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 choose whether to use opioids recreationally, knowing the probabilities of addiction and dying. These odds are functions of recreational opioid usage. The model is fit to estimated Markov chains from the US data that summarize the transitions into and out of opioid addiction as well as to a deadly overdose. The epidemic is broken down into two subperiods: 2000–2010 and 2010–2019. The opioid epidemic's drivers and the impact of medical interventions are examined. Lax prescribing practices and misinformation about the risk of addiction are important drivers of the first half of the epidemic. Falling prices for black-market opioids combined with an increase in their lethality are found to be important for the second half.

Keywords: addiction, college/non-college educated, deaths, fentanyl, Markov chain, medical interventions, opioids, OxyContin, pain, prices, prescribing practices, state-contingent preferences, structural model, subjective and objective beliefs
JEL Nos: D11, D12, E13, I12, I14, I31, J11, J17

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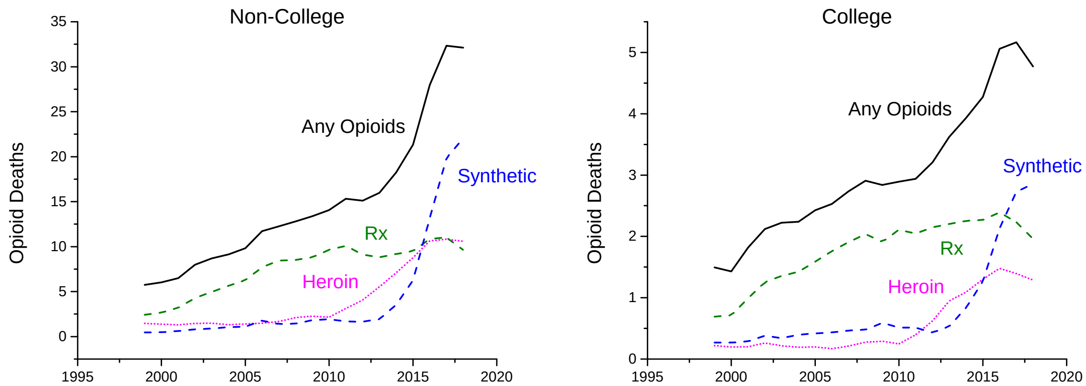

Figure 1: Opioid deaths for both the non-college and college educated as measured per 100,000 people in the respective education class.

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 deaths from kidney disease, 14.2 from suicides, 14.7 from 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 be been from Figure 1, most of these opioid deaths arose from prescription (Rx) overdoses prior to 2015, but afterward they came from synthetic opioids—in particular, fentanyl.[1] From 2000 to 2019, the overdose death rate was five to seven times higher for those without a college degree compared to 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.[2] Merck started selling it in 1827. In the later part of the 19th century, opium and morphine were widely available in the 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.

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

[1]The sources for all the data displayed in the figures are presented in Appendix A.

[2]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.”

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.

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 affected women. Aspirin wasn't invented until 1899. Morphine may have served as 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. 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. Addiction was viewed by the general public as a problem. The US Congress passed the Harrison Narcotics Act in 1914 to control the distribution of opioids.[3]

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 underprescribing 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.

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

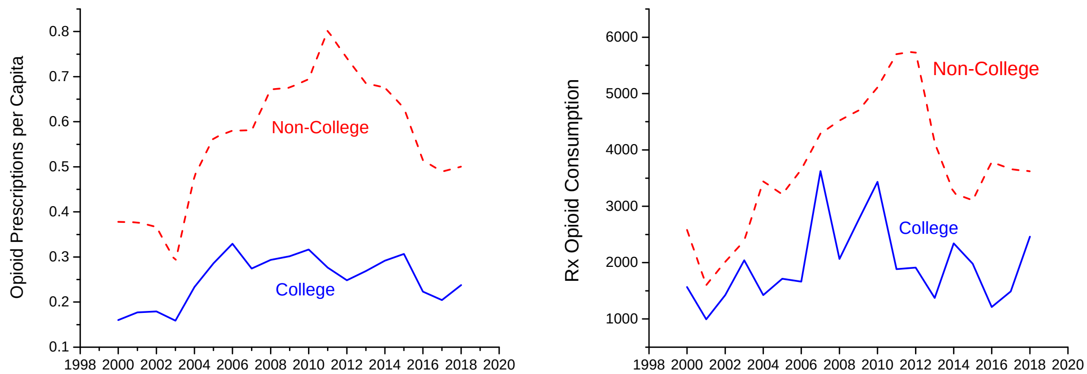

Figure 3: Opioid prescriptions per person by education (left panel) and Rx opioid consumption, conditional on having a prescription, measured in morphine milligram equivalents (MMEs) per person by education (right panel).

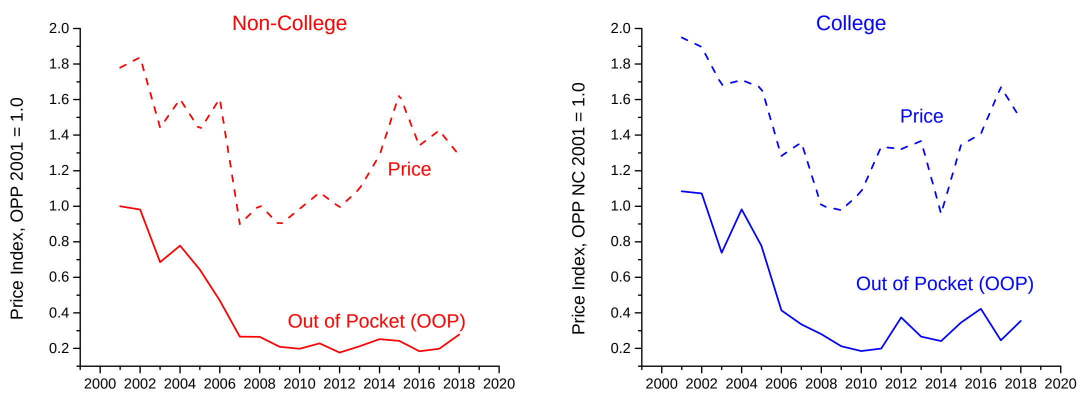

Figure 4: Price of prescription opioids for both the non-college- and college-educated populations (left and right panels, respectively). The series have been normalized so that the out-of-pocket price for the non-college educated is 1.0 in 2001.

In 1996 Purdue Pharma introduced OxyContin with an aggressive marketing campaign.[4] "Oxy" came from the opioid-based painkiller oxycodine, and "Contin" meant continuous. Purdue Pharma asserted that because the drug released its effect in a prolonged, slow, and continuous manner the rate of addiction was less than one percent.[5] 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

[4]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).

[5]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.

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).

During the first stage of the opioid crisis, the period from the late 1990s to 2010, there was a dramatic increase in the 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 also fell dramatically during this period. Figure 4 shows that the out-of-pocket expense for prescription opioids fell by a factor of 5 between 2001 and 2010. This price decline has been attributed to two factors: First, the advent of generic prescription opioids. Second, the expansion of social programs such as Medicare and Medicaid that subsidized the purchase of opioids, as can be seen from Figure 5. Medicaid funds a smaller portion of opioid purchases than private payers for college-educated individuals while the reverse is true for the non-college educated. 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 were prescribed to people who needed relief from pain caused by either disability or illness. After 2010, opioid prescriptions per person and the amount of Rx opioids consumed by those with a prescription fell due to a tightening in opioid prescribing practices. At this time, the out-of-pocket price of prescription opioids also ceased to decline.

The street price of opioids has also fallen substantially since 2001 dropping by a factor of 2.5 (Figure 6). Most of the decline in the street price occurred after 2010 during the second stage of the opioid crisis. The decline during this period has been chalked up to the illegal imports of inexpensive powerful synthetic opioids, for example fentanyl, from China and elsewhere. Additionally, throughout the crisis, opioids have been diverted from legal sources onto the black market via fraudulent prescriptions, family and friends giving away and/or selling their prescriptions, and theft. The rise of illegal imports after 2010 is ascribed to the tightening of prescribing practices and the introduction of a tamper-proof form of OxyContin in 2010. 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 cocaine usage. The upshot is that opioids are much less expensive now than they were in

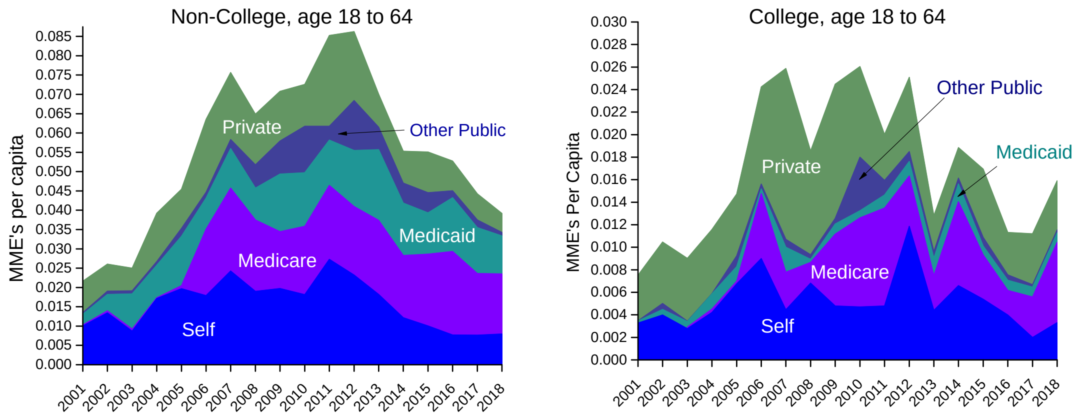

Figure 5: Primary payer by morphine milligram equivalents (MME's). The left panel is for the non-college educated while the right panel is for the college educated.

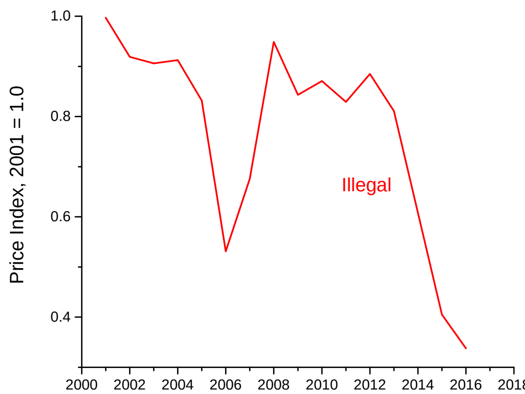

Figure 6: Price of Illegal Opioids. Source: *Economic Report of the President, 2020.*

2001.

1.2 What's Done Here

A model is developed where some people use recreational opioids and others don't. There are two routes to recreational opioid usage: some individuals start off as nonusers who decide to experiment with opioids, while others begin using prescription opioids to reduce pain and then decide that they like them. Individuals who misuse opioids, through either experimentation or as pain killers, 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 extensive margin decision to misuse opioids in the first place, and the intensive margin decision on the amount of opioids used, are both endogenous. Opioid abusers and addicts may also choose whether to work or not. This decision is a function of how opioid usage affects a person, which varies across individuals. The choices about opioid usage and work depend on an array of factors: idiosyncratic predilections toward opioid usage; incomes; the chance of experiencing pain; how opioid usage affects the odds of becoming an addict and dying; abuser's and addict's individualized inclinations to work; whether or not an opportunity to obtain opioids at the prescription price arises; and the street price of opioids. For the most part, a person makes fully rational decisions, while cognizant about the chances of becoming unemployed, addicted, and dying. In the quantitative analysis, people's subjective beliefs in the early stage of the crisis about the probability of opioid addiction are allowed to differ from the objective probability, which captures misinformation transmitted by drug companies and others. Stops in opioid usage can occur, and users can return to being nonusers.

The quantitative analysis divides the opioid crisis into two subperiods, 2000 to 2010 and 2010 to 2019. The first period was characterized by lax prescribing behavior, a decline in the price of prescription opioids, and misinformation about the addictiveness of opioids. As can be seen from Figure 3, Rx opioid use peaked in 2010. By then the out-of-pocket cost of prescription opioids had stopped falling and the medical profession was well aware of the addictive nature of Rx opioids. The second period saw the introduction of black market opioids. Prescribing protocols were tighter during this period and Figure 6 shows that the price of illegal opioids fell dramatically after 2010. Black market opioids tended to be more deadly too, due to their unknown strength and purity.

The benchmark model is calibrated to 2019 cross-sectional data on opioid usage for the United States. 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 are also calculated. Information on the prices for prescription and black market opioids is also gathered. 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 conditional probabilities 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.

To obtain a calibration for 2010 the observed changes in medical practices, e.g. prescribing rates and Rx strengths, and opioid prices, both Rx and black market, are fed into the 2019 benchmark calibration. The lethality of opioids is then reduced to match the observed 2010 death rate for addicts. For the year 2000 once again the observed changes in medical practices and opioid prices are inputted into the 2019 benchmark calibration. Misperceptions about the addictiveness of opioids are now incorporated in addition to changes in the lethality of opioids. To do this, the differences in the death rates across triplicate and non-triplicate states are used. Triplicate states regulated opioid prescriptions more strictly and allowed less advertising. The idea here is that this led to less misinformation about opioid use in triplicate states.

The calibrated model is then used to highlight the forces underlying the recent opioid epidemic. Through the lens of the model, the primary drivers of the rise in deaths during the second stage of the crisis, 2010 to 2019, are the decline in the illegal price of opioids and the rise in the death rates of addicts due to the shift in opioid consumption towards more deadly fentanyl. The tightening of prescribing practices over this period offset these forces, but only partially. The primary drivers of the rise in deaths during the first stage of the crisis, 2000 to 2010, are the looser prescribing practices (relative to the second period) coupled with a decline in the price of prescription opioids. These had a big effect. Especially important are the increase in the number of individuals prescribed opioids and the duration of time doctors kept them on their prescriptions. Early on in the crisis, people might have underestimated the risk of becoming addicted from opioid usage. This also appears to have been a powerful driver of opioid usage in the initial stages of the crisis. Last, an analysis is conducted of 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, for example, Pierce and Schott (2020) and Ruhm (2019). In contrast, Currie and Schwandt (2021), Cutler and Glaeser (2021), and Mulligan (2020) suggest that lower prices combined with easy access to opioids were the main drivers. Alpert et al. (2022) exploit cross-state variation in exposure to OxyContin to show that the introduction and marketing of OxyContin can explain a substantial share of overdose deaths over the last two decades.[6]

Theoretical analyses of addiction started with Becker and Murphy (1988).[7] 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) deterministic habit-formation model with a stochastic framework involving state-contingent preferences. In particular, individuals' preferences evolve randomly through various addiction stages in a manner that is a function of their opioid usage. Individuals may 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. As was mentioned, in the quantitative analysis, individuals' objective and subjective beliefs are allowed to differ for the early part of the crisis. As will be seen, the state-contingent preference structure captures all of the key aspects (complementarity, withdrawal, and tolerance) of the Becker and Murphy (1988) model. It is much better suited for modeling risky behavior and matching the stages of substance abuse cataloged in the medical literature. On this, the 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 these features distinguish the current work from the above research.

