Addicts	13.46	12.28	8.34	20.83	45.09
Total Population	10.38	7.19	7.24	19.24	55.96

B.2 The Medical Expenditure Panel Survey

The Medical Expenditure Panel Survey (MEPS) provides the most comprehensive data source on the cost and use of health care and health insurance coverage in the United States. The survey is conducted by the United States Census Bureau for the Agency for Healthcare Research and Quality (AHRQ), part of the Department of Health and Human Services. It has two major components: the Household Component and the Insurance Component. The Household Component is used in the analysis. It contains extensive information on demographic characteristics, health conditions, health status, usage of medical services, access to care, satisfaction with care, health insurance coverage, income, and employment, at both the individual and household levels, supplemented by information from their medical providers. The survey has a rotating panel structure in which each individual is interviewed five times during two years and then replaced. The sample includes about 31,000 individuals per year, with some variation across years, and is representative of the US population.

The empirical analysis is based on surveys from 2000 to 2018. The sample is restricted to individuals between the ages of 18 and 64, who are not students. An individual is characterized as having pain/prescription if they report having any opioid prescription. For those with opioid prescriptions, average per-capita morphine milligram equivalent (MME) consumption and per-capita out-of-pocket expenditure on opioid prescriptions are calculated. Using the panel dimension, the transitions between the pain/prescription and no-pain/no-prescription states are calculated by counting the number of people who move across these states between two consecutive years. The data used from the MEPS for the calibration is summarized in Table 18.

Table 18: MEPS, Opioid Prescription Use

	Prescription Users (%)		**Num. of Prescriptions (per person)**		**Usage, $\underline{o}$ (MME)**		**Out of Pocket Exp. ($, per person)**	
	Non-Coll.	*Coll.*	*Non-Coll.*	*Coll.*	*Non-Coll.*	*Coll.*	*Non-Coll.*	*Coll.*
2000	10.66	6.90	0.38	0.16	2582.0	1566.4	83.6	69.8
2001	12.28	8.21	0.38	0.18	1601.7	955.0	76.6	52.1
2002	10.91	8.21	0.37	0.18	2013.5	1424.4	96.0	66.1
2003	8.64	5.74	0.29	0.16	2391.3	2042.5	84.0	61.2
2004	13.38	9.23	0.48	0.23	3443.1	1425.5	113.7	57.3
2005	15.62	11.07	0.56	0.29	3210.7	1712.7	91.9	48.5
2006	15.89	12.03	0.58	0.33	3651.3	1664.3	96.9	48.7
2007	18.97	10.37	0.58	0.27	4288.0	3623.0	59.3	45.1
2008	15.68	11.30	0.67	0.29	4520.5	2065.8	66.8	32.2
2009	16.09	11.72	0.68	0.30	4697.7	2755.8	51.9	33.9
2010	16.08	11.05	0.80	0.28	5107.3	3433.0	51.3	35.9
2011	17.35	11.43	0.74	0.25	5702.4	1885.9	60.8	21.3
2012	16.84	10.01	0.69	0.27	5744.5	1910.9	51.0	33.1
2013	16.51	11.16	0.68	0.29	4132.2	1372.8	50.5	21.3
2014	17.24	10.98	0.63	0.31	3232.3	2341.5	43.6	24.7
2015	13.89	11.14	0.51	0.22	3106.4	1979.8	43.5	36.1
2016	11.67	10.09	0.49	0.20	3788.3	1211.2	35.8	37.2
2017	11.00	7.98	0.50	0.24	3660.2	1488.3	48.4	21.1
2018	14.43	7.52	0.57	0.25	3620.0	2460.7	65.9	54.0

B.3 The Centers for Disease Control and Prevention (CDC) - Vital Statistics

The number of opioid overdose deaths are calculated using the CDC's "Mortality Multiple Cause Files." The following International Classification of Disease (ICD) codes are used to calculate opioid overdose deaths: T40.0, T40.1, T40.2, T40.3, T40.4, and T40.6. For deaths from specific opioids, the following classification is used: Heroin (T40.1), Prescription (T40.2, T40.3), Synthetic (T40.4), and Other opioids (T40.6). The number of opioid overdose deaths is reported in Table 19. Note that the sum of deaths from different opioids can be larger than those from any opioids since fatalities can result from using multiple types of opioids.

