2-24-2020

A Dynamic Model of the Opioid Drug Epidemic with Implications for Policy

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Word count: xxxx
Figures: 2
Tables: 3

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Financial Disclosure and Funding Source

The initial version of the model described in this paper was developed under a contract funded by Herc Litigation Services LLC and the law firms of Levin Papantonio and Baron & Budd. Consulting fees were paid to Homer Consulting and Wayne Wakeland. The funders are aware of and support publication of the modified version presented herein.

Abstract

Background: The U.S. opioid epidemic has caused substantial harm for over 20 years. Policy interventions have had limited impact and sometimes backfired. Experts recommend a systems modeling approach to address the complexities of opioid policymaking.

Objectives: Develop a system dynamics simulation model that reflects the complexities and can anticipate intended and unintended intervention effects.

Methods: The model was developed from literature review and data gathering. Its outputs, starting 1990, were compared against 12 historical time series. Illustrative interventions were simulated for 2020-2030: reducing prescription dosage by 20%, cutting diversion by 30%, increasing addiction treatment from 45% to 65%, and increasing lay naloxone use from 4% to 20%. Sensitivity testing was performed to determine effects of uncertainties. No human subjects were studied.

Results: The model fits historical data well with error percentage averaging 9% across 201 data points. Interventions to reduce dosage and diversion reduce the number of persons with

opioid use disorder (PWOUD) by 11% and 16%, respectively, but each reduces overdoses by only 1%. Boosting treatment reduces overdoses by 3% but increases PWOUD by 1%. Expanding naloxone reduces overdose deaths by 12% but increases PWOUD by 2% and overdoses by 3%. Combining all four interventions reduces PWOUD by 24%, overdoses by 4%, and deaths by 18%. Uncertainties may affect these numerical results, but policy findings are unchanged.

Conclusion: No single intervention significantly reduces both PWOUD and overdose deaths, but a combination strategy can do so. Entering the 2020s, only protective measures like naloxone expansion could significantly reduce overdose deaths.

Background and Purpose

The epidemic of opioid abuse in the United States started in the late 1990s and is still unabated. The story is well-known: excessive prescriptions, followed by diversion to a black market, growing addiction, the shift to heroin, and then the ravages of deadly illicit fentanyl (1-4). The number of persons with opioid use disorder (PWOUD) tripled from 1995 to 2010, rising to more than 2 million (5); and since then has remained stubbornly at that level despite addiction treatment more than tripling from 2003 to 2015 (6). The number of opioid overdose deaths rose from about 8,000 in 1999, to 21,000 in 2010, to 49,000 in 2017 (7). Hundreds of thousands have lost their lives to the epidemic, and the estimated economic costs of opioid addiction and death are nearly $100 billion per year (8-9).

A variety of policy interventions have been proposed to address the epidemic. These include efforts to control opioid prescribing and dosage strength, to control diversion, to expand and improve addiction treatment, and to reduce overdose deaths and other harms (1). Past intervention efforts have had limited success and have sometimes backfired. One example is the introduction of tamper-resistant OxyContin in 2010, which did reduce abuse of that drug but also caused many PWOUD to switch from prescription opioids to heroin (10)—a risky switch given the later widespread fentanyl contamination of heroin. Similarly, there is a concern that efforts to limit prescription and diversion of legal opioids might leave street users more vulnerable to dangerous counterfeit fentanyl pills (1). Even the "obvious" policy of expanding naloxone distribution to reduce overdose deaths has been questioned by some, because it might encourage more opioid abuse (11, 12).

A committee of the National Academies of Science, Engineering, and Medicine has recommended that a systems modeling approach be taken to deal with such complexities and policy uncertainties (1). Their report cited modeling work by Wakeland and colleagues (13-14) as a first step in that direction. Other opioid systems frameworks and models have also been presented recently (15-18).

Here we present a new systems model at the U.S. national level that uses the same system dynamics simulation methodology as the original Wakeland work (which traced the epidemic through 2011) but updates and extends beyond the scope of the older model. For example, the new model includes the effects of fentanyl in the black markets for prescription opioids and heroin. It can be used to evaluate a wide variety of policy interventions, quantifying their intended and unintended consequences over time. We first describe the model's basic

structure and outputs, and then describe the results of illustrative intervention testing using the model.

Methods

(An IRB consent process/ethics committee is not applicable. This study did not involve human subjects.)

Model Description

1. System dynamics (SD) modeling

System dynamics was developed in the 1950s and is used to study complex issues of business strategy and public policy. An SD model consists of interlinked differential equations, linear and nonlinear algebraic relationships, and input assumptions. It produces outputs that replicate historical trajectories and projects them into the future, along with the impacts of potential interventions and uncertainties. The approach has been applied to many population health and drug abuse issues (19-22).

SD models typically divide populations of interest into separate compartments or stocks, detailing the flows that go into, between, and out of the stocks.