Other papers zoom into specific factors related to the supply side of illicit drugs. Galenianos and Gavazza (2017) estimate a search model of crack cocaine consumption, where buyers search for sellers with high-quality drugs, but the quality is not observable. A search

[6] The impact of the opioid crisis on labor-force participation and employment is studied by Aliprantis, Fee, and Schweitzer (2019), Charles, Hurst, and Schwartz (2019), Currie, Jin, and Schnell (2019), Greenwood, Guner, and Kopecky (2022), Harris et al. (2020), Krueger (2017), Ouimet, Simintzi, and Ye (2020), and Powell (2021). Agarwal et al. (2022) study the impact of the crisis on consumer credit markets.

[7] For empirical tests of rational addiction models, see, among others, Chaloupka (1991) and Becker, Grossman, and Murphy (1994). Cawley and Ruhm (2011) provide a review.

model for opioids is estimated by Schnell (2022). In her framework, patients search for physicians in a primary market but can also access opioids in an illegal secondary market. Patients can resell legal opioids in the primary market, which affects physicians' prescription behaviors.

The paper also 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 et al. (2020), Eichenbaum, Rebelo, and Trabandt (2021), Greenwood et al. (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 transition probability σ_{ij}. These transition probabilities depend both upon chance and opioid usage. 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.[8] Abuse, b, occurs with endogenous transition probability σ_{pb}. An individual who follows their prescription for pain returns to normality with exogenous probability σ_{pn}. Even when a person starts off as nonuser who doesn't experience pain, they may still 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 7.

An individual has one unit of time that they split between work 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 usage 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

[8] The variable p is used to represent two things; namely, the price of prescription opioids and the pain state. From the context it will be clear what p is representing.

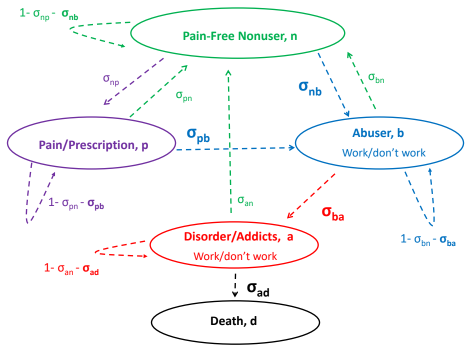

Figure 7: Stages of Opioid Usage. The transition probabilities in bold are endogenous.

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 factor β.

A prescription user can always acquire $\underline{o}$ units of opioids at the per unit legal price p. If they exceed the prescription level of opioids, $\underline{o}$, in the current period, then with probability ρ_m they can still purchase the excess, $o - \underline{o}$, at the prescription price. But, with complementary probability $1 - \rho_m$ they have to buy the overage on the black market. Similarly, a nonuser who decides to use opioids can purchase the drug in the current period at the prescription price with odds ρ_m. With the odds $1 - \rho_m$ they must go to the black market. Abusers and addicts may also have the opportunity to purchase opioids at prescription price p. This occurs with probability ρ_m for misusers and probability ρ_a for addicts. With probabilities $1 - \rho_m$ and $1 - \rho_a$ they can only purchase at black market price q. Let the variable $i = p, q$ indicate whether or not an individual will buy unauthorized opioids at the prescription, p, or black market price, q. The budget constraint for an individual in the s-th stage (for $s \neq d$) reads

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

Utilities are state dependent. The stage-s utility function for regular goods, c, is

$$U(c) = (1 - \mu_s)(1 - \eta)(c^{1-\rho} - 1)/(1 - \rho), \text{ with } \rho \geq 0 \text{ and for } s = n, p, b, a.$$

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 desires to work or not. This shock is drawn after they make their opioid decision. Let λ_s come from a Gumbel distribution so that

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

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

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

where γ is the Euler–Mascheroni constant.

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

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

(In the above $\psi \ge 0$.) 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 euphoria that a user obtains in states n or p. This variable triggers opioid usage. It is drawn from a Gumbel distribution so that

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

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

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

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

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 $\mu_a > \mu_b > \mu_p \ge \mu_n$.

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 negative impact of opioids on other facets of their lives.

The *objective* probability of transiting from the abuse stage, b, to the addiction stage, a, denoted by σ_{ba}, is given by

$$\sigma_{ba} = S_{ba}(o) = \sigma_a \sqrt{o}. \tag{2}$$

The odds of transition are an increasing function of opioid usage, o. The *subjective* probabilities, $\widetilde{\sigma}_{ba}$, of transiting from the abuse to addiction stage may differ from the objective ones, σ_{ba}. In particular, the calibration exercise assumes that in the early period of the opioid crisis some individuals were misinformed about the odds of becoming addicted. Specifically,

$$\widetilde{\sigma}_{ba} = S_{ba}(o) = \alpha\sigma_a \sqrt{o}, \text{ with } 0 \leq \alpha \leq 1. \tag{3}$$

If $\alpha < 1$, then a person believes that their odds of transiting from abuse to addiction are $\widetilde{\sigma}_{ba}$, which are less than the actual odds, σ_{ba}. This will increase recreational opioid usage.

The odds of transition from the addiction to the death stage, σ_{ad}, are slightly more complicated. Here,

$$\sigma_{ad} = S_{ad}(o) = \begin{cases} \sigma_d \sqrt{o}, & \text{if } o < \mathfrak{o}; \\ \min\{\sigma_d \sqrt{o} + 1/(\mathbf{a} - o) - 1/(\mathbf{a} - \mathfrak{o}), 1\}, & \text{otherwise.} \end{cases} \tag{4}$$

Figure 8 portrays the situation. When o surpasses $\mathfrak{o}$ the odds of death start to rapidly increase. As o approaches $\mathbf{a}$ an overdose death occurs with near certainty. As in the real world an overdose death is governed by the amount of opioids consumed, o, and the lethality of the drug as proxied by σ_d. The calibration exercise suggests that the recent introduction of black market fentanyl, sold in unbeknown potencies and mixed with other drugs, increased the lethality of opioids.

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, all else equal. This implies that withdrawal for an addict will be costly because the marginal utility of opioid consumption is high. So, it mimics the withdrawal property of the Becker and Murphy (1988) model.

The framework also duplicates the key complementarity (or reinforcement) feature of

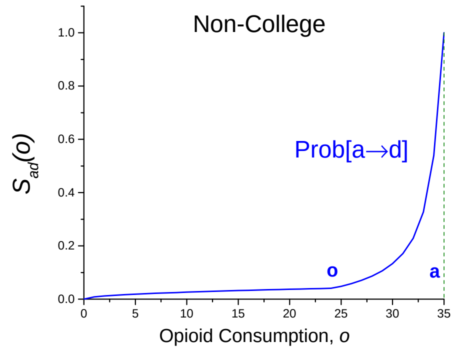

Figure 8: The $S_{ad}(o)$ function used for the non-college educated in the benchmark 2019 calibration.

the Becker and Murphy (1988) model in that an increase in an abuser's current opioid consumption is likely to spur increased future consumption by increasing the probability of moving to the addiction stage. Also, an opioid user's productivity at work declines in the later stages b and a; given this property 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 presence of ω_a in an addict's utility function implies that addiction is costly. Furthermore, and importantly, the fact that an addict is just a stage away from death operates to lower their expected lifetime utility, as will be seen. Therefore, the framework captures the Becker and Murphy feature that utility declines with opioid usage, which is called tolerance (or negativity) in the literature.

Last, one might think that opioid abusers and addicts have lower discount factors than nonusers and prescription users. This could be true. The state-contingent preference structure adopted here is able to match the US data on opioid usage without differences in discount factors. Similarly, heterogeneity in risk aversion across individuals is unnecessary, although perhaps abusers and addicts are indeed less risk averse in nature. Differences in tastes concerning the enjoyment from opioids are sufficient and serve as a more direct route.

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_i represent the expected lifetime utility for a nonuser without pain who has not yet drawn the opioid euphoria shock and who can currently purchase nonprescription opioids at the price i, for $i = p, q$; P_i denote the expected lifetime utility for a person with pain who still has to draw the opioid euphoria shock and who can purchase opioids beyond the prescription level at the price i; B_i signify the expected lifetime utility of an abuser before the leisure shock and who can currently purchase opioids at the price i; and A_i indicate the expected lifetime utility of an addict before the leisure shock and who can currently purchase opioids at the price i.

4.1 Nonuser

Start with a nonuser who isn't experiencing pain and who can buy opioids at the price i. Assume they will use opioids when ε_n exceeds some threshold value, ε_{ni}^*, and won't otherwise. Their opioid-use decision is then

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

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

$$\begin{aligned} N_i = {} & \Gamma(\varepsilon_{ni}^*)\{U(\pi_n \mathfrak{h}) + L_n(1-\mathfrak{h}) + \beta[(1-\sigma_{np})N + \sigma_{np}P]\} \\ & + [1-\Gamma(\varepsilon_{ni}^*)]\{\max_{o>\underline{o}} U(\pi_n \mathfrak{h} - io) + O_n(o-\underline{o}) + \mathbf{E}[\varepsilon_n | \varepsilon_n \geq \varepsilon_{ni}^*] + L_n(1-\mathfrak{h}) \\ & + \beta[(1-\sigma_{bn})B + \sigma_{bn}N]\}, \text{ for } i = p, q, \end{aligned} \tag{5}$$

where

$$N \equiv \rho_m N_p + (1-\rho_m)N_q, \; P \equiv \rho_m P_p + (1-\rho_m)P_q, \text{and} B \equiv \rho_m B_p + (1-\rho_m)B_q.$$

The first line on the righthand side gives the expected utility for a nonuser, which occurs with probability $\Gamma(\varepsilon_{ni}^*)$. 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. In the current period the individual does not yet know whether next period they will be able buy unauthorized opioids at the prescription or black market price, should they choose to use. 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 $1-\Gamma(\varepsilon_{ni}^*)$. A nonuser purchases opioids at the price i, which might be the prescription price, p, or the black market price, q. Next period the individual will either reenter the nonuser state with probability σ_{bn}, which returns a discounted expected utility of βN. The person enters the abuser state with complementary probability $1-\sigma_{bn}$, in which case their discounted expected utility is βB. A user gets euphoria from opioid usage, which delivers $\mathbf{E}[\varepsilon_n|\varepsilon_n \geq \varepsilon^*_{ni}]$. At this stage a person always works.

The euphoria threshold, ε^*_{ni}, must equate the utility from nonusing and using so that

$$\begin{aligned}\varepsilon^*_{ni} &= U(\pi_n\mathfrak{h}) + L_n(1-\mathfrak{h}) + \beta[(1-\sigma_{np})N + \sigma_{np}P] \\ &- \max_{o>\underline{o}}\{U\left(\pi_n\mathfrak{h} - io\right) + L_n(1-\mathfrak{h}) + O_n(o-\underline{o}) + \beta[(1-\sigma_{bn})B + \sigma_{bn}N]\}, \text{ for } i = p, q. \quad (6)\end{aligned}$$

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 i (either the price p or q) falls, then ε^*_{ni} drops, implying that there will be more users. In terms of the model's stages in Figure 7, it is clear that $1-\Gamma(\varepsilon^*_{ni})$ will determine the endogenous transition σ_{nb}. The opioid euphoria shock can be thought of as a short cut device for factors outside the model, such as genetic susceptibility, or environmental factors, such as having friends who use opioids.

4.2 Prescription User

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

$$\begin{aligned}P_i &= \Gamma(\varepsilon^*_{pi})\left\{U(\pi_p\mathfrak{h} - p\underline{o}) + L_p(1-\mathfrak{h}) + \beta[(1-\sigma_{pn})P + \sigma_{pn}N]\right\} \\ &+ [1-\Gamma(\varepsilon^*_{pi})]\{\max_{o>\underline{o}} U\left(\pi_p\mathfrak{h} - p\underline{o} - i(o-\underline{o})\right) + O_p(o-\underline{o}) + \mathbf{E}[\varepsilon_p|\varepsilon_p \geq \varepsilon^*_{pi}] + L_p(1-\mathfrak{h}) \\ &+ \beta[(1-\sigma_{bn})B + \sigma_{bn}N]\}, \text{ for } i = p, q. \quad (7)\end{aligned}$$

Here $\underline{o}$ denotes the level of opioids obtained from the prescription. Consuming anything above this level is improper usage. Opioids below the prescription level $\underline{o}$ are purchased at the legal price p, while any overage is bought at the price i. This recursion is analogous to (5), 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_{pi}^* is given by the equation

$$\varepsilon_{pi}^* = U(\pi_p \mathfrak{h} - p\underline{o}) + L_p(1-\mathfrak{h}) + \beta[(1-\sigma_{pn})P + \sigma_{pn}N]$$
$$-\max_{o>\underline{o}}\{U\left(\pi_p\mathfrak{h} - p\underline{o} - i(o-\underline{o})\right) + L_p(1-\mathfrak{h}) + O_p(o-\underline{o}) + \beta[(1-\sigma_{bn})B + \sigma_{bn}N]\},\ \text{for } i = p, q. \tag{8}$$

With respect to Figure 7, $1-\Gamma(\varepsilon_{pi}^*)$ determines the endogenous transition σ_{pb}.

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

$$O_s'(o-\underline{o}) = U'\left(\pi_s\mathfrak{h} - io + I_s(i-p)\underline{o}\right) i,\ \text{for } i = p, q \text{ and } s = n, p, \tag{9}$$

with $I_n \equiv 0$ and $I_p \equiv 1$. The lefthand side is the marginal benefit from using opioids, while the righthand side is the marginal cost. At the margin the price for a unit of opioids is i, which reduces the utility of consumption by $U'\left(\pi_s\mathfrak{h} - io + I_s(i-p)\underline{o}\right)$ per dollar spent.