Table 19: Vital Statistics, Number of Opioid Overdose Deaths

	Any		**Heroin**		**Prescription**		**Synthetic**		**Others**	
	Non-Coll.	*Coll.*	*Non-Coll.*	*Coll.*	*Non-Coll.*	*Coll.*	*Non-Coll.*	*Coll.*	*Non-Coll.*	*Coll.*
1999	7189	626	1835	91	3025	289	572	112	2638	195
2000	7549	629	1736	87	3338	314	619	119	2644	177
2001	8375	816	1668	90	4136	444	779	129	2582	221
2002	10579	954	1948	118	5652	564	1058	172	2885	190
2003	11465	1048	1950	101	6536	640	1165	160	2818	215
2004	12185	1077	1755	94	7527	685	1404	189	2489	194
2005	13180	1189	1888	97	8432	778	1443	206	2582	202
2006	15621	1312	1971	87	10231	913	2382	226	2619	198
2007	16383	1448	2247	113	11306	1009	1852	246	2389	195
2008	17322	1536	2855	145	11522	1077	1948	253	2631	201
2009	18096	1536	3073	158	11923	1031	2468	319	2379	173
2010	18642	1665	2857	142	12789	1215	2568	295	2132	170
2011	20172	1758	4104	237	13272	1224	2221	306	2544	181
2012	20436	1827	5501	355	12343	1224	2237	244	2510	171
2013	22010	2008	7620	526	12144	1222	2668	296	2419	192
2014	25172	2242	9782	623	12671	1286	4864	477	2264	172
2015	29200	2509	10004	764	12997	1331	8564	743	2458	193
2016	37477	3105	14248	908	14578	1468	17625	1308	2432	170
2017	42309	3377	14175	912	14416	1459	25974	1785	2103	163
2018	41398	3190	13662	861	12442	1310	28446	1909	1619	118

B.4 Figures

- *Figure 1* reports the number of opioid overdose deaths involving different types of opioids. The underlying numbers come from Table 19, divided by the numbers of non-college- and college-educated people between the ages of 18 and 64.

- *Figure 3* shows the number of opioid prescriptions per person (left panel) and the total amount of opioid used by those with a Rx measured in MME (right panel), as reported in Table 18.

- *Figure 4* displays the opioid prescription price per MME. For each year, the total MME of all opioid prescriptions is calculated for the non-student population between the ages of 18 and 64. The division of the total expenditure for these prescriptions by the total MME gives the supply price. The division of total out-of-pocket (OOP) expenditure by the total MME gives the OOP price.

- *Figure 5* shows how MME per capita is financed by different primary payers. The primary payer is defined as the party that covers the largest share of the prescription.

Primary payers include out-of-pocket, Medicare, Medicaid, other public agencies, and private insurance companies. The total MME from prescriptions is allocated to the primary payer.

- *Figure 6* reports the price of illicit opioids, as reported in Figure 7.19 of the 2020 *Economic Report of the President*. The price is calculated as the weighted average of the street price of heroin and fentanyl, where weights are obtained by using the amounts of heroin and fentanyl seized by law enforcement agencies.

C Appendix: Markov Chain Estimation, Alternative

Using the panel structure in the MEPS, it is possible to calculate the fraction of individuals who transit between states $\mathtt{n}$ and $\mathtt{p}$, $\mathtt{T_{np}}$ and $\mathtt{T_{pn}}$. The average values for the 2015-2018 period are presented in Table 20, together with other transitions from Table 4.

Table 20: Transitions, US Population

	Source	**Non-College**	**College**
$\mathtt{T_{np}}$	MEPS	0.0721	0.0675
$\mathtt{T_{pn}}$	MEPS	0.6199	0.7277
$\mathtt{T_{nm}}$	NSDUH	0.0044	0.0033
$\mathtt{T_{pm}}$	NSDUH	0.0263	0.0313
$\mathtt{T_{ad}}$	NSDUH, CDC	0.0212	0.0106
$\mathtt{T_{an}}$	NSDUH, Medical Studies	0.0444	0.0287

With $\mathtt{T_{np}}$ and $\mathtt{T_{pn}}$ taken from the data, there only two transition probabilities to be determined: $\mathtt{T_{mn}}$ and $\mathtt{T_{ma}}$. The estimated Markov chains for the non-college and college (in italics) populations are

$$\mathtt{T} = \begin{bmatrix} 0.9235,\ \mathit{0.9292} & 0.0721,\ \mathit{0.0675} & 0.0044,\ \mathit{0.0033} & 0 & 0 \\ 0.6199,\ \mathit{0.7277} & 0.3538,\ \mathit{0.2410} & 0.0263,\ \mathit{0.0313} & 0 & 0 \\ 0.1188,\ \mathit{0.1748} & 0 & 0.8616,\ \mathit{0.8195} & 0.0195,\ \mathit{0.0057} & 0 \\ 0.0444,\ \mathit{0.0287} & 0 & 0.0000,\ \mathit{0.0000} & 0.9334,\ \mathit{0.9607} & 0.0212,\ \mathit{0.0106} \\ 1,\ \mathit{1} & 0 & 0,\ 0 & 0 & 0 \end{bmatrix}. \tag{15}$$

The long-run transition probabilities, $\mathtt{t}$, connected with these Markov chains are reported in Table 21. The estimated values are $\mathtt{T_{mn}} = 0.1189$ and $\mathtt{T_{ma}} = 0.0195$ for the non-college population and $\mathtt{T_{mn}} = 0.1748$ and $\mathtt{T_{ma}} = 0.057$ for the college population.