SD models also include behavioral feedback loops that can cause annual flow rates (also called transition rates) to change predictably over time rather than remaining fixed. For example, new initiates to opioid non-medical use might initially be attracted by the presence of plentiful availability on the street; but a large increase in the number of non-medical users might subsequently cause street availability to diminish, thus limiting further initiation.

The inclusion of such feedback loops distinguishes fully realized SD models from less elaborate model types that assume fixed or exogenous transition rates. Such simpler models have been used for studying the opioid epidemic (15-16); but without explicit feedback loops, they cannot systematically anticipate the dynamic consequences of potential interventions.

2. Model development and overview

We followed established procedures for SD model development (19). This involved first updating our understanding of the epidemic (beyond the original Wakeland work) based on the latest reports and analysis, including studies of recent trends. From these studies, as well as our own analysis of several online datasets, we developed longitudinal time series starting from as far back as 1990 to the present (24-47). We then developed, through multiple iterations, a dynamic structure (involving stocks, flows, feedback loops, and external factors) capable of explaining the historical trends. We also did extensive sensitivity testing (see online Appendix) to determine what effect uncertainties might have on model outputs looking as much as a decade into the future.

This process resulted in a model (comprising 8 stocks, some 200 algebraic variables, and some 80 input parameters) that conforms with the literature, reproduces a variety of national-level historical trends, and is fit for policy analysis. The model was implemented using Vensim™ (version 7.3.5), a standard for advanced SD modeling. Full details of the model's structure, equations, and input parameters are presented elsewhere (23). Figure 1 presents an overview of the model's causal structure. Table 1 lists variables for which we assembled longitudinal

historical data, including 8 time series used to calibrate model inputs and 12 time series against which model outputs are compared.

<Figure 1 goes about here>

<Table 1 goes about here>

At the heart of the model are non-medical users (NMUs) of opioids, subdivided into six mutually exclusive stocks defined by two dimensions, the first of which is drug type used: during any given year, some NMUs use prescription opioids (PO) but not heroin, some use heroin but not PO, and some use both PO and heroin. The second dimension is the presence or absence of opioid use disorder (OUD).

Associated with the six NMU stocks are 30 inflows, outflows, and interconnecting flows. These fall into five categories: flows of initiation, becoming addicted, shifting among drug type used (PO and/or heroin), quitting (abstinent for a year), and death (from overdose and all other causes).

3. PO non-medical use initiation, addiction, and quitting

One source of PO NMU initiation and addiction is from medical users, those who have scripts and initially use as directed. The number of medical users is modeled based on the number of PO scripts written per month. PO script volume is modeled exogenously reflecting historical values (see Table 1) and projected forward based on population growth and aging; one may also simulate a future policy intervention to reduce script volume.

Medical users of PO may transition to non-medical use (OUD or non-OUD). But only a minority of new PO NMUs have their own script (39, 44), the great majority being "street" initiates who use diverted PO that is shared or obtained on the black market.

Street initiates to PO grew from 1990 to the early 2000s, before starting a long and uneven decline. The growth likely occurred for two reasons: first, the snowball effect of social diffusion; and second, a gradual increase in PO availability (and decrease in price) on the street. The decline likely occurred initially because of the fear of overdose: PO NMU overdose deaths nearly tripled from 1999 to 2011 (47). The decline in PO initiation after 2010 was also likely due to availability disruptions (14, 39; and discussed below). Both availability and fear are well-known factors affecting illicit drug initiation (21, 48).

The likelihood of medical users becoming addicted (transitioning to OUD) increases with higher prescribed dose strengths (measured in milligrams of morphine equivalent or MME) (49). Average dose strength (as a proxy for the entire distribution of different dose strengths being prescribed) is modeled exogenously to reproduce the historical MME trend (28-29); one may also simulate a future policy intervention to reduce average prescribed dose strength.

The more common path to PO OUD, rather than from medical use, is through escalation from non-OUD street use. If the relative availability of diverted PO were to grow, the risk of escalation would also increase, because greater accessibility tends to boost frequency of use (13, 50).

Our model-based analysis of the historical data suggests that the factors of fear and availability that affected PO initiation also affected rates of quitting among PO NMUs. Another factor

affecting quitting is medication-assisted treatment (MAT). MAT can boost the likelihood of a PWOUD quitting by a factor of 2 or more. MAT also reduces the frequency of street use and the risk of overdose (51-52). The fraction of PWOUD receiving MAT (at some point during the year) more than doubled during 2003-2016, rising from less than 20% to more than 40% (5-6, 29). One may simulate a future policy intervention to further increase the fraction of PWOUD receiving MAT.