4.3 Abuser

Attention is now directed to the abuse and addiction stages. In these stages a person may or may not work. Start with the abuser. An abuser who can currently purchase opioids at price i will not work when the leisure shock λ_b exceeds some threshold value, λ_{bi}^*, and will work otherwise. Hours worked, h, is then given by

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

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

$$\begin{aligned} B_i = \max_{o>\underline{o}} \Big\{ & \Lambda(\lambda_{bi}^*)\{U\left(\pi_b\mathfrak{h} - io\right) + O_b(o-\underline{o}) + L_b(1-\mathfrak{h}) \\ & + [1-S_{ba}(o)]\beta[(1-\sigma_{bn})B + \sigma_{bn}N] + S_{ba}(o)\beta A\} \\ & + [1-\Lambda(\lambda_{bi}^*)]\{U\left(t - io\right) + O_b(o-\underline{o}) + L_b(1) + \mathbf{E}[\lambda_b|\lambda_b \geq \lambda_{bi}^*] \\ & + [1-S_{ba}(o)]\beta[(1-\sigma_{bn})B + \sigma_{bn}N] + S_{ba}(o)\beta A\}\Big\},\ \text{for } i = p, q, \end{aligned} \tag{10}$$

where

$$B \equiv \rho_m B_p + (1-\rho_m)B_q \text{ and } A \equiv \rho_a A_p + (1-\rho_a)A_q.$$

The first and second lines pertain to an abuser who works, which happens by the chance $\Lambda(\lambda^*_{bi})$. 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 usage, 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 fourth lines are for an unemployed abuser. An unemployed abuser enjoys the leisure shock, which has the expected value $\mathbf{E}[\lambda_b | \lambda_b \geq \lambda^*_{bi}]$. 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 (10).

The leisure threshold λ^*_{bi} equates the utility from working and not working so that

$$\lambda^*_{bi} = U\left(\pi_b \mathfrak{h} - io\right) + L_b(1 - \mathfrak{h}) - U\left(t - io\right) - L_b(1), \text{ for } i = p, q. \tag{11}$$

Notice the threshold level of the leisure shock is just the difference in utility between working or not working. This decision is static, given a value for opioid usage, o. The leisure shock inserts a form of complementarity for abusers and addicts between opioid usage and leisure. That is, only a person who is either an abuser or addict may draw the leisure shock which increases the value of leisure. In a more a general setting, people could randomly move into unemployment with this transition increasing the value of opioids. This would capture Case and Deaton's (2020) "deaths of despair" hypothesis. Analogously, the provision of unemployment insurance and disability benefits could encourage unemployment and drug use in line with Mulligan (2022).

The first-order condition for an abuser's opioid usage, o, connected with (10) is

$$\begin{aligned} O'_b(o - \underline{o}) = \Lambda(\lambda^*_{bi}) U'\left(\pi_b \mathfrak{h} - io\right) i + [1 - \Lambda(\lambda^*_{bi})] U'\left(t - io\right) i \\ + S'_{ba}(o) \beta [(1 - \sigma_{bn}) B + \sigma_{bn} N - A], \text{ for } i = p, q. \end{aligned} \tag{12}$$

The lefthand side is the current marginal benefit from using opioids, $O'_b(o - \underline{o})$. The righthand side is the expected marginal cost, which is made up of two components: First, the person must pay i for each unit of opioids, which results in an expected stage-b momentary utility loss of $\Lambda(\lambda^*_{bi}) U'\left(\pi_b \mathfrak{h} - io\right) i + [1 - \Lambda(\lambda^*_{bi})] U'\left(t - io\right) i$. 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 usage can create such euphoria that an addict is happier than an abuser.

4.4 Addict

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

$$
\begin{aligned}
A_i = \max_{o > \underline{o}} \{ \Lambda(\lambda^*_{ai}) \{ & U(\pi_a \mathfrak{h} - io) + O_a(o - \underline{o}) + L_a(1 - \mathfrak{h}) \\
& + [1 - S_{ad}(o)]\beta[(1 - \sigma_{an})A + \sigma_{an} N] + S_{ad}(o)\beta\delta \} \\
+ [1 - \Lambda(\lambda^*_{ai})] \{ & U(t - io) + O_a(o - \underline{o}) + L_a(1) + \mathbf{E}[\lambda_a | \lambda_a \geq \lambda^*_{ai}] \\
& + [1 - S_{ad}(o)]\beta[(1 - \sigma_{an})A + \sigma_{an} N] + S_{ad}(o)\beta\delta \} \}, \text{ for } i = p, q, \quad (13)
\end{aligned}
$$

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 usage, o. An addict rehabilitates with probability σ_{an}, in which case they return to the pain-free nonuser state. The leisure threshold, λ^*_{ai}, is given by

$$
\lambda^*_{ai} = U(\pi_a \mathfrak{h} - io) + L_a(1 - \mathfrak{h}) - U(t - io) - L_a(1), \text{ for } i = p, q. \quad (14)
$$

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

$$
\begin{aligned}
O'_a(o - \underline{o}) = \Lambda(\lambda^*_{ai}) U'(\pi_a \mathfrak{h} - io)\, i + [1 - \Lambda(\lambda^*_{ai})] U'(t - io)\, i \\
+ S'_{ad}(o)\beta[(1 - \sigma_{an})A + \sigma_{an} N - \delta], \text{ for } i = p, q. \quad (15)
\end{aligned}
$$

Opioid usage by abusers and addicts determines the endogenous transitions σ_{ba} and σ_{ad} in Figure 7 via the $S_{ba}(o)$ and $S_{ad}(o)$ functions. Also note that when a person transits from an abuser of opioids to an addict, their hunger for opioids increases as reflected by a shift in their opioid utility function from $O_b(o - \underline{o})$ to $O_a(o - \underline{o})$—recall equation (1). This can be interpreted as increased dependence on the drug and is similar to the tolerance property in the Becker and Murphy (1988) model.

4.5 The Path Forward

Between 2000 and 2019, more than 450,000 individuals between the ages of 18 and 64 died from opioid overdoses. What can account for the dramatic rise in opioid usage and overdose deaths during the last two decades? The model will be used as a quantitative laboratory to answer this question. Four candidates are entertained: namely, the fall in the black market price of opioids, the increase in the lethality of opioids conditional on addiction, changes in the extent of misinformation about the odds of opioid addiction, and changes in prescribing practices together with the fall in prescription opioid prices.

The model is first calibrated to the year 2019 using primarily cross-sectional data. Once this is done, attention is directed to two other periods, the years 2000 and 2010. These two years correspond, respectively, to the start of the opioid pandemic and to (roughly) the peak year for the number of prescription opioid overdose deaths (Figure 1). Over the 2000 to 2019 period, prescribing practices first became more lenient and then less so. In particular, from 2000 to 2010, opioid prescribing rates increased, prescriptions became more powerful and patients were kept on their prescriptions longer. After 2010, these trends were reversed. After 2010 the street price of opioids plummeted, counteracting this reversal in prescribing practices. Using the 2019 benchmark model, the *observed* changes in medical practices and street prices are inputted into the framework for both 2000 and 2010. Then, the lethality of opioids and degree of misinformation are calibrated to match conditional death rates in each of these two periods. After this, various counterfactual exercises are conducted using these calibrations to decompose the driving forces of the opioid crisis for the periods 2000 to 2010 and 2010 to 2019. Finally, the impact of medical advances and the value of recreational opioids are studied.

5 Calibrating the 2019 Benchmark Economy

5.1 Fitting a Markov Chain to the 2019 US Data

The schematic in Figure 7 suggests that the model can be represented by a Markov chain. In light of this, the first step in the quantitative analysis is to fit a Markov chain to the 2019 US data. Consider a generic Markov chain representation of the schematic in Figure 7 for the model—there will be separate Markov chains for the college and non-college populations. The transition probabilities across the model states n, p, b, a, and d are:

$$
\begin{aligned}
E &\equiv [i \to j]_{i,j} \\
&\equiv \begin{bmatrix}
\Gamma(\varepsilon_n^*)(1-\sigma_{np}) + [1-\Gamma(\varepsilon_n^*)]\sigma_{bn} & \Gamma(\varepsilon_n^*)\sigma_{np} & [1-\Gamma(\varepsilon_n^*)](1-\sigma_{bn}) & 0 & 0 \\
\Gamma(\varepsilon_p^*)\sigma_{pn} + [1-\Gamma(\varepsilon_p^*)]\sigma_{bn} & \Gamma(\varepsilon_p^*)(1-\sigma_{pn}) & [1-\Gamma(\varepsilon_p^*)](1-\sigma_{bn}) & 0 & 0 \\
[1-S_{ba}(o)]\sigma_{bn} & 0 & [1-S_{ba}(o)](1-\sigma_{bn}) & S_{ba}(o) & 0 \\
[1-S_{ad}(o)]\sigma_{an} & 0 & 0 & [1-S_{ad}(o)](1-\sigma_{an}) & S_{ad}(o) \\
1 & 0 & 0 & 0 & 0
\end{bmatrix}. \qquad (16)
\end{aligned}
$$

These transition probabilities have both endogenous and exogenous components. For example, the entry $E_{aa} = [1 - S_{ad}(o)](1 - \sigma_{an})$ represents the odds that a person who is currently an addict will remain an addict next period. For this to happen, the addict must not return to the nonuser state, which occurs with the exogenous probability $1 - \sigma_{an}$, and also must not die from an overdose which occurs with the endogenous probability $1 - S_{ad}(o)$. As another example, consider $E_{np} = \Gamma(\varepsilon_n^*)\sigma_{np}$, the odds that a non-user moves to prescription opioids. This will happen if the euphoria from using opioids is low and the person does not start abusing, which happens with probability $\Gamma(\varepsilon_n^*)$. The person must also start using prescription opioids, which transpires with probability σ_{np}. The ergodic steady state, $e = [e_n, e_p, e_b, e_a, e_d]$, associated with this Markov chain solves

$$e = eE.$$

The ergodic steady state gives the unconditional probabilities of being in each of the states.

The first stage of the quantitative analysis is to fill in the cells for E using facts from 2019 cross-sectional US data. Since for any row the sum across its columns equals one, data for only 8 of the nonzero cells is required. The mapping between the data and model is quite involved so the big picture is presented here with the details being relegated to Appendix B.

Three data sets are used. 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), which classifies individuals as nonusers, misusers, and addicts. A misuser, denoted by m, is defined slightly differently in the data than an abuser, b, is in the model. This is fully taken into account when matching the model with the data. To determine the number of individuals who use prescription opioids for pain, the household component of the Medical Expenditure Panel Survey (MEPS) is used. Last, the CDC's Vital Statistics provides information on opioid-overdose-related deaths. This data allows values to be assigned directly to the 4 transition probabilities, $E_{nb} = [1 - \Gamma(\varepsilon_n^*)](1 - \sigma_{bn})$, $E_{pb} = [1 - \Gamma(\varepsilon_p^*)](1 - \sigma_{bn})$, $E_{ad} = S_{ad}(o)$, and $E_{an} = [1 - S_{ad}(o)]\sigma_{an}$. The transition from addiction to death, E_{ad}, for example, can be calculated by simply dividing the number of deaths from opioid overdoses by the number of addicts. Entries for the remaining 4 need to be estimated so that the steady-state distribution of the population across the five states matches the fraction of individuals in each state according to the data.

The upshot of fitting the Markov Chain to the data is Tables 1, 2, and 3. Table 1 shows the fraction of users in each of the 5 addiction states for both the 2019 US data and the estimated Markov chain. The match is perfect. There are 4.13 percent misusers among non-college graduates, while the share is lower, 2.85 percent, among college graduates. The gap in addiction is even larger, with 0.97 percent of non-college being addicts versus only 0.37 percent of college graduates. Prescription opioids are also more common among non-college. From this, the odds ratios reported in Table 2 follow. As can be seen, the non-college population are over-represented in the misuser and addict categories and underrepresented in the nonuser one. Compared to a random person in the population, the odds of being a

Table 1: Opioid Usage, Fractions—Data and Markov Chain

	Nonuser	***Rx user***	***Misuser***	***Addict***	***Dead***
Non-College					
Data	0.8515	0.0972	0.0413	0.0097	0.0003
Markov Chain	0.8515	0.0972	0.0413	0.0097	0.0003
College					
Data	0.9008	0.0670	0.0285	0.0037	0.0001
Markov Chain	0.9008	0.0670	0.0285	0.0037	0.0001

Table 2: Opioid Users by Education, Odds Ratios

	Nonuser	***Misuser***	***Addict***
Non-College	0.9795	1.1211	1.2772
College	1.0359	0.7738	0.4822

misuser or an addict are 12 and 28 percent higher for a non-college individual. In constrast, for a college individual, these odds are 23 and 52 percent lower.

Table 3 reports the implications of the fitting procedure for various objects of interest in the model. The first block in this table (σ_{np},σ_{pn}, σ_{bn}, and σ_{an}) are exogenous parameters in the model. The parameters σ_{np} and σ_{pn} determine the likelihood non-users become prescription users and remain prescription users. As will become apparent below, in the 2000 and 2010 steady states, these parameters change due to changing medical practices. The other entries in the table are targets for the 2019 benchmark economy. For example, $S_{ad}(o)$ is the probability of death among addicts. It is much higher for non-college, which might reflect different opioid usage levels, different types of opioids used, or differential access to medical services in an overdose incidence. In the model, $S_{ad}(o)$, is an endogenous object; it depends on both opioid use and the lethality of opioids both of which will differ with education. Again, these deaths probabilities will change in the 2000 and 2010 steady states.

Table 3: Parameters for the Model´s Markov Chain Representations

Parameter	Explanation	Non-College	College
σ_{np}	Prob[$n \to p$]	0.0442	0.0155
σ_{pn}	Prob[$p \to n$]	0.3399	0.1549
σ_{bn}	Prob[$b \to n$]	0.1272	0.1984
σ_{an}	Prob[$a \to n$]	0.0481	0.0315
$\Gamma(\varepsilon_n^*)$	Non-misusers $\div$ Nonusers	0.9985	0.9975
$\Gamma(\varepsilon_p^*)$	Non-misusers $\div$ Prescription users	0.9546	0.9495
$S_{ba}(o)$	Prob[$b \to a$]	0.0222	0.0072
$S_{ad}(o)$	Prob[$a \to d$]	0.0345	0.0134

5.2 Parameter Values Set based on 2019 Cross-Sectional Data

To calibrate the model to 2019 some parameters are set directly to data counterparts while others are chosen so that the model is consistent with a set of data moments. A few parameters are standard in the literature. The coefficient of relative risk aversion, ρ, is assumed to be 1.5. 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. The exogenous transition probabilities between the different stages, σ_{np}, σ_{pn}, σ_{bn}, and σ_{an}, are read from Table 3. It is assumed that individuals fully understood the risk of addiction from opioid use in 2019. Thus, there is no misinformation in the benchmark economy implying $\alpha = 1$. The parameters set directly based on the data are now discussed.