Table 21: Opioid Use, Fractions–Data and Markov Chain

	Nonuser	***Prescription***	***Misuser***	***Addict***	***Dead***
	$\mathtt{t_n}$	$\mathtt{t_p}$	$\mathtt{t_m}$	$\mathtt{t_a}$	$\mathtt{t_d}$
Non-College					
Data	0.80688	0.13477	0.04479	0.01327	0.00028
Markov Chain	0.8471	0.0945	0.0448	0.0133	0.0003
College					
Data	0.87342	0.09182	0.03040	0.00432	0.00005
Markov Chain	0.8869	0.0789	0.0298	0.0043	0.0000

Compared to Table 5, the fit is worse. In the above Markov chain estimation, the transitions between states $\mathtt{n}$ and $\mathtt{p}$, $\mathtt{T_{np}}$ and $\mathtt{T_{pn}}$, are taken from MEPS. The target for the fraction of people in state $\mathtt{p}$, $\mathtt{t_p}$, is also borrowed from the same source. In the Markov chain these transitions and the fraction of people in state $\mathtt{p}$ are tightly linked. The above estimation has a hard time squaring these values; i.e., given the transitions taken from the data there are too few people in state $\mathtt{p}$. As a result, $\mathtt{T_{np}}$ and $\mathtt{T_{pn}}$ are taken as free parameters in the estimation in Section 5.

D Appendix: Compensating Variations

Let again α be the fraction of current income that a nonuser is willing to give up to reduce the probability of dying while being addicted. In the prescription-user stage, p, the compensating variation solves

$$\begin{aligned}
&\Gamma(\varepsilon_p^{*\prime})\,\{U((1-\alpha)\pi_p\mathfrak{h} - p\underline{o}) + L_p(1-\mathfrak{h}) + \beta[(1-\sigma_{pn})P' + \sigma_{pn}N']\} \\
&\quad + [1-\Gamma(\varepsilon_p^{*\prime})]\{U\left((1-\alpha)\pi_p\mathfrak{h} - p\underline{o} - q(o'-\underline{o})\right) + O_p(o'-\underline{o}) + \mathbf{E}[\varepsilon_p \geq \varepsilon_p^{*\prime}] + L_p(1-\mathfrak{h}) \\
&\qquad\qquad + \beta[(1-\sigma_{bn})B' + \sigma_{bn}N']\} = P.
\end{aligned}$$

The analogous formulae for the abuser, b, and addict, a, states are:

$$\begin{aligned}
&\{\Lambda(\lambda_b^{*\prime})\{U\left((1-\alpha)\pi_b\mathfrak{h} - p\underline{o} - q(o'-\underline{o})\right) + O_b(o'-\underline{o}) + L_b(1-\mathfrak{h}) \\
&\qquad + [1-S_{ba}(o')]\beta[(1-\sigma_{bn})B' + \sigma_{bn}N'] + S_{ba}(o)\beta A'\} \\
&\quad + [1-\Lambda(\lambda_b^{*\prime})]\{U\left(t - \alpha\pi_b\mathfrak{h} - p\underline{o} - q(o'-\underline{o})\right) + O_b(o'-\underline{o}) + L_b(1) + \mathbf{E}[\lambda_b \geq \lambda_b^{*\prime}] \\
&\qquad + [1-S_{ba}(o')]\beta[(1-\sigma_{bn})B' + \sigma_{bn}N'] + S_{ba}(o)\beta A'\}\} = B,
\end{aligned}$$

and

$$
\begin{aligned}
\{\Lambda(\lambda_a^{*\prime})\{U\left((1-\alpha)\pi_a\mathfrak{h} - p\underline{o} - q(o' - \underline{o})\right) + O_a(o' - \underline{o}) + L_a(1-\mathfrak{h})& \\
+ [1 - S_{ad}(o')]\beta_a[(1-\sigma_{an})A' + \sigma_{an}N'] + S_{ad}(o')\beta_a\delta\}& \\
+ [1 - \Lambda(\lambda_a^{*\prime})]\{U\left(t - \alpha\pi_a\mathfrak{h} - p\underline{o} - q(o' - \underline{o})\right) + O_a(o' - \underline{o}) + L_a(1) + \mathbf{E}[\lambda_a \geq \lambda_a^{*\prime}]& \\
+ [1 - S_{ad}(o')]\beta_a[(1-\sigma_{an})A' + \sigma_{an}N'] + S_{ad}(o')\beta_a\delta\}\} = A.&
\end{aligned}
$$

In the abuser and addict stages, α is the fraction of current working income that the individual is willing to give up to obtain the reduction in risk.