4. PO street availability, price, and diversion

PO relative street availability is modeled through a pair of stocks, one representing all apparent PO on the street (both authentic and counterfeit) and the other representing only counterfeit (fentanyl) pills; these stocks are measured in actual or apparent MME. These stocks have inflows of newly diverted PO and newly arriving counterfeit pills. They have outflows of street demand or consumption, driven by the number of PO NMUs (OUD as well as non-OUD). PO relative availability on the street is the ratio of the combined stock to current street demand.

Street availability per se is not tracked in real life, but a closely related measure is average street price. (We model average PO street price per MME as an inverse function of relative availability.) Large, mostly reliable samples of PO street prices may be found at crowdsourcing websites such as StreetRx.com and Bluelight.org (45-46, 53). These data suggest that PO street price generally decreased from 2007 to 2018, except for a large upward spike during 2011-2013.

In order to approximate this pattern in the model, we allow the diverted fraction of PO to vary over time, in two ways. First, we assume the existence of a balancing feedback loop, reflecting

a profit motive for suppliers (50), in which low current street availability (thus, higher street price) spurs more diversion, while high current availability (lower price) inhibits further diversion.

Second, we assume that interventions had the effect of reducing diversion and street availability during the period 2011-2013, causing the price to spike during those years. One was the introduction of tamper-resistant OxyContin in late 2010 (1, 10). The other was a crackdown on "pill mills" (for example, in Florida and Texas) that dole out large quantities of PO based on fraudulent scripts (54-55). These control efforts had mostly run their course by 2014. One may, however, simulate other possible future efforts to control diversion.

5. Heroin initiation, addiction, and quitting

We model two routes of initiation to heroin: from prior PO NMU and not. Since the National Survey on Drug Abuse and Health (NSDUH) first starting tracking this in 2000, most new heroin users (OUD and non-OUD) have come from prior PO NMU as opposed to coming directly to heroin (3, 44).

The historical pattern of heroin initiation was uneven growth from 1990 through the early 2010s followed by decline. The growth through 2010 likely reflects a few factors: social diffusion; the steady decline in heroin price (33-35); and the growth (during 2002-2011) in the non-oral abuse of PO (injecting or inhaling, which typically precede the transition from PO to heroin) (31-32, 56). Further growth in heroin initiation during 2011-2013 reflects the upward spike in PO price that occurred during those years (45-46), relative to a heroin price that was

continuing to decline (10). We model heroin price as an exogenous time series that can be modified when testing future scenarios.

The rapid decline in heroin initiation seen in the data since 2014 likely reflects fear of overdose; heroin user overdoses grew dramatically during this recent period largely due to contamination of street heroin by illicit fentanyl (4, 47).

We model two routes of becoming a heroin user with OUD: from prior PO OUD (the more common route) and through escalation from non-OUD heroin use. NSDUH data for 2000-2014 indicate that 50-63% of heroin users have OUD (44).

Treatment (MAT) affects the rate of quitting for heroin addicts. However, MAT is about 20% less effective at generating quits in persons with heroin OUD than in persons with PO OUD (57).

6. Opioid overdoses and overdose deaths

Heroin users and persons with PO OUD using non-orally (injecting and inhaling) are at a risk of overdosing twice or more that of persons with PO OUD using orally (58) and, we estimate, 20-25 times that of non-OUD PO NMUs. Risks for all opioid NMUs (both PO and heroin users) increased after 2013 due to the rise of illicit fentanyl (and even more dangerous analogs such as carfentanil), resulting in a doubling of annual opioid overdose deaths from 2013 to 2017 (4, 47). Recent data suggest that, since 2017, the growth in opioid overdose deaths has finally slowed and perhaps peaked (59, 60).

For PO NMUs, the illicit fentanyl risk is from look-alike counterfeit pills, and this risk is calculated in the model by comparing the simulated stock of such counterfeits to the total stock

of PO available on the street. For heroin users, the risk is from fentanyl powder that looks identical to heroin. We model the influx of fentanyl pills and fentanyl powder as exogenous time series that can be modified when testing future scenarios.

Most overdose deaths occur at home or otherwise outside a medical facility; this fraction increased during 1999-2015 from 65% to 73% (61). Laypersons thus have a key role to play in administering naloxone to reverse overdoses, and it has been demonstrated that they can do so effectively (62-63). An increasing number of public health departments, pharmacies, and other organizations provide naloxone kits to laypersons. More than 26,000 opioid overdose reversals were reported through mid-2014 by such organizations and more than 8,000 in 2013 alone (64). We estimate that this represented only about 3% of the potential opportunity for naloxone reversal by laypersons in 2013, and perhaps 4% by 2017. One may simulate a future policy intervention to increase the lay use of naloxone.