Nonusers' Incomes. In the 2019 Current Population Survey (CPS), annual hours worked by non-college and college graduates are 1,925 and 2,076, respectively. These represent 38.5 and 41.5 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 \$45,816 in the NSDUH for 2019. Hence, π_n corresponds to $\$45,816/0.385 = \$110,345$, which is used to normalize all dollar values borrowed from the data. For an employed college nonuser, $\pi_n\mathfrak{h}$ was about \$72,074, so π_n is roughly $\$72,074/0.415 = \$173,583$, or 1.57 after normalizing. 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 \$9,587 and \$19,700, respectively, which implies $t = 0.087$=$\$9,587/\$110,345$ ($\mathit{0.179} = \$\mathit{19,700}/\$\mathit{110,345}$) relative to a non-college, nonuser's average productivity.

Table 4: 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

Prescription Prices, Street Prices, and Prescription Consumption of Opioids. Next turn to the cost of opioids. Start with prescription prices. Based on MEPS, the average out-of-pocket expenses per person, for all outpatient opioid prescriptions among adults with one or more prescription opioid purchases, was about \$46.23 for those without a college degree and \$26.00 for college graduates in 2019. MEPS can also be used to calculate how much prescription opioids patients take. In 2019, the average yearly opioid usage for non-college prescription patients was about 3,187.80 morphine milligram equivalences (MME) or about 8.73 MME per day. The average usage for college ones was about 1,483.86 MME (about 4.07 MME per day).[9] Hence, set $\underline{o}$ to 3,187.80 and p to \$0.0145 per MME (=\$46.23/3,187.80) for those without a college degree. For college graduates, $\underline{o}$ is 1,483.86 and p is \$0.0175 per MME (=\$26.00/1,483.86). Like changes in σ_{np} and σ_{pn}, the likelihoods of becoming and remaining a prescription-user, changes in $\underline{o}$ reflect prevailing medical practices, specifically, how lenient doctors are about prescribing high dosages of opioids.

The cost of opioids on the street is much higher than via prescription. Table 4 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 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.[12]

[9] To put this in context, 8.73 MME per day would be equal to 5.8 (= 8.73/1.5) OxyContin 1 mg pills per day (the lowest dosage), while 4.07 MME per day corresponds to 2.7 pills.

[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.

[12] See also Surrat et al. (2013) and Lebin et al. (2017).

Given the large gap between prescription and street prices along with 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, relatives, or theft. In the NSDUH, 35.5 percent of misusers and 31.0 percent of addicts obtain opioids from doctor prescriptions. The share is about 32.4 and 29.2 percent for misusers and addicts without a college degree, and 43.9 and 37.8 percent for those who are college graduates (Table 5). These percentages are used to determine the probabilities that a misuser and an addict can obtain opioids at the prescription price, ρ_m and ρ_a.

Table 5: Source of Opioids for Misusers and Addicts, %

Source	**Misusers**	**Addicts**	**Total**
Non-College			
Prescribed by one or more doctor	32.35	29.18	31.85
Given from friends/relatives	43.77	23.84	40.64
Bought from friends/relatives	7.95	22.63	10.26
Stolen (hospitals, friends/relatives)	5.04	2.43	4.63
Bought from dealer	6.32	16.62	7.94
Other	4.56	5.30	4.67
College			
Prescribed by one or more doctor	43.87	37.81	43.16
Given from friends/relatives	35.72	11.26	32.86
Bought from friends/relatives	5.34	24.67	7.59
Stolen (hospitals, friends/relatives)	4.27	13.55	5.35
Bought from dealer	2.59	12.71	3.77
Other	8.22	0.00	7.26

Besides prescriptions, opioids are also obtained from friends and family (either free as a gift or through purchases), or are stolen. The probability of obtaining opioids from friends and family as a gift is higher among misusers: 43.8 percent for those without a college degree and 35.7 percent for those with one. Among addicts, the probabilities are 23.8 percent and 11.3 percent for non-college and college graduates, respectively. According to the survey, 5.04 percent and 2.43 percent of non-college misusers and addicts obtain opioids by stealing them. For college graduates, 4.27 percent and 13.55 percent are obtained through theft. Thus, the majority of misusers and addicts without a prescription obtain their opioids for free. Specifically, absent a prescription, only 33.58 percent of opioids are bought by misusers and addicts without a college degree. Likewise, only 32.76 percent are bought among college graduates. The effective price of opioids for misusers and addicts is therefore $q = 0.3358 \times \$0.67/\text{MME} = \$0.2250/\text{MME}$ for the non-college population, and $q = 0.3276 \times \$0.67/\text{MME} = \$0.2195/\text{MME}$ 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 $110,345.[13]

Table 6 summarizes the parameters chosen based on outside information from either the literature or the US data.

Table 6: Parameters, Chosen Directly from Outside Information

Parameter	Explanation	Non-College	College	Comment
		From the Literature		
ρ	Relative risk aversion	1.5		Standard
η	Weight on leisure	0.64		C.&P. (1995)
β	Discount factor	0.96		Standard
		From the US Data		
Transitions				
σ_{np}	Prob[$n \to p$]	0.0442	0.0155	Table 3
σ_{pn}	Prob[$p \to n$]	0.3399	0.1549	Table 3
σ_{bn}	Prob[$b \to n$]	0.1272	0.1984	Table 3
σ_{an}	Prob[$a \to n$]	0.0481	0.0315	Table 3
Employment				
$\mathfrak{h}$	Hours worked	0.385	0.415	CPS
π_n	Productivity, nonusers	1	1.57	normalization
t	Income, non-employed	0.087	0.179	CPS
Opioids				
$\underline{o}$	Rx usage, MME	3,187.80	1,483.86	MEPS
p	Rx price/1,000 MME	0.000131	0.000159	MEPS
q	Street price/1,000 MME	0.00204	0.00199	Dasgupta et al. (2013)/NSDUH
Probability obtain opioids at Rx price				
ρ_m	Misusers	0.3235	0.4387	NSDUH
ρ_a	Addicts	0.2918	0.3781	NSDUH

5.3 Parameters Values Set by Targeting Moments from 2019 Cross-Sectional Data

The remaining model parameters specify preferences, the relative labor market productivities of abusers and addicts, and how opioid usage 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; misusers' and addicts' opioid consumptions, employment rates, and incomes; the transition probabilities from misuse to addiction and addiction to death; the cross-sectional elasticity of opioid consumption with respect to opioid prices; and the values of statistical lives for non-college and college individuals.[14]

[13] To obtain 33.58% *[32.76%]*, take the share of non-stolen opioids in categories other than prescribed by one or more doctors.

[14] There are concerns that surveys, such as the NSDUH, potentially undercount the extent of misuse and addiction (see, for example, Barocas et al. 2018). As a result, the extents of misuse and addiction targeted

Leisure Shock Parameters. In the NSDUH, 70.0 percent of non-college nonusers between ages 18 and 64 are employed. Employment declines to 65.5 percent for misusers and to 54.0 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, viz 94 and 77 percent, are targeted in the calibration. For college graduates, the employment rates of misusers and addicts, relative to nonusers, are 100 and 72 percent. These employment targets are used to determine the parameters of the leisure-shock Gumbel distributions for abusers and addicts.[15] The scale parameter for each 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 model parameter, ι_s, is selected so that the mean of the leisure shock distribution is normalized to 0.

Productivities for Misusers and Addicts. The employment patterns are mirrored in relative incomes. For the non-college educated, misusers have about 16.7 percent lower income than nonusers, while addicts' incomes are only 67.2 percent of nonusers. For college graduates, the incomes of misusers and addicts are 94.2 and 74.1 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. Recall that π_n is normalized to 1 for non-college nonusers and 1.57 for college nonusers. It is assumed that prescription users have the same productivity as nonusers, so in each education group, $\pi_n = \pi_p$.

Euphoria Shock Parameters. Next, turn attention to the fraction of misusers and the transitions to misuse. The opioid euphoria 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, $\Gamma(\varepsilon_n^*) = 0.9985$ of nonusers and $\Gamma(\varepsilon_p^*) = 0.9546$ of prescription users do not misuse opioids. The rest, or $1 - \Gamma(\varepsilon_n^*)$ and $1 - \Gamma(\varepsilon_p^*)$, are misusers each period (Table 3). The fractions of non-misusers among nonusers and prescription users for college graduates are 0.9975 and 0.9495. Given the optimal decisions for ε_n^* and ε_p^*, the shapes of the Gumbel distributions determine these fractions. Each scale parameter, ζ_s, is chosen to match the population fractions.

in the model can be considered as lower bounds.

[15]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.

Transitions to Addiction and Death. According to the data, 2.22 percent of non-college and 0.72 percent of college misusers become addicts each period, while 3.45 percent of non-college addicts and 1.34 percent of college addicts die (Table 3). The addictiveness and lethality of opioids governed by the parameters σ_s, for $s = a, d$, control through equations (2) and (4) how opioid usage affects the transitions from abuse to addiction and addiction to death. These parameters are chosen so that the transition probabilities in the model match the data.[16] According to Gable (2004), the acute lethal dosage of heroin is 6 times the average dosage used for non-medical purposes. The asymptote parameter in the death probability function, $\mathbf{a}$, is set such that death occurs with probability one for levels of usage 6 times the average level of usage of misusers and addicts. The inflection point parameter, $\mathfrak{o}$, is set such that death rates start increasing at an increasing rate when usage levels exceed 4 times the average level.

Preferences. The curvature, ψ, and weights, μ_s, of the utility function for opioids for $s = n, p, b, a$; the utility cost of addiction, ω_a; the utility associated with death, δ; and the modes of the Gumbel distributions for opioid euphoria shocks, ν_s, remain to be determined. Three sets of targets are used to discipline these parameters: opioid consumption, the value of a statistical life, and the cross-sectional price elasticity of opioid demand.

(1) Opioid Consumption. The first set of targets is opioid consumption by misusers and addicts. Unfortunately, consumption data is limited mainly to prescription patients, so some bold assumptions have to be made to arrive at numbers that can be used for calibration. Glanz et al. (2019) 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 20 in Appendix C shows the daily opioid usage 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 at 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

[16] The number of opioid overdose deaths is calculated from death certificates using the CDC's Vital Statistics. This data does not include medical histories, so not all deaths are necessarily those of addicts. While the model can be extended to allow for opioid deaths among abusers, constructing moments to discipline such a model would be challenging. Studies that link deaths to medical histories are often restricted to small samples (see Park et al. 2016 for a review).

line with those reported by Glanz et al. (2019). 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.

Since the model period is a year, calculations have to be made to arrive at annual opioid consumption. In the NSDUH, misusers and addicts are also asked how many days they misused opioids during the last month (Table 21 in Appendix C). For the non-college educated, opioids are misused 6.19 days per month by misusers and 15.95 days per month by addicts (20.64 and 53.18 percent of the time). Thus, for the non-college educated, the annual levels of opioid misuse are $0.2064 \times 365 \times 50$ MME $= 3,766.4$ MME for misusers and $0.5318 \times 365 \times 90$ MME $= 17,470.7$ MME for addicts. For the college educated, misuse of opioids occurs 4.34 days per month for misusers and 12.60 days per month for addicts (14.48 and 41.99 percent of the time). Therefore, for the college educated, annual opioid consumption is $0.1448 \times 365 \times 50$ MME $= 2,643.1$ MME for misusers and $0.419 \times 365 \times 90$ MME $= 13,794.1$ MME for addicts.[17]

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 3,766.4 MME. The number for college misusers is 2,643.1 MME, or about 30 percent less. For addicts, the targeted level of opioid consumption of college graduates is 7,470.5 MME, while the targeted level for non-college graduates at 13,794.1 MME, or about 21 percent less.

In the model, the opioid consumption of first-time users in stages n and p is determined by the generic static first-order condition (9),

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

with $I_n \equiv 0$ and $I_p \equiv 1$. 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 3,766.4 MME and 2,643.1 MME, respectively, when averaging across those who purchase nonprescription

[17]On this, as noted above, the average yearly opioid consumption of *prescription* patients in MEPS is about 3,190 MME for the non-college educated and 1,480 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 is 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. Clearly, when going from daily usage to annual usage, an adjustment has to made for the frequency of use.

opioids at price p and those who purchase at price q. The generic first-order conditions (12) and (15) 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) Value of a Statistical Life. 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 based on their willingness to pay (`WTP`) for a small reduction in mortality risk. 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."[18] [19] It is useful for determining the utility value of death, δ.

In the model, only addicts face death risk. The willingness to reduce death risk conditional on addiction is not necessarily the same as the unconditional willingness to reduce death risk since addicts have lower utility. Therefore, instead of computing the average `WTP` for a small reduction in death risk, the `VSL` is calculated by computing the average compensation across individuals that must be paid to a person in the benchmark economy for a small (one in 10,000) increase in death risk. With the increase in death risk, the probability an addict dies next period is higher by one in 10,000 with non-addicts facing the same hike in the probability of dying next period.[20] Then, the VSL is given by the average compensation divided by the increase 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 that are reported in the literature—see Viscusi and Aldy (2003).

(3) Cross-Sectional Price Elasticity of Opioid Usage. The final set of targets used to determine the preference parameters are the estimates of the cross-sectional price elasticity of opioid usage. The price elasticity, in particular, helps to determine the utility cost of addiction, ω_a, and the modes of the Gumbel distributions for opioid euphoria shocks, ν_s. An excellent summary of the available evidence on this price elasticity is provided in the 2020 *Economic Report of the President.* Based on this evidence, a reasonable range for the price elasticity is -0.56 to -0.27. The calibration targets the midpoint of this range, or a price elasticity of -0.34.

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[18]See Trottenberg and Rivkin (2013).

[19]The `VSL` prorates the `WTP` for a reduction in risk in a linear fashion: "The assumption of a linear relationship between risk and `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."

[20]Details on the calculations of the compensating differentials are presented in Appendix E.

