

Surfacing the hidden demand for opioid dependent treatments for drug policy makers

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Abstract:

Illicit drug policy has been the subject of important SD studies addressing the interaction between policing and medical treatment and estimating the prevalence of national cocaine use. Here we modeled the impacts of policy changes associated with wider use of newer opioid pharmacotherapies besides methadone. These newer drugs allow less supervision of dosing and changes in the mix of prescribing and dispensing arrangements. Key aspects of the model were estimation of potential demand for the enhanced range of therapies and the cost and treatment impacts of changes in cycling on and off treatments due to pricing and service configurations.

*Here we describe the use of SD models to provide a logical consistent framework for stimulating debate about incomplete and ambiguous data and clarifying the differences in expectations and goals of treatment among broad groups of policy makers. Our methodology included incorporating key concepts accepted from previous economic equilibrium Markov models and control phase plots from previous modeling in the area. Funded by the Australian National Council on Drugs www.ancd.org.au
This material is yet to be released.*

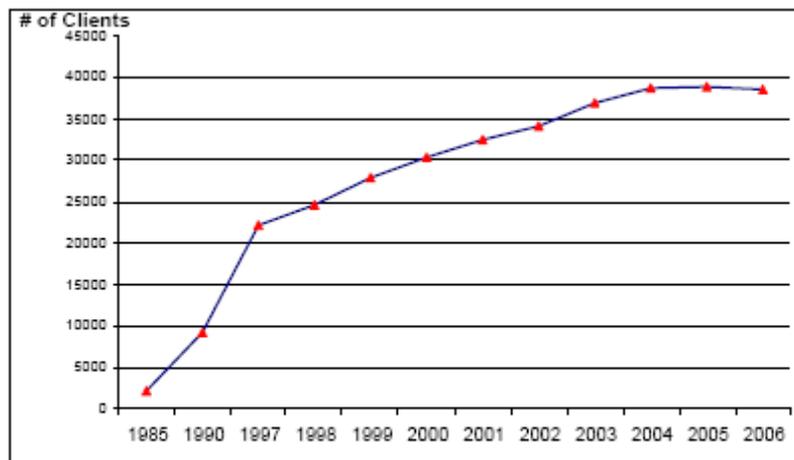
Introduction

The early use of system dynamics in framing the interaction between medical treatments and policing interventions resulted in publication of the classic book, *The Persistent Poppy* by Levin, Roberts and Hirsch in 1975. This book outlined the delicate balance between criminal and medical activities and the potential intolerable consequences of extreme policies of “full prohibition” and “full legalization” mediated through feedback effects via the price of heroin. The policy interventions described in this book include educational effort, police effort, community education, re-entry programs, available methadone treatments and counseling. An updated causal loop diagram, kindly supplied by one of the original authors, Gary Hirsch, nicely illustrates the dynamic complexity of illicit drug policy.

This paper describes the results of a current project which again uses system dynamics modeling to develop and test the impacts of future government policy options in the provision of medical treatments for illicit drug users.

Background

Methadone maintenance therapy has been the mainstay of medical treatment for opioid dependence for many years. Newer oral drug substitutes for methadone are now becoming widely available, particularly Buprenorphine (BuP), used alone or combined with the narcotic antagonist, Naloxone. The Australian National Council on Drugs (ANCD), a peak policy group, commissioned the Drug Policy Modeling Program (DPMP) of the National Drug and Alcohol Research Centre to investigate the issues related to new opioid dependent pharmacotherapies and advise on potential changes in policy and practice.



Source: Australian Institute of Health and Welfare. *Alcohol and other drug treatment services in Australia: Report on the National Minimum Data Sets 2000-2006*. Drug Treatment Series: Numbers 1 – 7. Canberra, ACT, 2002-2007; Shannon (undated).
* For the years 1985 through 2000 methadone is the only pharmacotherapy drug. From 2000 onwards buprenorphine and ultimately buprenorphine-naloxone is included. In 2006 there were 27, 588 methadone patients; just over 70 per cent of all patients.