Model Testing and Results

Baseline simulation 1990-2030

We performed a baseline (or "status quo") simulation from 1990 to 2030 assuming no further changes beyond 2020 in any of the model's external inputs other than population growth and aging per Census projections (24). This includes no further decline in the per-capita (and age-standardized) opioid prescription rate, which relative to the 1995 level (=1.0) had risen to 1.75 by 2010 but was down to 1.3 by 2017 and still falling (27). It also includes no further decrease after 2020 in the average MME dosage prescribed, nor in the price of heroin; and no further

increase in the non-oral fraction of PO non-medical use, nor in the influx of fentanyl, nor in the MAT fraction of PWOUD, nor in lay naloxone usage.

Figure 2 presents time graphs for 12 outputs from the baseline run and comparisons with historical data. The fit to history is quantified in Table 1 in terms of the mean absolute error as a percentage of the mean (MAEM), a commonly used metric for such comparisons (19). The MAEM is less than 18% for all 12 output variables and averages 9% across the 201 data points they encompass. This may be considered good model performance, especially because some of the survey data are erratic, including data for heroin users, PO and heroin initiation, and PO street price.

<Figure 2 goes about here>

Under the status quo assumptions, the model projects flattening in the number of PO NMUs after 2020, continued gradual decline in persons with PO OUD (Figure 2 panel A), and a decline in heroin users (panel B) reversing the rapid growth of 2005-2015. These patterns reflect low rates of initiation (panel C) due to continued fear of overdosing; as well as fewer persons with PO OUD transitioning to heroin (panels C and D) due to lower simulated PO street price. The lower simulated PO street price (panel E), in turn, reflects less consumption demand due to fewer persons with PO OUD, thus greater relative availability on the street.

Overdose deaths decline gradually after 2020 (panel F) reflecting the decline in PWOUD. But fentanyl remains a scourge, responsible for a great majority of overdose deaths in heroin users, as well as more than 50% of overdose deaths in PO NMUs by the early 2020s. The latter

reflects the greater exposure of PO NMUs to counterfeit pills as the street supply of authentic (diverted) PO declines, reflecting a gradual decline in diversion as PO street demand softens.

Note that the baseline projections of our model are in some cases different from the projections of other previous models (15-16). The other models agree that the prevalence of PO non-medical use is on a steady decline, but whereas we project a decline in heroin use they project a continued increase. Likewise, whereas we project a decline in opioid overdose deaths during the 2020s, they project a continued increase. The apparent peaking in recent overdose deaths data (59-60) may call into question these projections of continued growth made by other models.

Intervention tests 2020-2030

Table 2 presents four categories of intervention that can be tested using the model, along with real-world examples of each. These intervention strategies and tactics have been described by the National Academies committee and other policy analysts (1, 15, 65-69). Of the 11 consensus recommendations in the National Academies report, the only ones that do not fall into one of our four categories are behavioral counseling of pain patients to prevent addiction, and syringe exchanges to reduce disease transmission (1).

<Table 2 goes about here>

We have experimented with various plausible magnitudes of intervention, as well as combinations of interventions. Here we consider 5 illustrative tests, all implemented starting in 2020 and maintained through the end of the simulation in 2030:

1. Reduce the average prescribed opioid MME dose by 20%. (We estimate this would reduce average dose to its 2002 value, and 28% below its 2011 peak.)

2. Cut PO diversion by 30%. (This would be stronger than the diversion control efforts of 2011-2013 which we estimate cut diversion temporarily by 20%.)

3. Increase the fraction of addicts receiving MAT from its baseline 45% to 65%. (This would likely require improved insurance coverage for office-based MAT [66-69].)

4. Increase naloxone use by laypersons (for overdoses not treated in medical facilities) from its baseline 4% to 20%. (Lay naloxone use expanded six-fold from 2010 to 2015 [64]; here we consider another five-fold expansion, perhaps through multiple strategies [65].)

5. Combine the above four interventions.

Table 3 presents simulated outcomes under these interventions (and the baseline run for comparison) in the year 2030 for three variables: persons with OUD (PWOUD), opioid overdoses seen at hospital emergency departments, and opioid overdose deaths. These are variables for which we have baseline data (see Table 1) and are the three variables in the model that in real life most directly indicate the burden of opioid abuse (8-9). We have also produced graphs showing a variety of outcome variables as they change continuously over time from 2020 to 2030 (see online Appendix). With these outputs, we can tell the following story about each simulation relative to the baseline run:

<Table 3 goes about here>

Reduce average dose by 20%: Medical user addiction is reduced, as is PO street supply (thus boosting PO street price). The increase in PO street price pushes more PO NMUs into heroin use. Also, the reduction in authentic PO on the street exposes more PO NMUs to counterfeit pills. As a result, overdoses from authentic PO decline, while heroin and fentanyl overdoses increase. These impacts are mostly complete by 2026. By 2030, PWOUD are reduced 11%, but total opioid overdoses and deaths are reduced by only 1%.

Cut PO diversion by 30%: Although this intervention does not affect medical user addiction, it otherwise has consequences like those of the previous intervention. It more strongly reduces persons with PO OUD but also more strongly boosts heroin users. By 2030, PWOUD are reduced 16%, but total overdoses and deaths are reduced by only 1%.