Table 7: Parameters: Calibrated using 2015–2019 Cross-Sectional Data

Parameter	Explanation	Non-College	College
ψ	elasticity of opioid usage	1.3249	
μ_n=μ_p,	utility weight on opioids	0.00031	
μ_b	utility weight on opioids	0.1445	0.1121
μ_a	utility weight on opioids	0.4381	0.1284
ζ_n,ν_n	euphoria shock, nonusers	0.1456, 10.7717	0.0478, 1.1853
ζ_p, ν_p	euphoria shock, Rx users	0.3525, 10.6523	0.1176, 1.1450
ξ_b,ι_b	leisure shock, abusers	0.400, -0.2309	0.060, -0.0346
ξ_a,ι_a	leisure shock, addicts	0.870, -0.5022	0.780, -0.4502
π_b	relative productivity, abusers	0.8451	0.9306
π_a	relative productivity, addicts	0.8026	0.9209
σ_a	constant, Prob[$b \to a$]	0.01144	0.00443
σ_d	constant, Prob[$a \to d$]	0.00831	0.00364
$\mathbf{a}$	asymptote in $S_{ad}(o)$	35,700	
$\mathfrak{o}$	inflection point in $S_{ad}(o)$	24,200	
δ	utility associated with death	-137.750	-88.263
ω_a	utility cost of addiction	10.956	5.400

The calibrated parameters based on 2019 cross-sectional data are presented in Table 7. Notice that the scales of the euphoria shocks, ζ_n and ζ_p, are larger for prescription users as compared to nonusers. The larger values reflect the relatively higher rates of misuse among prescription users targeted in the calibration. As shown in Table 19, the transition rate of prescription users to becoming misusers is about 10 times higher than the transition rate of nonusers to misusers. The relatively higher misuse rates of prescription users may be due to selection or a causal effect of prescription usage on an individual's taste for opioids. The match between the model and data targets is provided in Table 8. The fit of the model to the data targets is excellent. The cross-sectional opioid price elasticity in the model at -0.57 is at the upper end of the range estimated in the literature.

6 Calibrating the 2000 and 2010 Steady States

The 2019 benchmark calibration serves as the starting point for calibrating the 2000 and 2010 steady states. From this point of departure, the observed changes in the US data for opioid prices and prescription practice are inputted into the model. Then, the parameters governing the lethality of opioids, conditional on being an addict, are adjusted so that the model matches the observed death rate for addicts in 2000 and 2010. The degree of misinformation in 2000 about the risk of addiction is obtained by harmonizing the model's

Table 8: 2015-2019 Cross-Sectional Data Targets and the Model's Fit for 2019

Targets	**Model**	**Data**	**Model**	**Data**
	Non-College		*College*	
Opioid Consumption				
Usage, first-time misusers, MME	3,766.5	3,766.4	2,643.0	2,643.1
Usage, abusers, MME	3,766.3	3,766.4	2,643.8	2,643.1
Usage, addicts, MME	17,470.9	17,470.7	13,793.5	13,794.1
Fraction non-misusers in n	0.9985	0.9985	0.9975	0.9975
Fraction non-misusers in p	0.9546	0.9546	0.9495	0.9495
Transitions				
$S_{ba}(o)$ =Prob[$b \rightarrow \mathtt{a}$]	0.0222	0.0222	0.0072	0.0072
$S_{ad}(o)$ =Prob[$\mathtt{a} \rightarrow \mathtt{d}$]	0.0345	0.0345	0.0134	0.0134
Employment (fraction)				
All misusers/Nonusers	0.94	0.94	1.00	1.00
Addicts/Nonusers	0.77	0.77	0.72	0.72
Income				
All misusers/Nonusers	0.83	0.83	0.94	0.94
Addicts/Nonusers	0.67	0.67	0.74	0.74
VSL *(millions of 2018 dollars)*	8.9	9.0	11.8	11.8
Cross-Sectional Opioid price elasticity *(All)*	-0.57	-0.56 to -0.27		

predictions about deaths in triplicate and non-triplicate states with the US data. The changes in these exogenous forces are summarized in Table 9. All other parameters are kept at their benchmark values, as shown in Tables 6 and 7.

Opioid prices. Both the illegal and prescription prices of opioids have declined drastically since the turn of the century. Prescription prices declined more rapidly in the first half of the crisis (Figure 4) while illegal prices dropped more quickly in the second half (Figure 6). Between 2000 and 2010, prescription prices fell by a factor of 5 while street prices only declined by about 15 percent. From 2010 to 2019, there was essentially no change in prescription prices but street prices fell by a factor of 2.125.

Prescribing practices. During the first half of the crisis, while prescription opioid prices were falling rapidly, both the number of opioid prescriptions per person and the amount of opioids per prescription significantly increased (Figure 3). Indeed, between 2000 and 2010, the average opioid prescription potency, $\underline{o}$, more than doubled. It increased from 2,582.01 to 5,107.26 MME for non-college graduates and from 1,566.41 to 3,432.96 for college graduates.[21] The increase in the number of opioid prescriptions per person indicates that individuals were either more likely to get a prescription (σ_{np} increased), more likely to keep one longer once they had it (σ_{pn} decreased), or both. To calculate these transition probabilities in 2000 and 2010, MEPS is utilized.[22] From 2000 to 2010 the probability of starting a prescription, σ_{np}, increased from 5.5 to 7 percent for non-college graduates and from 1.6 to 2.2 percent for college graduates. At the same time the probability of stopping to take prescription opioids, σ_{pn}, declined for both groups. It dropped from 40.8 percent to 31 percent for those without a college degree and from 16.9 percent to 14.7 percent for those with one. These trends reversed after 2010. Consequently, prescription potency, the duration of time individuals are kept on them, and prescribing rates are all lower in the 2019 benchmark than in 2010. In fact, prescribing rates in 2019 are even lower than those in 2000.

Also included in changing prescribing practices are changes in the probabilities of obtaining opioids from a doctor's prescription for misusers and addicts, ρ_m and ρ_a.[23] Except in one case (the decline in ρ_m from 0.2025 in 2000 to 0.1725 in 2010 for non-college graduates), these probabilities increased between 2000 and 2010. Interestingly, they also increased between 2010 and 2019 despite the overall decline in prescribing rates over this period. For both education groups, the probabilities increased more rapidly for addicts during the first half of the crisis and more rapidly for misusers during the second half.

Death rates. The death rate of addicts was 0.99 percent for non-college graduates and 0.71 percent for college graduates in 2000. These death rates increased to 1.29 percent and 0.86 percent, respectively, in 2010. Between 2010 and 2019 the death rates increased more rapidly, especially for the non-college population. Consequently, in the 2019 benchmark, 3.45 percent of non-college addicts and 1.34 percent of college addicts die each period. In the model, these probabilities depend on the lethality of opioids, σ_d, and opioid usage, o, regulated by $S_{ad}(o)$. As in the 2019 benchmark, σ_d is calibrated in the 2000 and 2010 steady states to match the death rates conditional on addiction.

Misinformation about addiction risk. In the benchmark economy, it is assumed that $\alpha = 1$ and individuals understand fully the probability of becoming an addict from opioid use. It is unlikely that this was the case back at the start of the opioid pandemic. In a recent paper, Alpert et al. (2022) exploit cross-state variation in exposure to OxyContin's intro-

[21] The changes are based on the average MME content of prescriptions in 2000 and 2010 in MEPS. See Nahin et al. (2019) for a similar analysis using MEPS.

[22] The calculations are based on transitions from 2000 to 2001 and from 2009 to 2010 in MEPS.

[23] The values of ρ_m and ρ_a in 2010 are taken from the NSDUH. The fraction of misusers and addicts that obtained opioids from a doctor is not available in 2000. Values for 2000 are imputed by extrapolating the trend over the 2005 to 2019 period back to 2000.

Table 9: Parameter Values and Targets: 2000, 2010, and the 2019 Benchmark

Parameter	**2000**	**2010**	**2019 Bmk.**	**2000**	**2010**	**2019 Bmk.**
		Non-College			*College*	
Directly obtained from US Data						
p^* *(All)*	5	1	1			
q^* *(All)*	2.5	2.125	1			
$\underline{o}$ (MME)	2,582.01	5,107.26	3,187.80	1,566.41	3,432.96	1,483.86
σ_{pn}	0.4075	0.3100	0.3399	0.1688	0.1472	0.1549
σ_{np}	0.0548	0.0704	0.0442	0.0158	0.0224	0.0155
ρ_m	0.2025	0.1725	0.3235	0.2057	0.2156	0.4387
ρ_a	0.2419	0.2814	0.2918	0.0486	0.2543	0.3781
Calibrated so that the Model Matches Facts about Overdose Deaths						
$\sigma_d^\dagger$	0.00273	0.00340	0.00831	0.00257	0.00257	0.00364
$\alpha^\ddagger$ *(All)*	0.987	1	1			
Data Targets						
$S_{ad}(o)$ =Prob[$\texttt{a}\rightarrow\texttt{d}$]	0.0099	0.0129	0.0345	0.0071	0.0086	0.0134

*Relative to 2019 benchmark value.
†Calibrated in each steady state to match death rates conditional on addiction, $S_{ad}(o)$.
‡Year 2000 value is for the non-triplicate-state economy only. It is calibrated to generate the difference in deaths between non-triplicate and triplicate states with α set to 1 in the triplicate-state economy.

duction 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. Alpert et al. (2022) find that these programs made prescribing opioids more difficult, reducing OxyContin sales significantly in triplicate states. They also find that Purdue Pharma reduced OxyContin advertising in these states due to the presence of the triplicate programs. Consequently, OxyContin distribution was about 65 percent lower in triplicate states as compared to non-triplicate states in the years after its launch. Given the share of other prescription opioids, which were not affected by triplicate prescription programs, this corresponds to a 43 percent decline in the distribution of prescription opioids in triplicate states. The comparison between triplicate and non-triplicate states conducted by Alpert et al. (2022) implies that a state without a triplicate program could reduce opioid deaths by 45 percent by implementing one.

More stringent prescribing laws together with less advertising of OxyContin may have led to lower rates of misinformation about opioid addiction risk in triplicate states in 2000. Therefore, for 2000 two economies are simulated: one where $\alpha = 1$ (no misinformation) and another where $\alpha < 1$. These two economies correspond to triplicate and non-triplicate states in the data. In addition to having no misinformation, prescription opioid distribution is 43 percent lower in the triplicate-state model economy as compared to the non-triplicate-state one. To calculate aggregate statistics for 2000, the triplicate and non-triplicate state economies are aggregated using the shares of college and non-college graduates living in triplicate and non-triplicate states in the US.[24]

In the model, the quantity of prescription opioids distributed is given by the number of opioid prescription users times the level of opioids prescribed to them. Lower distribution of prescription opioids can be implemented by reducing the number of prescription users, or by lowering the transition rate from the nonuser state to the pain state, σ_{np}. It can also be implemented by a reduction in prescription opioid strength, $\underline{o}$. The first approach assumes that the lower rate of prescription opioid distribution in triplicate states is due to a lower fraction of individuals who are prescribed opioids, while the second assumes it is due to lower dosages per prescription-user. The differences in prescription opioid distribution between triplicate and non-triplicate states was likely due to some combination of the two. For simplicity, an equal percent reduction of both is assumed. Thus, σ_{np} and $\underline{o}$ are set in the triplicate and non-triplicate state economies such that they average to the values in Table 9, but subject to the constraint that there are 24 ($\simeq 1 - \sqrt{1 - 0.43}$) percent less opioid prescription users plus a 24 percent reduction in the amount of opioids prescribed per user in the triplicate-state economy relative to the non-triplicate-state one.

All other parameters are the same in the two economies. In particular, the two economies face the same prescription and street prices for opioids and σ_{pn} values, as shown in Table 9 for 2000. They also share the same value for σ_d, which is chosen to generate the aggregate death probabilities for college and non-college addicts in Table 9 for 2000. The extent of misinformation in the non-triplicate-state economy, which is assumed to be the same for the non-college and the college educated, is then calibrated so that the number of deaths is 45 percent lower in the triplicate-state economy. The estimated value for α is 0.987.

Finally, it is assumed that by 2010, with all the media focusing on the Federal law suit against Purdue Pharma, the public became much more informed about opioids and ceased to underestimate the true addiction risk. Thus, in the 2010 steady state $\alpha = 1$. The next section will entertain how changes in the exogenous parameters displayed in Table 9 affect the economy.

[24]The share of college and non-college graduates in triplicate states were 33 and 31 percent respectively.

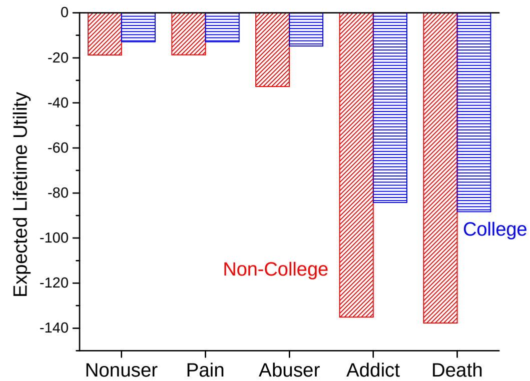

Figure 9: The downward spiral: a person's expected lifetime utility sinks into the abyss as they advance through the various stages of opioid addiction.

7 Understanding the Downward Spiral

In 2019, 47,304 individuals between ages 18 and 64 died of opioid overdoses. A large majority of them, 43,867, did not have a college degree. The rest, 3,437 of them, were college graduates.[25] The benchmark economy matches these statistics exactly. The downward spiral in the benchmark economy from opioid usage is portrayed in Figure 9. It shows how college- and non-college-educated individuals' expected utilities steadily decline as they move through the stages of opioid addiction. The descent appears fairly gradual until one hits the addiction stage, with little further loss in utility associated with death. Utility is always higher for college graduates, and the relative drop in utility from nonuse to death is larger for non-college individuals. The state-contingent preference structure adopted here captures the Becker and Murphy (1988) feature that utility declines with opioid usage (which they refer to as tolerance or negativity).

Back in 2000, the number of opioid-related deaths was only 8,179 (7,549 deaths among the non-college educated and 629 among college graduates). How much of the increase in the number of deaths can the model economy account for? Since the calibration of the model to year 2019 is based almost exclusively on 2019 cross-sectional data, it is not a forgone conclusion that it will be able to explain the rise in opioid deaths over the 2000 to 2019 period. In the 2000 steady state, there are 17,927 deaths from opioid overdoses among non-college graduates, in contrast to 43,867 deaths in the 2019 benchmark setting. Hence, the model can generate about 71 percent of the increase in deaths between 2000 and 2019 for non-college graduates, $(43,867-17,927)/(43,867-7,549)$. Among college graduates, there

[25] 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.

are 1,763 deaths in the 2000 steady state, whereas 3,437 college graduates die from opioids every year in the benchmark economy. So, the model accounts for about 60 percent of the increase in deaths among college graduates between 2000 and 2019.

What are the driving forces of the opioid epidemic according to the model? Recall the four forces in the model driving changes in opioid usage and death are the fall in the black market price of opioids, the increase in the lethality of opioids, changes in the extent of misinformation about the odds of addiction, and changes in prescribing practices (which includes changes in prescription opioid prices). The calibrated model is now used to assess the relative importance of each of these forces in accounting for the substantial increase in opioid overdose deaths since 2000. First, their relative contributions to the increase in deaths during the first half of the crisis, 2000 to 2010, is explored. This is followed by an assessment of their contributions to the rise in deaths during the second half of the crisis, 2010 to 2019. The changes in the exogenous forces over these two periods can be seen in Table 9.