National Pharmacotherapy treatment patients from 1985 to 2006. Chalmers et al (2008)

This consultative project has produced a Pharmacotherapies Issues Paper (yet to be released) and joint system dynamics modeling around the demand for services and costs and benefits to the government and the community.

Currently the National and State Governments subsidises and provides a range of legal prescribing and dispensing options for medications in addition to counseling and support services. Medications are prescribed by public clinics, private doctors (primary care practitioners' offices or clinics or prisons services). The drugs are dispensed and administered supervised at the public or private clinics, the community pharmacy or prisons. In some cases "take-away" doses are available for partially supervised patients.

Regular reporting of patient numbers and medications dispensed is required by law, but this data is not available through the life course of an individual patient. Therefore system dynamics modeling was selected to assist the project to make sense of disparate datasets and ‘triangulate’ estimates in order to gain consensus on the overall current state and the consequences of future policy options.

Approach to Model Development

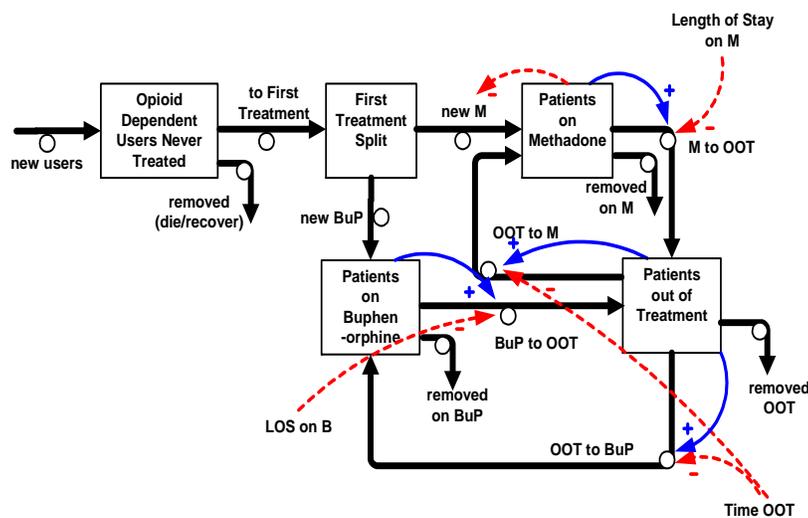
The DPMP was experienced in reviewing international and national literature and synthesizing data from studies, surveys and reports. It had used a variety of economic, stochastic, biostatistical and agent based models in the illicit drug policy area, but not system dynamics. The most similar approach to system dynamics (that they were familiar with) was a simple compartmental Markov model of illicit drug use. Parameters for this model had been estimated using the usual Markov assumption of an equilibrium final absorbing state.

The structure and behavior of this model was replicated using an ithink stock flow model and the team then learnt that it was possible to relax the assumptions of the Markov model and explore non-equilibrium conditions, including non-linear feedback interactions.

We then proceeded to develop a stock-flow model of the flow of patients on opioid dependent therapies, through various prescribing and dispensing locations.

Model structure

A simplified version of the model structure is illustrated in the following diagram.



The detailed model includes splitting the patients on treatment into their various prescribing and dispensing locations and allocating costs to the various payers (National and State Governments and Users).

Within the methadone treatment sector there are a number of sub-sectors. To enter treatment patients must be prescribed methadone by a medical practitioner, registered to

prescribe methadone. The model differentiates between three types of prescribing medical practitioners, on the basis of who pays for the prescribing and the cost of that prescribing; those employed by public treatment clinics, those working in private practices (including those prescribing out of private clinics) and those employed to work in the prison system. The Commonwealth government pays for prescribing in private practices while the state government covers the cost of prescribing in prisons and public clinics. The cost of prescribing in prisons and public clinics differs. Patients flow between the three prescriber types, as well as flowing in and out of treatment. There is also a dispensing sub-sector differentiating again between methadone dispensing locations on the basis of who pays for dispensing and the cost of that dispensing. Dispensing is undertaken under the control of a pharmacist. Prison patients are all prescribed and dispensed in prison pharmacies. While the majority of patients prescribed in a public clinic will be dispensed their methadone in that clinic some are dispensed methadone by community pharmacists in the pharmacy. The pharmacy might be more convenient; perhaps closer to home than the public clinic. All of the patients whose prescriber is a medical practitioner in private practice are dispensed in a community pharmacy. The State government pays for dispensing undertaken in public clinics and in prisons while the patient pays for dispensing in community pharmacies. Hence there is a patient flow from the prescribing sector to the dispensing sector and information flows from both those sectors to the costs sector. Here the model calculates the costs borne by the patient, State and Commonwealth Governments. Those costs only accrue when the patient is in treatment, that is, when the patient is taking his/her methadone prescription.