Increase MAT to 65%: This intervention nicely reduces overdoses and deaths within the first year of implementation, but its longer-term effects are more modest. Most treated PWOUD do not become permanent abstainers, but their frequency of street use is reduced (51-52). Less frequent PO use means less street demand, resulting in an increase in street availability—which attracts more PO NMUs. As a result, though MAT reduces persons with heroin OUD, persons with PO OUD increase, enough to cause a net 1% increase in total PWOUD by 2030. With persons with PO OUD up and persons with heroin OUD down, total overdoses and deaths end up being reduced by a net 3% by 2030.

Increase lay naloxone use to 20%: This intervention immediately reduces overdose deaths. It does allow PWOUD to stay alive longer and is the only intervention we have tested that leads

to some increase in the number of overdoses. By 2030, overdose deaths are down 12% relative to the baseline, but PWOUD are up 2% and total overdoses by 3%.

Combine the four interventions: Combining the four interventions reduces PWOUD by 24%, overdoses by 4%, and deaths by 18% by 2030. This is approximately what one would get from simply summing the individual intervention impacts, an indication that the interventions are complementary rather than mutually interfering or redundant.

Sensitivity testing of intervention findings

We have tested the sensitivity of intervention findings to two types of uncertainty (see online Appendix). The first is uncertainty regarding some 50 of the model's input constants. To address this uncertainty, we have performed extensive Monte Carlo testing, identified hundreds of "qualifying parameter sets" based on fit-to-history, and then tested the interventions against each of these parameter sets (70). We have determined that the model's policy findings are unaffected by uncertainty of constants, although the numerical results may change somewhat.

We have also tested against future uncertainty in exogenous inputs (aside from interventions), including future non-oral use of PO, heroin price, and influxes of fentanyl powder and counterfeit pills. We find that the basic policy findings are unaffected by this type of uncertainty as well.

Conclusion

The opioid epidemic is complex and warrants a systems modeling approach. The significance of the model presented here is that it includes behavioral feedback loops and has greater breadth than other models to date, reproduces the epidemic's entire history along several interacting dimensions, and demonstrates both intended and unintended consequences of policy intervention.

Model testing indicates that no single intervention significantly reduces both persons with OUD and overdose deaths, but this can be accomplished by a combination strategy. At this advanced stage of the opioid epidemic, entering the 2020s, only protective measures like naloxone expansion (or perhaps European-style drug checking services (71)) could significantly reduce overdose deaths.

The model's policy findings are insensitive to uncertainties in inputs, a sign of its robustness. However, it is still a simplified version of reality subject to improvement as are all models. For example, in modeling the fear of overdose, we have assumed that fatal and nonfatal overdoses are perceived as equally frightening. Such was the conclusion of a previous study (21), but perhaps this assumption should be explored further, as it could affect conclusions about the impact of naloxone expansion. Other possible improvements include greater detail in our depictions of medical use, diversion, street supply, and treatment, as well as more detailed policy analyses.

Acknowledgments

We would like to acknowledge the substantial contributions of our colleagues: data analyst Christina Ingersoll, researcher Elizabeth Etherton, methodological advisors John Sterman and Tom Fiddaman, and project supervisor Rayford Etherton.