7.1 The first half of the crisis: 2000 to 2010

Between 2000 and 2010, the number of deaths from opioid overdose more than doubled, increasing from 7,549 to 18,642 for non-college population and from 629 to 1,665 for college graduates. What are the contributions of the different factors documented in Table 9 to this increase? To answer this question, the number of deaths in the 2000 and 2010 steady states are compared when different forces in 2010 are kept at their 2000 values, where the changes in $\underline{o}$, σ_{pn}, σ_{np} , ρ_m, ρ_a, and p are grouped together to capture changing *prescribing practices*. The results are presented in Table 10.

Through the lens of the model, the major contributor to the increase in the number of deaths between 2000 and 2010 is changing prescribing practices. During this period, prescription opioid prices fell substantially. At the same time prescribing behavior changed leading to an increase in the strength of Rx opioids, the fraction of people prescribed opioids, and the duration of time they are on them. About 97 percent of the increase in the number of deaths for non-college graduates can be explained by these changes in prescribing practices. For college graduates, these changes played an even more significant role, accounting for 110 percent of the increase in deaths.

As for other drivers of the opioid crisis during this period the decline in illegal opioid prices was a second major factor, accounting for 49 percent of the rise in deaths among those without a college degree and 23 percent of the rise among college graduates. The increase in the lethality of opioids conditional on addiction also played an important role for non-college graduates, accounting for 33 percent of the rise in their deaths.

Table 10: Decomposition of Driving Forces

	Illegal Price	**Prescribing Practices** including **Rx Price**	**Lethality**	**Information**
	q	$\underline{o}$,σ_{pn}, σ_{np}, ρ_m, ρ_a, and p	σ_d	α
		Deaths Accounted by (%)		
2000 to 2010				
Non-College	49.29	96.52	32.62	-88.43
College	22.77	110.46	0.00	-44.78
2010 to 2019				
Non-College	105.79	-91.30	11.24	0
College	79.43	-67.23	47.14	0

Recall that in the 2000 steady state, $\alpha < 1$ for both education groups. The assumption is that by 2010 the public was informed about the perils of opioids implying that α is equal to 1. In the model, better information about the probability of addiction reduces the number of deaths significantly, by 88 percent for non-college and 23 percent for college. For both groups, better information helps to counteract the rise in opioid deaths ignited by changing prescribing practices.

Given the importance of changing prescribing practices during the first half of the crisis, Table 11 presents a breakdown of the relative contributions of each component. Within changing prescribing practices the most important factor accounting for the rise in deaths during this period was the increase in opioid prescribing rates, σ_{np}. Higher prescribing rates account for 45 percent of the increase in deaths for non-college graduates between 2000 and 2010 and 65 percent for college graduates. For the non-college population, changes in the duration of time people were kept on prescription opioids, σ_{pn}, were also important. For the college population, the second most important factor was the changes in the probabilities of obtaining prescription opioids for misusers and addicts, ρ_m and ρ_a, with other factors playing a relatively smaller role.

7.2 The second half of the crisis: 2010 to 2019

The number of opioid overdose deaths more than doubled again between 2010 and 2019. Deaths among non-college graduates shot up from 18,642 to 43,867. Deaths among college graduates increased from 1,665 to 3,437. Which forces drove the increase in opioid overdose death rates during the second phase of the crisis? Here, a comparison is provided between the 2019 benchmark and a counterfactual where different forces are kept at their 2010 values. Now, a very different picture emerges in Table 10. The trends in prescribing practices

Table 11: Contribution of Different Prescribing Practices

	Rx strength	Rx length	Prescribing rate	Pr misuser/addict buy at Rx price	Rx price
	$\underline{\varrho}$	σ_{pn}	σ_{np}	ρ_m and ρ_a	p
			Deaths Accounted by (%)		
2000 to 2010					
Non-College	3.21	40.25	45.46	9.05	5.32
College	-2.12	16.57	59.33	46.71	11.51
2010 to 2019					
Non-College	-0.66	-11.98	-88.74	12.17	0.00
College	-0.81	-7.40	-90.26	30.31	0.00

are reversed. If only prescribing practices changed, specifically the strength of opioid prescriptions, prescribing rates and prescription durations declined, then the number of deaths among non-college graduates would have decreased by about 91 percent. The decline for college graduates would be about 67 percent. Table 11 shows that among these forces, the decline in prescribing rates had the largest impact reducing the numbers of deaths by 89 percent for non-college graduates and 90 percent for those with a college degree.

Unfortunately, however, at the same time that changes in prescribing practices were making access to opioids more stringent, the street price of opioids was declining dramatically. As the availability of prescription opioids declined, users first moved to heroin and then to synthetic opioids, which are both cheaper and more lethal. In the model, the combination of these two forces (cheaper street prices and higher lethality rates conditional on addiction) more than overcomes the decline in deaths due to changing prescribing practices. Of these two forces, the decline in street prices was the primary driver. It explains 106 percent of the rise in non-college deaths and 79 percent of the rise in college deaths. For college graduates, the increase in the lethality of opioids conditional on addiction was also an important factor, accounting for 47 percent of the rise. The increase in lethality had a smaller impact on non-college graduates, explaining only 11 percent of the rise in deaths.

7.3 Opioid usage and employment patterns during the crisis

Table 12 reports how opioid consumption, the fraction of opioid users, and the employment rates of users vary across the three model steady states. The changes in per capita opioid consumption for both the entire population and for misusers and addicts are consistent with the forces driving the two phases of the crisis depicted in Table 10. Start with the early period, 2000–2010. Despite only a minor decline in the street price of illegal opioids, q, and people becoming better informed about addiction risk (an increase in α between 2000 and

2010), there is a significant increase in opioid consumption. The consumption of users rises by about 6 percent for non-college graduates and by 24 percent for college graduates. Same as for the rise in deaths, this increase is driven by changes in prescribing practices that make opioids more accessible.

From 2010 to 2019 the number of opioid deaths continues to increase but, in contrast to the first half of the crisis, opioid consumption conditional on using declines for the non-college population and is essentially flat for college graduates. The overall decline in the consumption of misusers and addicts is driven, in part, by changing prescribing practices that now make Rx opioid access more difficult. However, it was also driven by the large rise in the lethality of opioids conditional on addiction, σ_d, which makes usage more risky leading, simultaneously, to an increase in opioid deaths and a fall in opioid consumption. These two forces together have a larger impact on non-college misusers' and addicts' opioid consumptions than the fall in street prices which pushes to increase consumption during this period.

What about the fraction of users in the population? For both non-college and college graduates, there is a slight increase in the number of abusers and addicts in the model between 2000 and 2010 and a slight decline between 2010 and 2019, generating a $\cap$-shape. Similar to the consumption levels of misusers and addicts, these changes are driven by the offsetting effects of the various driving forces. The patterns are surprisingly close to what is observed in the data, as Figure 10 illustrates. For both non-college and college graduates, the fraction of users in the population increases slightly between 2002 and 2010 then declines between 2010 and 2019.

Finally, turning to employment, the fraction of misusers and addicts working declines from 2000 to 2010 and then again from 2010 to 2019. These declines are driven by the drop in the effective price misusers and addicts pay for opioids. In the first half of the crisis, not only do the prescription and illegal prices of opioids fall, but the share of misusers and addicts obtaining opioids at the relatively lower prescription price rises due to the loosening of prescribing practices. In the second half of the crisis, opioid price declines are driven by falls in the illegal price and an increasing share of users who surreptitiously obtain opioids from a doctor's prescription (i.e., ρ_m and ρ_n). These price declines make opioids more affordable, reducing the need for misusers and addicts to work.

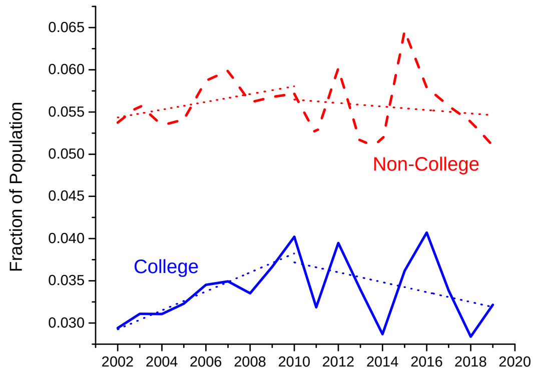

Figure 10: Fraction of the US population that are opioid users (misusers and addicts), 2002–2018. The dotted lines illustrate the trends for the 2002–2010 and 2010–2019 sub-periods. They *suggest* a $\cap$ shape.

Table 12: Three Steady States

	2000	**2010**	**2019**
Non-College			
Opioid Consumption	0.342	0.437	0.323
Opioid Consumption, Mis. & Add.	6,201	6,559	6,372
Users, Mis. & Add.	0.055	0.067	0.051
Misusers working	0.954	0.951	0.937
Addicts working	0.843	0.819	0.771
College			
Opioid Consumption	0.087	0.136	0.127
Opioid Consumption, Mis. & Add.	3,139	3,899	3,919
Users, Mis. & Add.	0.028	0.035	0.032
Misusers working	1	1	1
Addicts working	0.750	0.738	0.723

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 $\sigma_{ba} = S_{ba}(o)$ and $\sigma_{ad} = S_{ad}(o)$ as defined in equations (2) and (4). Both of these transitions are endogenous, depending on current usage, o. To undertake these experiments, the constants σ_a and σ_d governing the lethality and addictiveness of opioids will be lowered in turn. The experiments will focus on the non-college population in the 2019 benchmark, with $\alpha = 1$.

8.1 Probability of Death

Start with the probability of death for addicts. The death rate conditional on addiction increased over the course of the crisis (Table 9). According to the analysis, the fact that opioids became more lethal over time accounted for most of this increase, especially in the latter period. Table 13 presents a decomposition of an addict's death rate, $S_{ad}(o)$, between increases in opioids' lethality, σ_d, and an increase in the addict's consumption, o.[26] Increases in the lethality of opioids, as opposed to a ratcheting up in addicts' consumptions, accounted for most of the rise in their death rate conditional on addiction, $S_{ad}(o)$. Importantly, note that increases in the lethality of opioids reduce both opioid consumption and the odds of becoming a misuser or addict in the first place. So, as discussed earlier, other factors such as misinformation, prices, and prescribing practices played crucial roles by driving up usage rates despite rising opioid lethality.

Reasons for the uptick in the deadliness of opioids are multifaceted. The rise of black market opioids meant that more people started buying drugs of unknown strengths and purities, often mixed with other dangerous substances. Additionally, more people started using more deadly delivery methods, such as injecting, smoking, and snorting opioids. The early period saw a shift in Rx prescribing away from drugs like hydrocodone and towards the more potent oxycodone (Alpert et al., 2022). The latter period saw the rapid rise of the more lethal fentanyl (Figure 1).

[26]The decomposition is done as follows. First, note that $S_{ad}(o)$ is a function of both of σ_d and o, so instead express the function as $D_{ad}(\sigma_d, o)$. Second, consider two situations, namely $D_{ad}(\sigma'_d, o')$ and $D_{ad}(\sigma_d, o)$. Last, the change in the death rate across these two situations can be expressed as

$$\begin{aligned} D_{ad}(\sigma'_d, o') - D_{ad}(\sigma_d, o) = &\frac{1}{2}[D_{ad}(\sigma'_d, o') - D_{ad}(\sigma_d, o') + D_{ad}(\sigma'_d, o) - D_{ad}(\sigma_d, o)] \\ &+ \frac{1}{2}[D_{ad}(\sigma_d, o') - D_{ad}(\sigma_d, o) + D_{ad}(\sigma'_d, o') - D_{ad}(\sigma'_d, o)]. \end{aligned}$$

Consider the righthand side. The term on the first line, gives the contribution of a change in lethality, σ_d, on the change in $D_{ad}(\sigma_d, o)$. It averages across the two situations for o. The term on the second line gives the contribution of a change in consumption, o, on the change in $D_{ad}(\sigma_d, o)$, while averaging across the two situations for σ_d. When doing this decomposition, consumption is averaged across all addicts.

Table 13: Decomposition of the Change in Addicts' Death Rate

	Consumption o	**Lethality** σ_d
	Change in $S_{ad}(o)$	Accounted by (%)
2000 to 2010		
Non-College	16.7	83.3
College	100.0	0.0
2010 to 2019		
Non-College	9.4	90.6
College	21.4	78.6

In the 2019 benchmark economy, the lethality of opioids conditional on addiction, σ_d, is 0.00831 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 United States. People can use it without medical training or authorization according to the 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 11 shows how the number of non-college deaths varies with σ_d (left panel). The plot also displays how much a non-college-educated person would be willing to pay in terms of the average compensating variation, CV, across states to reduce the lethality of opioids.[27] As σ_d falls the number of deaths first increases slightly and then declines. The initial slight rise in deaths occurs because as σ_d declines the number of opioid users (misusers and addicts) and their opioid consumption increases. A 50 percent decline in opioid lethality conditional on addiction, for example, increases users by about 60 percent and the amount of consumption conditional on usage by 13 percent. The 50 percent decline in lethality is completely offset by the rise in usage resulting in no change in the number of deaths. When the probability of

[27] Details on the CV calculations are presented in Appendix E.

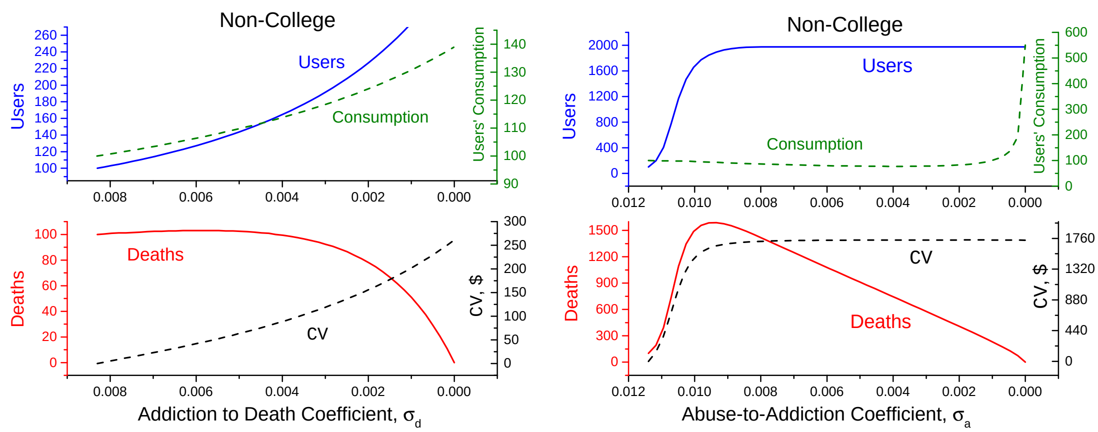

Figure 11: Left panel: Changes in the lethality of opioids conditional on addiction, σ_d. Right Panel: Changes in the addictiveness of opioids conditional on abusing them, σ_a. In both panels, users (misusers and addicts), opioid consumption, and deaths are set to 100 in the benchmark equilibrium.

death is zero, the number of users increases by 340 percent. Yet, this is still only 17.2 percent of the non-college population, instead of 5.1 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. Interestingly, research by Doleac and Mukherjee (2021) suggests that increased access to naloxone may have in fact increased opioid consumption and emergency room visits, suggesting that naloxone, in and of itself, isn't a cure for the opioid crisis.