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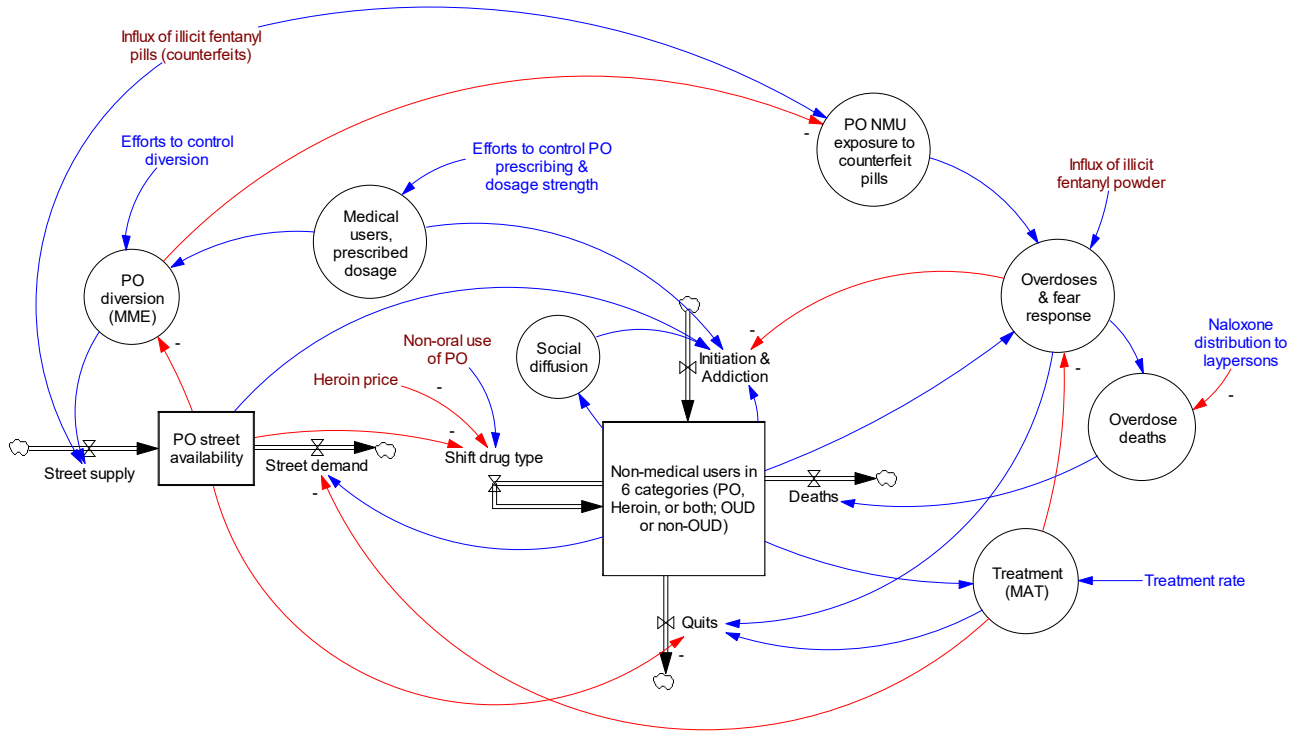


Figure 1. Model overview diagram

(Rectangle=stock variable; Thick arrow with valve symbol=flow variable; Circle=other calculated variable; Blue text=intervention input variable; Brown text=other input variable; Blue arrow= causal link with positive polarity; Red arrow with minus sign=causal link with negative polarity; PO=prescription opioids; NMU=non-medical users; OUD=opioid use disorder; MME=milligrams morphine equivalent; MAT=medication-assisted treatment.)

Table 1. Longitudinal data sources and baseline run fit to history in terms of mean absolute error as percentage of historical mean (MAEM %)

Variable	Datasets and Sources	Year range	# of data points	MAEM %
Data used for calibration of model inputs				
US population ages 20-39, 40-59, 60+	US Census tables (24-25)	1990-2030	15	(not applicable)
PO scripts	IQVIA NPA/Xponent (26-27)	1992-2017	26	
PO script morphine mg. equiv. (MME)	ARCOS (28-30)	1994-2018	25	
Persons with OUD treated	N-SSATS, ARCOS (6, 29)	2003-2016	14	
% PO OUD who use non-orally	TEDS (31-32)	1994-2014	21	
Avg heroin street price per pure mg	STRIDE (33-35)	1993-2016	22	
Illicit fentanyl trend (quantity seized)	NFLIS (36-37)	2001-2017	17	
ED visits for opioid overdose	NHAMCS (38)	1993-2010	9	
Data used for comparison of model outputs with history				
PO total NMUs	NSDUH (13, 39-40)	1995-2018	24	6.4%
PO NMUs with OUD	NSDUH (5, 13, 39-41)	2000-2017	18	9.0%
PO NMU initiates	NSDUH (13, 38, 42-43)	1990-2018	27	10.3%
Heroin total users	NSDUH (39-41, 44)	1990-2018	19	12.4%
Heroin addicted users	NSDUH (40-41, 44)	2000-2014	14	9.0%
Heroin initiates	NSDUH (39)	2002-2018	17	17.8%
% Heroin users also PO NMU	NSDUH (44)	1990-2016	7	13.9%
% Heroin initiates previously PO NMU	NSDUH (3, 44)	2000-2016	8	10.1%
Avg PO street price per MME	StreetRx, Bluelight (30, 45-46)	2007-2018	12	17.9%
OD deaths from PO	WONDER (47)	1999-2016	18	5.2%
OD deaths from illicit opioids	WONDER (47)	1999-2016	18	3.5%
OD deaths total	WONDER (47)	1999-2017	19	3.7%

Key to dataset acronyms:

NPA: National Prescription Audit (IQVIA, Inc.)