8.2 Probability of Addiction

Next, turn to σ_a, which governs how addictive opioids are for abusers. The benchmark value σ_a is 0.01144 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 the right panel of Figure 11. As the odds of addiction fall, the number of users (misusers and addicts) increases dramatically. When addictiveness conditional on abusing declines by 50 percent, the fraction of non-college users increases by a factor of 200. Yet, average opioid consumption by users becomes 20 percent lower. 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 ∩-shaped response to a decline in σ_a. With a 50 percent decline in addictiveness, the number of deaths increases by a factor of 10 due to the dramatic increase in users. Eventually, as addictiveness declines further, the lower

Table 14: Value of Recreational Opioids

	Non-College		**College**	
	\$	*%*	*\$*	*%*
Nonuser	148.42		89.04	
Prescription user	272.66		276.95	
Average	162.72	0.36	106.13	0.15

number of 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. This topic is turned to now.

9 Value of Recreational Opioids

Individuals enjoy recreational opioids, as they do alcohol, marijuana, and tobacco. This makes controlling substance abuse difficult. What value do consumers place on recreational opioids? Imagine a world where the illicit consumption of opioids can be stamped out. Prohibition and the war on drugs suggest that this is impossible to do. In the dust-free model laboratory, however, this can be operationalized by setting the price of illegal opioids to infinity. The question is: How much would a consumer be willing to pay out of their current income to move from the world with no illicit consumption of opioids to the current situation with black market opioids?

The results are shown in Table 14. On average, a non-college individual is willing to pay \$162.72 annually to remain in the current situation with black market opioids. This amounts to 0.36 percent of their current income. College-educated people would pay less. Also, prescription users place a higher value on illicit opioid consumption than non-users. This calculation does not factor in the cost of rehabilitation and the crime linked with illegal opioids. These factors would reduce the societal value of recreational opioids. It also does not take into account the value that prescription opioids have in reducing pain; this would increase the consumer value of opioids.

10 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 these factors 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. Hence, controls were placed on prescribing opioid-based painkillers such as OxyContin. This led to illegal imports of fentanyl, which were cheap and powerful.

There are some parallels between the opioid epidemic and Prohibition.[28] The 18th Amendment to the Constitution prohibited "the manufacture, sale, or transportation of intoxicating liquors." It took effect 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, as shown in Figure 12, left panel. By the end of Prohibition, it had grown back to about 60 to 70 percent of the pre-Prohibition levels due to the emergence of a black market for alcohol. 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 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:

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

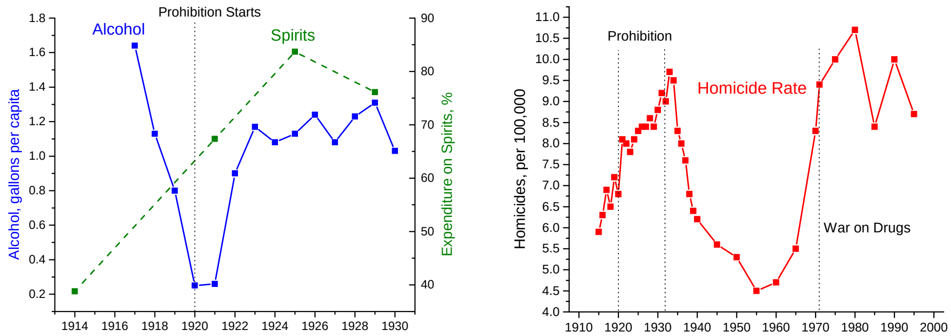

Figure 12: Prohibition, 1920–1933. The rise in alcohol consumption throughout the Prohibition era and the shift in expenditure toward spirits (left panel). After prohibition expenditure reverted back to the pre-Prohibition pattern. The rise in the homicide rate during prohibition (right panel). Sources: Warburton (1932, Tables 1, 30, and 86) and Carter et al. (2006, Series Ab951)

> 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 black market 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.

To analyze the opioid epidemic, a model is constructed where there are two routes to recreational opioid usage. Some nonusers experiment with opioids for enjoyment, while others start opioids because they are suffering pain and end up misusing them for recreation. Abuse leads to addiction with some odds, and there is a chance that addiction results in death. The probabilities of addiction and death are increasing functions of the extent of opioid usage, 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 opioid crisis is broken down into two subperiods; viz, 2000 to 2010 and 2010 to 2019. The model suggests that loose prescribing practices together with a drop in the price of prescription opioids and misinformation about the risk of addiction were the primary drivers of the first half of the opioid epidemic. The decline in the price of illicit opioids combined with a rise in the death rates for addicts due to the shift in consumption towards more lethal fentanyl were the major drivers of the second half. 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 the number of users rises dramatically. Despite this, both types of interventions are valued by consumers.

An interesting topic for future research is the relationship between opioid addiction and labor-force participation. Opioid addicts have lower labor-force participation rates than nonusers and prescription users. Greenwood, Guner, and Kopecky (2022) report that increased substance abuse during the COVID-19 pandemic may account for between 9 and 26 percent of the decline in prime-age labor-force participation between February 2020 and June 2021. Chiocchio et al. (2024) find that US states that were more exposed to opioids before the COVID-19 pandemic have a slower recovery in labor force participation after the pandemic. Some researchers, such as Case and Deaton (2020), feel that increased substance abuse results from the despair of poor economic conditions. Others, such as Mulligan (2022), argue that generous disability and unemployment benefits have encouraged drug use and a drop in labor-force participation. This topic is ripe for examination through the lens of a structural model.

As Table 5 shows, many users obtain opioids through friends and relatives. This suggests that friends and relatives may play an important role in opioid addiction. Another potential extension of the current framework is analyzing how peers affect opioid consumption. Using an instrumental variable approach, Adamopoulou et al. (2024) show that opioid misuse is significantly affected by a best friend's misuse.

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Online Appendix for "The Downward Spiral"

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Date: July 2, 2024

A Data

A.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, 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, an individual can be a user or a nonuser of an opioid prescription pain reliever (PPR) or heroin based on opioid usage during the previous 12 months. 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, disabilities, 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 a dependence on or has developed an abuse for prescription opioids or heroin is labeled as an *addict*. If someone is misusing a prescription opioid or heroin but is not an addict, they are simply labeled as a *misuser*. The analysis is based on the 2019 survey. The sample is restricted to individuals between ages 18 and 64 who are not students.

Table 15 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 conditional on usage is shown in Table 16. 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, \$98,050, is chosen so that the average income for the sample is equal to the average value for individual income in the 2019 Current Population Survey (around \$48,000).

Table 15: NSDUH, Population Characteristics, 18-64

	Non-College	**College**
Gender (% male)		
Nonusers	52.65	47.69
Misusers	56.27	54.17
Addicts	51.95	39.89
Total Population	50.75	46.79
Employed (%)		
Nonusers	69.99	87.09
Misusers	65.48	87.37
Addicts	54.03	63.00
Total Population	67.86	86.18
Education (%)		
Nonusers	62.34	37.66
Misusers	73.02	26.98
Addicts	83.19	16.81
Total Population	65.14	34.86

Table 16: NSDUH, Income

	< \$10,000	**\$10,000 -\$19,999**	**\$20,000 -\$29,999**	**\$30,000 -\$49,000**	**\$50,000+**
Non-College					
Nonusers	24.09	18.37	15.03	22.21	20.30
Misusers	26.81	22.57	15.75	21.64	13.22
Addicts	40.16	25.00	11.71	11.54	11.59
Total Population	23.88	23.88	14.68	22.21	19.95
College					
Nonusers	9.78	6.97	7.05	17.49	58.72
Misusers	7.15	13.00	8.23	18.47	53.15
Addicts	25.02	17.85	2.18	13.92	41.03
Total Population	9.42	7.45	6.95	17.85	58.33

A.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. Information is provided 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 2019. 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 17.

Table 17: 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	15.97	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	0.69	0.32	5107.3	3433.0	51.3	35.9
2011	17.35	11.43	0.80	0.28	5702.4	1885.9	60.8	21.3
2012	16.84	10.01	0.74	0.25	5744.5	1910.9	51.0	33.1
2013	16.51	11.16	0.69	0.27	4132.2	1372.8	50.5	21.3
2014	17.24	10.98	0.68	0.29	3232.3	2341.5	43.6	24.7
2015	17.36	11.14	0.63	0.31	3106.4	1979.8	43.5	36.1
2016	13.89	10.09	0.51	0.22	3788.3	1211.2	35.8	37.2
2017	11.67	7.98	0.49	0.20	3660.2	1488.3	48.4	21.1
2018	11.00	7.52	0.50	0.24	3620.0	2460.7	65.9	54.0
2019	9.72	6.70	0.38	0.17	3187.8	1483.9	46.24	26.0

A.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." Following the CDC, the following International Classification of Disease (ICD) codes is used to calculate and classify opioid overdose deaths: T40.0, T40.1, T40.2, T40.3, T40.4, and T40.6. For deaths from specific opioids, the following classifications are 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 18. Prescription deaths include both deaths from natural and semisynthetic opioids (T40.2) and deaths from Methadone (T40.3). The majority of prescription deaths each year and nearly all the rise in prescription deaths over the 1999–2019 period are from natural and semisynthetic opioids as opposed to Methadone (see, for instance, Spencer et al. (2022)). Note that the sum of deaths from the different opioids columns can be larger than those from the "Any" column since fatalities can result from using multiple types of opioids.

Table 18: 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
2019	43867	3437	12622	822	11672	1188	32691	2362	1349	94

A.4 Figures

- *Figure 1* reports the number of opioid overdose deaths involving different types of opioids. The underlying numbers come from Table 18 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 opioids used by those with a Rx measured in MME (right panel), as reported in Table 17.

- *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.

- Figure *10* shows the fraction of the US population that are opioid users, the sum of misusers and addicts in the NSDUH, for non-college- and college-educated people between the ages of 18 and 64 for the 2002-2018 period.

B The Markov Chain in the Data and the Model

B.1 Procedure

To estimate the Markov chain a consistent mapping between the model and the data must be defined. 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. The fractions of individuals in each state derive from the model's ergodic distribution.

(In the model when an addict dies they are replaced by a young nonuser.) 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, while 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. The mapping between data and model categories is developed now.

Let $\mathtt{T_{ij}}$ be the fraction of individuals, as estimated from the 2019 US data, who move from state i to state j for $i, j = \mathtt{n}, \mathtt{p}, \mathtt{m}, \mathtt{a}, \mathtt{d}$. Let $\mathtt{t_n}, \mathtt{t_p}, \mathtt{t_m}, \mathtt{t_a}$, and $\mathtt{t_d}$ represent the fractions of the 2019 US population in these states. Assume that these fractions are invariant over time so that 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

$$\mathtt{t} = \mathtt{tT},$$

where $\mathtt{T}$ is the 5×5 transition matrix associated with the $\mathtt{T_{ij}}$'s. While the Markov chain is estimated for both the non-college- and college-educated segments of the population, the representation of the Markov chain will be cast generically to save on notation. A period corresponds to one year. Some of the cells in the transition matrix $\mathtt{T}$ 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 estimates of the fractions of the US population in each of the five addiction states.

The first task is to construct a Markov chain representation of the US data for the model, which differs from the theoretical one presented by equation (16). 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

$$T \equiv [i \to j]_{i,j}$$
$$\equiv \begin{bmatrix} \Gamma(\varepsilon_n^*)(1-\sigma_{np}) & \Gamma(\varepsilon_p^*)\sigma_{np} & [1-\Gamma(\varepsilon_n^*)](1-\sigma_{np}) + [1-\Gamma(\varepsilon_p^*)]\sigma_{np} & 0 & 0 \\ \Gamma(\varepsilon_n^*)\sigma_{pn} & \Gamma(\varepsilon_p^*)(1-\sigma_{pn}) & [1-\Gamma(\varepsilon_n^*)]\sigma_{pn} + [1-\Gamma(\varepsilon_p^*)](1-\sigma_{pn}) & 0 & 0 \\ \{\tilde{e}_b[1-S_{ba}(o)] + \tilde{e}_n + \tilde{e}_p\}\Gamma(\varepsilon_n^*)\sigma_{bn} & 0 & T_{\mathtt{mm}} & \tilde{e}_b S_{ba}(o) & 0 \\ [1-S_{ad}(o)]\sigma_{an}\Gamma(\varepsilon_n^*) & 0 & [1-S_{ad}(o)]\sigma_{an}[1-\Gamma(\varepsilon_n^*)] & [1-S_{ad}(o)](1-\sigma_{an}) & S_{ad}(o) \\ \Gamma(\varepsilon_n^*) & 0 & 1-\Gamma(\varepsilon_n^*) & 0 & 0 \end{bmatrix}, \quad (17)$$

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 below.

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 $\texttt{n}$ who will remain nonusers, or in $\texttt{n}$, 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 $\texttt{p}$ to category $\texttt{m}$ 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, $\texttt{m}$, into an addict, $\texttt{a}$. 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. 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.