ARCOS: Automated Reports and Consolidated Ordering System (DEA)

N-SSATS: National Survey of Substance Abuse Treatment Services (SAMHSA)

TEDS: Treatment Episode Data Set (SAMHSA)

STRIDE: System to Retrieve Information from Drug Evidence (DEA)

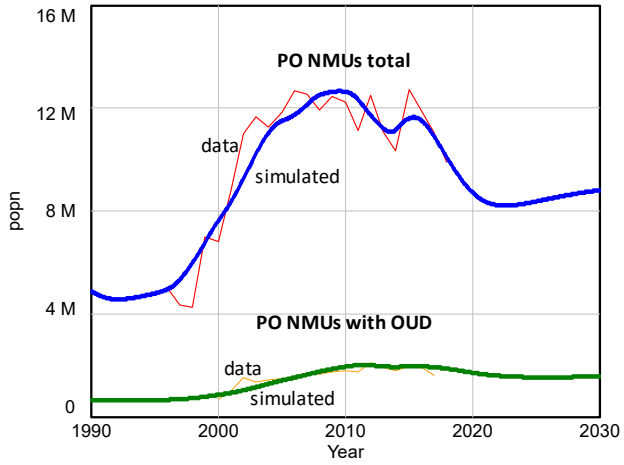
NFLIS: National Forensic Laboratory Information System (DEA)

NHAMCS: National Hospital Ambulatory Medical Care Survey (CDC)

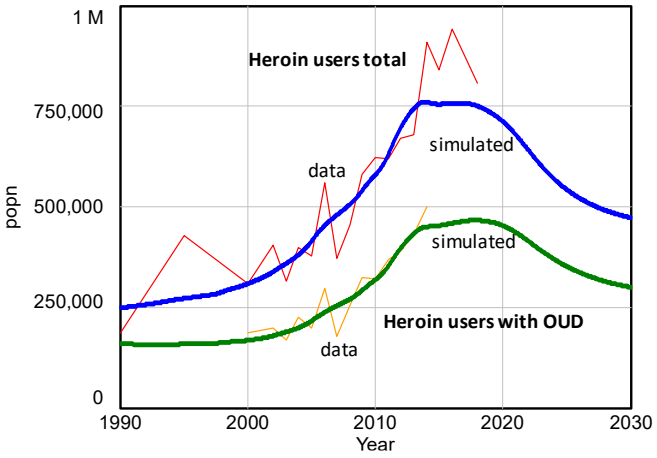
NSDUH: National Survey of Drug Use and Health (SAMHSA)

WONDER: Wide-ranging Online Data for Epidemiologic Research (CDC)

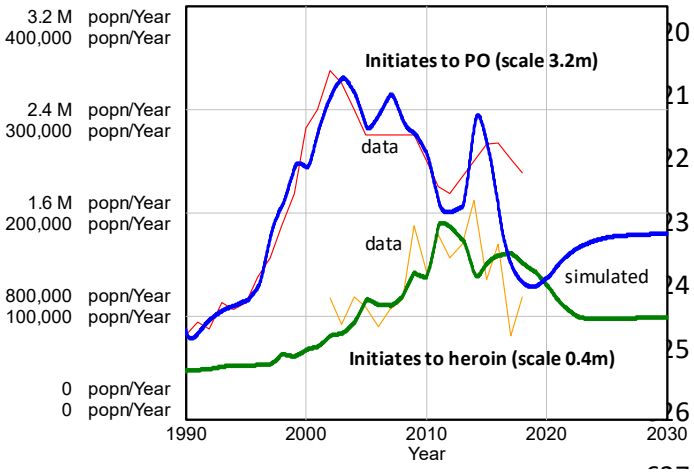
(a)


PO non-medical users: total and with OUD
16 M
12 M
8 M
4 M
0
popn
PO NMUs total
data
simulated
PO NMUs with OUD
data
simulated
1990
2000
2010
2020
2030
Year

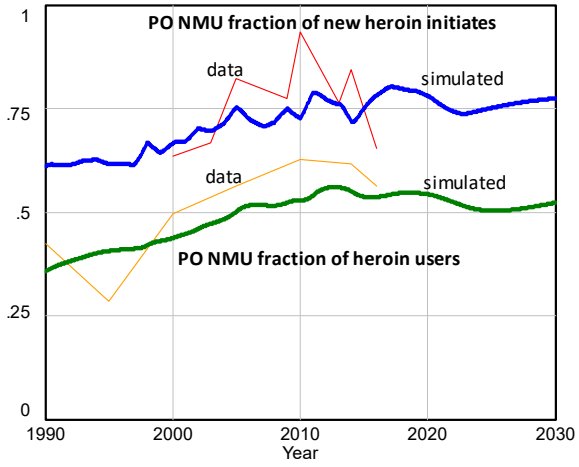
(b)


Heroin users: total and with OUD
1 M
750,000
500,000
250,000
0
popn
Heroin users total
data
simulated
simulated
Heroin users with OUD
data
1990
2000
2010
2020
2030
Year

(c)


Initiates per year to PO and heroin
3.2 M popn/Year
400,000 popn/Year
2.4 M popn/Year
300,000 popn/Year
1.6 M popn/Year
200,000 popn/Year
800,000 popn/Year
100,000 popn/Year
0 popn/Year
0 popn/Year
Initiates to PO (scale 3.2m)
data
data
simulated
Initiates to heroin (scale 0.4m)
1990
2000
2010
2020
2030
Year

(d)


Fraction of heroin users and initiates also PO NMU
1
.75
.5
.25
0
PO NMU fraction of new heroin initiates
data
simulated
data
simulated
PO NMU fraction of heroin users
1990
2000
2010
2020
2030
Year

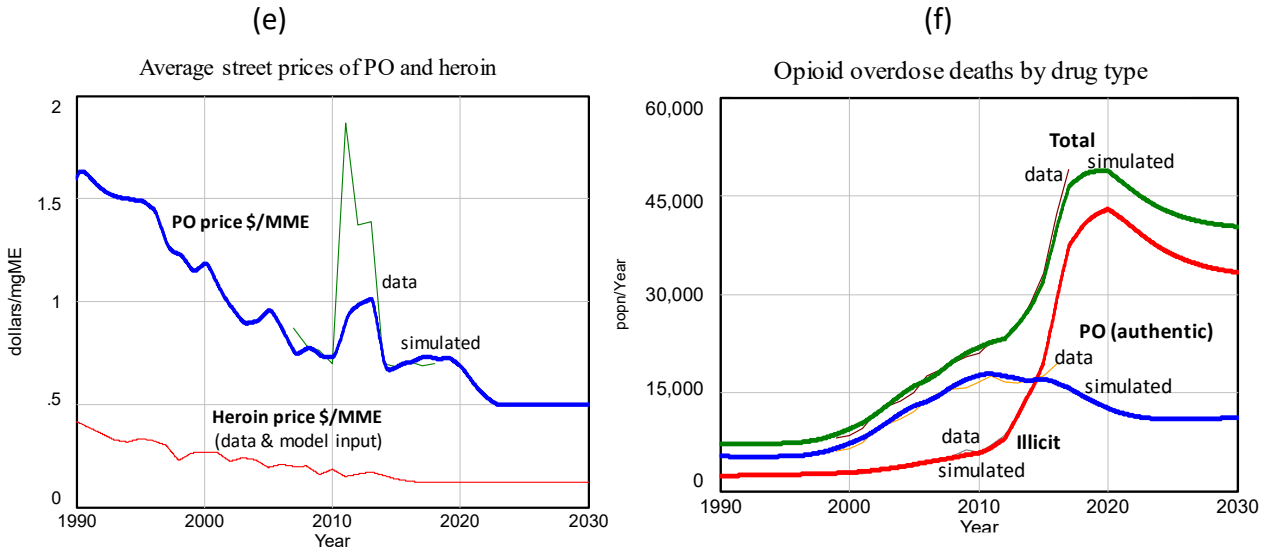


Figure 2. Model outputs compared with historical data and projected under baseline assumptions to 2030

(a) PO nonmedical users, total and OUD; (b) Heroin users, total and OUD; (c) New initiates to PO nonmedical use and heroin use; (d) Fractions of heroin users and heroin initiates who are also PO NMUs; (e) Average PO and heroin street prices per MME; (f) Overdose deaths from prescription opioids, illicit opioids, and all opioids

649 **Table 2. Intervention categories and examples**

Intervention category	Examples
Efforts to control PO prescribing & dosage strength	Provider education
	Prescription guidelines
	Electronic decision support
	Prescription drug monitoring programs
	Prescription drug rescheduling (to reduce refills)
Efforts to control diversion	Patient and public education
	Abuse-deterrent formulations
	Rx drug take-back programs
	Law enforcement crackdowns
Efforts to expand and improve addiction treatment	Improve insurance coverage of MAT
	Mandate MAT access in hospitals, prisons, and substance abuse programs
	Mandate MAT training for medical providers
	Expand psychosocial supports for treated addicts
	Refer patients to MAT after ED overdose rescue
Efforts to reduce risks of deadly overdose	Naloxone laws and subsidies facilitating distribution through pharmacies and medical providers
	Naloxone training for first responders and laypersons
	Laws allowing supervised injection facilities
	Laws allowing drug checking (for adulteration and counterfeits)

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653 **Table 3. Intervention testing outcomes as of 2030**

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	Simulated results as of 2030			Percent change from baseline		
Simulation	**Persons with OUD (thou.)**	**Overdoses seen at ED**	**Overdose deaths**	**Persons with OUD**	**Overdoses seen at ED**	**Overdose deaths**
Baseline	1,694	154,710	40,323			
Avg MME dose down 20%	1,510	152,686	39,796	-10.9%	-1.3%	-1.3%
Diversion control 30%	1,428	153,076	39,897	-15.7%	-1.1%	-1.1%
Treatment rate 65% (from 45%)	1,713	150,095	39,120	1.1%	-3.0%	-3.0%
Naloxone lay use 20% (from 4%)	1,728	159,228	35,302	2.0%	2.9%	-12.5%
All 4 policies combined	1,285	148,395	32,900	-24.1%	-4.1%	-18.4%

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