The generic Markov transition matrix for the data estimation is

$$\begin{aligned} \texttt{T} &\equiv [i \to j]_{i,j} \\ &\equiv \begin{bmatrix} \texttt{T}_{\texttt{nn}} = 1 - \texttt{T}_{\texttt{np}} - \texttt{T}_{\texttt{nm}} & \texttt{T}_{\texttt{np}} & \texttt{T}_{\texttt{nm}} & 0 & 0 \\ \texttt{T}_{\texttt{pn}} & \texttt{T}_{\texttt{pp}} = 1 - \texttt{T}_{\texttt{pn}} - \texttt{T}_{\texttt{pm}} & \texttt{T}_{\texttt{pm}} & 0 & 0 \\ \texttt{T}_{\texttt{mn}} & 0 & \texttt{T}_{\texttt{mm}} = 1 - \texttt{T}_{\texttt{mn}} - \texttt{T}_{\texttt{ma}} & \texttt{T}_{\texttt{ma}} & 0 \\ \texttt{T}_{\texttt{an}} & 0 & \texttt{T}_{\texttt{am}} = \texttt{T}_{\texttt{an}}(1 - \texttt{T}_{\texttt{dn}})/\texttt{T}_{\texttt{dn}} & \texttt{T}_{\texttt{aa}} = 1 - \texttt{T}_{\texttt{an}} - \texttt{T}_{\texttt{ad}} & \texttt{T}_{\texttt{ad}} \\ \texttt{T}_{\texttt{dn}} = (\texttt{T}_{\texttt{nn}}\texttt{T}_{\texttt{pp}} - \texttt{T}_{\texttt{np}}\texttt{T}_{\texttt{pn}})/(\texttt{T}_{\texttt{pp}} - \texttt{T}_{\texttt{np}}) & 0 & 1 - \texttt{T}_{\texttt{dn}} & 0 & 0 \end{bmatrix}. \end{aligned} \tag{18}$$

Each cell in generic matrix (18) is a function of model parameters as is shown in matrix

(17). The model imposes cross-parameter restrictions on the values of $\mathtt{T_{am}}$ and $\mathtt{T_{dn}}$ that can be derived from matrix (17). For instance, the restriction on $\mathtt{T_{am}}$ is due to the fact that cell (4,3) in matrix (17), 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 $\mathtt{T_{dn}}$.

Once the entries in matrix (18) are filled, the parameters in the model's matrix representation of the data (17) can be recovered. First note that $\sigma_{pn} = \mathtt{T_{pn}}/\Gamma(\varepsilon_n^*)$, $\sigma_{np} = \mathtt{T_{np}}/\Gamma(\varepsilon_p^*)$, and $\sigma_{an} = \mathtt{T_{an}}/[\mathtt{T_{dn}}(1 - \mathtt{T_{ad}})]$. These three equations, together with $\Gamma(\varepsilon_n^*) = \mathtt{T_{dn}}$ and $\Gamma(\varepsilon_p^*) = \mathtt{T_{pp}}/(1 - \sigma_{pn})$, 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 $S_{ad}(o) = \mathtt{T_{ad}}$, the endogenous transition rate from addiction to death, is also determined. Last, two other items can also be determined from matrix (18); 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,

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

and

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

with $\tilde{e}_n$, $\tilde{e}_p$, and $\tilde{e}_b$ as defined above.

B.2 Estimation

US Population by Addiction State

Take the population between ages 18 and 64, about 201 million individuals in 2019. 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 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.[29]

[29] Details on all data definitions and sources are provided in Data Appendix A.

The 2019 NSDUH is used for the analysis, where 34.86 percent of respondents are college graduates or about 70.1 million individuals when extrapolated to the entire population, and the rest, about 131.0 million, do not have a college degree. Among non-college individuals between the ages 18 and 64, 4.13 percent, about 5.4 million people, are classified as misusers, and an additional 0.97 percent, roughly 1.3 million people, are labeled addicts. Shares of misusers and addicts are lower for college graduates; 2.85 percent (2.0 million misusers) and 0.37 percent (0.26 million addicts).

To determine the number of individuals who use prescription opioids for pain, the household component of the Medical Expenditure Panel Survey (MEPS) is used. In 2019, about 9.72 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 6.70 percent. Finally, according to the CDC's Vital Statistics, there were on average 47,304 annual opioid-overdose-related deaths in 2019 among those ages 18 to 64. Of these deaths, about 92.7 percent (43,867 individuals) were people without college degrees.

Putting all these pieces together yields the first and third rows of Table 1, which show the fractions of the population in each of the five data categories for both education groups; 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 odds ratios for college and non-college graduates in the nonuser, misuser, and addict categories are reported in Table 2, where the fractions of misusers and addicts in each group are compared with the population at large. As can be seen, non-college graduates have a higher proclivity for opioid usage than college graduates.

Filling in the Transition Probabilities

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

Transition Probabilities Directly Assigned. According to the NSDUH, about 14.36 percent of non-college and 20.24 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, 70.03 percent of non-college misusers and 48.15 percent of non-college addicts report pain as their primary motivation for opioid usage. The fractions for college graduates are 67.54 and 45.99 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

Table 19: Transitions, US Population

	Source	Non-College	College
$\mathtt{T_{nm}}$	NSDUH	0.0035	0.0032
$\mathtt{T_{pm}}$	NSDUH	0.0305	0.0431
$\mathtt{T_{ad}}$	NSDUH, CDC	0.0345	0.0134
$\mathtt{T_{an}}$	NSDUH, Medical Studies	0.0463	0.0310

groups yields (numbers in *italics* in the brackets refer to *college* graduates)

$$\mathtt{T_{nm}}\mathtt{t_n} = 0.5 \times 0.1436[\mathit{0.2024}] \times \mathtt{t_m} \quad \text{and} \quad \mathtt{T_{pm}}\mathtt{t_p} = 0.5 \times 0.1436[\mathit{0.2024}] \times \mathtt{t_m},$$

delivering $\mathtt{T_{nm}}$ and $\mathtt{T_{pm}}$. given the observed values for $\mathtt{t_n}, \mathtt{t_p}$, and $\mathtt{t_m}$ in Table 1.[30]

Dividing the number of deaths by the number of addicts yields a value for $\mathtt{T_{ad}}$. To determine $\mathtt{T_{an}}$, 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 30.90 percent of non-college addicts and 20.66 percent of college addicts do so. Set $\mathtt{T_{an}}$ to be the product of the recovery and treatment rates. The transitions for each education class based on available information are reported in Table 19.

Estimated Transition Probabilities. *Estimated Transition Probabilities.* There are four transition probabilities left to be determined: namely, $\mathtt{T_{np}}$, $\mathtt{T_{pn}}$, $\mathtt{T_{mn}}$ and $\mathtt{T_{ma}}$. These are treated as free parameters and 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 delivers $\mathtt{T_{np}}$= 0.0422, $\mathtt{T_{pn}}$ = 0.3394 , $\mathtt{T_{mn}}$=0.1246 and $\mathtt{T_{ma}}$=0.0190 for the non-college population and $\mathtt{T_{np}}$= 0.0147, $\mathtt{T_{pn}}$ = 0.1545, $\mathtt{T_{mn}}$=0.1967 and $\mathtt{T_{ma}}$=0.0057 for the college population.

[30]Summing the above two conditions gives $\mathtt{T_{nm}}\mathtt{t_n} + \mathtt{T_{pm}}\mathtt{t_p} = 0.1436[\mathit{0.2024}] \times \mathtt{t_m}$; i.e., 14.36 percent of misusers without a college degree and 20.24 of those with one are new arrivals from the nonuser and prescription-user states.

Estimation Results

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

$$\mathtt{T} = \begin{bmatrix} 0.9543,\ \mathit{0.9821} & 0.0422,\ \mathit{0.0147} & 0.0035,\ \mathit{0.0032} & 0 & 0 \\ 0.3394,\ \mathit{0.1545} & 0.6301,\ \mathit{0.8024} & 0.0305,\ \mathit{0.0431} & 0 & 0 \\ 0.1246,\ \mathit{0.1967} & 0 & 0.8564,\ \mathit{0.7976} & 0.0190,\ \mathit{0.0057} & 0 \\ 0.0463,\ \mathit{0.0310} & 0 & 0.0001,\ \mathit{0.0001} & 0.9191,\ \mathit{0.9556} & 0.0345,\ \mathit{0.0134} \\ 0.9985,\ \mathit{0.9975} & 0 & 0.0015,\ \mathit{0.0025} & 0 & 0 \end{bmatrix}.$$

The long-run probabilities, $\mathtt{t}$, connected with these Markov chains are reported in Table 1. The model's transition probabilities can now be recovered from the estimated transition matrix $\mathtt{T}$. The transition probabilities σ_{np}, σ_{pn}, σ_{bn}, and σ_{an} are exogenous in the model and can be retrieved directly from the estimated transitions probabilities between the corresponding data categories, $\mathtt{T_{np}}$, $\mathtt{T_{pd}}$, $\mathtt{T_{bn}}$, and $\mathtt{T_{an}}$. For example, as can be seen from the above estimated transition matrix, $\mathtt{T_{np}}$ is 0.0422 for non-college and 0.0147 for college individuals. These values imply that in the model σ_{np} is 0.0442 for non-college and 0.0155 for college, where the slight mismatch is due to differences between model and data categories. The entries in the matrix $\mathtt{T}$ also determine observed values for $\Gamma(\varepsilon_n^*)$ and $\Gamma(\varepsilon_p^*)$, the fractions of nonusers and prescription users who do not experiment with opioids. Since ε_n^* and ε_p^* are endogenous, the 2019 benchmark model has to be calibrated to hit these datums, as discussed in Section 5. Finally, in the data $\mathtt{T_{ma}} = 0.0190$ of non-college misusers become addicts while $\mathtt{T_{ad}} = 0.0345$ of addicts die each period. The numbers for college individuals are 0.0057 and 0.0134. For the model, these entries give observations for the endogenous transition probabilities $S_{ba}(o)$ and $S_{ad}(o)$. Again, since o is an endogenous variable, the model is calibrated in Section 5 to match these statistics. Table 3 summarizes the model parameters obtained from the Markov chain $\mathtt{T}$.

C Calibration Inputs

Table 20: Daily Opioid Usage, 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

Table 21: Opioid Misuse Last Month

		Non-college		**College**	
		Misusers	**Addicts**	**Misusers**	**Addicts**
Frequency distribution of misuse					
Number of days	*Assigned value*	%	%	%	%
Less than 5	2.5	68.81	20.09	73.13	46.83
5-9	7	11.71	7.79	21.54	0.68
10-14	12	9.23	16.86	0.25	5.74
15-19	17	5.87	11.66	3.64	12.46
20-30	25	6.38	43.61	1.44	34.29
Average number of days misused		6.19	15.95	4.34	12.60

D VSL

To calculate the VSL, the increase in current consumption required to compensate each person for a small increase in their risk of dying in the next period, σ_δ, is computed. The calculation is made assuming individuals do not change their behavior in response to the change in their death risk or the compensating differential; i.e., there is no re-optimization. The amount they must be compensated is informative about the utility obtained in death, δ, relative to the utility while alive. This exercise is done in each of the four stages: $s = n, p, b, a$.

Focus on the nonuser stage n. Let $\mathtt{cv}_i$ be the additional fraction of current income that a nonuser must receive to compensate them for facing the risk of dying next period, σ_δ. The compensating variation, $\texttt{cv}_i$, must solve the nonlinear equation

$$\begin{aligned}
&\Gamma(\varepsilon^*_{ni})\{U((1+\texttt{cv}_i)\pi_n\mathfrak{h}) + L_n(1-\mathfrak{h}) + \beta(1-\sigma_\delta)[(1-\sigma_{np})N + \sigma_{np}P]\} \\
&\quad + [1-\Gamma(\varepsilon^*_{ni})]\{U\left((1+\texttt{cv}_i)\pi_n\mathfrak{h} - io\right) + O_n(o-\underline{o}) + \mathbf{E}[\varepsilon_{ni}|\varepsilon_n \geq \varepsilon^*_{ni}] + L_n(1-\mathfrak{h}) \\
&\qquad + \beta(1-\sigma_\delta)[(1-\sigma_{bn})B + \sigma_{bn}N]\} + \beta\sigma_\delta\delta = N_i, \text{ for } i = p, q.
\end{aligned}$$

The amount that the nonuser must be compensated is defined by $\texttt{CD} = \texttt{cv}_i \times \pi_n\mathfrak{h}$.

In the prescription-user stage, p, the compensating variation, $\texttt{cv}_i$, solves

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

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

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

and

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

In the abuser and addict stages, $\texttt{cv}$ is the additional fraction of current working income that the individual must receive to be compensated for the increase in the risk of dying next period.

E Compensating Variations

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

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

Now, consider a small change in this risk. Since it is endogenous, hold o fixed at the benchmark value and let σ_j change to obtain some desired change in $\sigma_j \sqrt{o}$. How much would a person be willing to pay out of current consumption to obtain this decline in risk? This exercise could be done in any of the four stages: $s = n, p, b, a$. Focus on the nonuser stage n and consider a small decline in σ_d. 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. Therefore, 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 $\mathtt{cv}_i$ 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, $\mathtt{cv}_i$, must solve the nonlinear equation

$$\begin{aligned}\Gamma(\varepsilon_{ni}^{*\prime})\{U((1-\mathtt{cv}_i)\pi_n\mathfrak{h}) + L_n(1-\mathfrak{h}) + \beta[(1-\sigma_{np})N' + \sigma_{np}P']\} \\ + [1-\Gamma(\varepsilon_{ni}^{*\prime})]\{U\left((1-\mathtt{cv}_i)\pi_n\mathfrak{h} - io'\right) + O_n(o' - \underline{o}) + \mathbf{E}[\varepsilon_{ni}|\varepsilon_n \geq \varepsilon_{ni}^{*\prime}] + L_n(1-\mathfrak{h}) \\ + \beta[(1-\sigma_{bn})B' + \sigma_{bn}N']\} = N_i, \text{ for } i = p, q,\end{aligned}$$

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. The willingness to pay for a nonuser is defined by $\mathtt{WTP} = \mathtt{cv}_i \times \pi_n\mathfrak{h}$. For the beginning stage, the value of $\mathtt{cv}_i$ is likely to be small; addiction is an unlikely event and it is off in the future.

In the prescription-user stage, p, the compensating variation, $\mathtt{cv}_i$, solves

$$\begin{aligned}\Gamma(\varepsilon_{pi}^{*\prime})\left\{U((1-\mathtt{cv}_i)\pi_p\mathfrak{h} - p\underline{o}) + L_p(1-\mathfrak{h}) + \beta[(1-\sigma_{pn})P' + \sigma_{pn}N']\right\} \\ + [1-\Gamma(\varepsilon_{pi}^{*\prime})]\{U\left((1-\mathtt{cv}_i)\pi_p\mathfrak{h} - p\underline{o} - i(o' - \underline{o})\right) + O_p(o' - \underline{o}) + \mathbf{E}[\varepsilon_p \geq \varepsilon_{pi}^{*\prime}] + L_p(1-\mathfrak{h}) \\ + \beta[(1-\sigma_{bn})B' + \sigma_{bn}N']\} = P_i, \text{for } i = p, q.\end{aligned}$$

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

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

and

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

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

References

[1] Spencer, Merianne R., Minino Arialdi M. and Margaret Warner. 2022. "Drug overdose deaths in the United States, 2001–2021." NCHS Data Brief, no 457. Hyattsville, MD: National Center for Health Statistics. DOI: https://dx.doi.org/10.15620/cdc:122556.