Model Calibration

The various parameters and data sources are listed in the following table:

Variable	Parameter	Reference / Notes
<i>Stocks at commencement of simulation</i>		
Treatment naïve opioid dependent population	12,000	= [3,500 x 4 yrs] – 1400 (10% outflow). Consensus estimate.
Methadone treatment Prescribers	27,346	2006 census data (unreleased).
	Public = 7,853	
	GP = 17,169	
	Prison = 2,324	
Buprenorphine treatment	11,071	2006 census data (unreleased)
Between treatment	30,000	Calibrated from the model, based on length of stay and steady state. At start of simulation. Data in Dietze et al 2003: 63% ever in treatment, 45% in treatment last 12 months; 26% in treatment on day of interview. Of the current intx stock, 40% b/n tx is the lower limit; 142% is the upper limit. Currently set at 100%

<i>Flows</i>		
Entrants to opioid dependency	3,500 per annum	Unknown. Estimates of new users, 5% of total IDU population (Razali et al., 2007, Caulkins et al; Law et al). 5% of 69,346 = 3,500 This initialisation figure also accommodates our recovery and death estimates.
Flow from treatment naïve opioid dependent population into treatment for first time	Average time to treatment is 4 years	Dietze et al (2003) median 3 yrs for methadone. ATOS 4 yrs (State reports: av. age first treatment 24-25 yrs, regular injector av. 20-21 yrs; 29%-40% meth 1 st tx). This figure is affected by the feedback loop (see below).
<i>Other</i>		
Allocation of inflow into first treatment by drug	43%: buprenorphine 57%: methadone	To equilibrate the model Based on census/state data
Allocation of inflow into first treatment		National census (28%, 62%, 8%) Bell et al. (2006) 31%, 56% and 9%. Back-calculated from static proportions in each allocation at any one time.
• Public	25%	
• GP	60%	
• Prison	15%	
Length of stay		ATOS, Bell et al., State data
Methadone		
• Public	7 month	
• GP	12 months	
• Prison	3 months	
• Between treatment	12 months	
Buprenorphine		
• In treatment	6 months	
• Between treatment	6 months	
Flow probabilities between prescribers		
From GP	to public 10% to prison 4.5% to b/w tment 83.2% death 0.8% abstinence 1.5%	
From public	to GP 10% to prison 5% to b/w tment 82.7% death 0.8% abstinence 1.5%	
From between treatment	to public 25.5% to GP 51% to prison 15% death 2% abstinence 1.5%	

Feedback loop		This figure depends on the ratio of no. in treatment (methadone + buprenorphine) to no. 'between treatment'. It is 4 when the ratio is less than 2, but falls at a declining rate as the ratio increases from 2. There is a limit on the years to entry of 2.
Death rate		
• Pre treatment	5% per annum	
• in treatment	0.8% per annum	Byrne, 2000, Caplehorn, 1996
• between treatment	2% per annum	
Abstinence rate (in and between treatment)	1.5% per annum	ATOS, Byrne, cross-checked against international figures (NTORS, DATOS, Hser)
Pre-treatment abstinence rate	5% per annum	Ravali et al., 2005; Caulkins et al., 2007

Costs		
Drug cost (per dose)	\$0.54	PBS \$36 per litre; 1mg = .72c. Av meth dose 70mg
Costs – maintenance		
• public	\$14.58 per day	NEPOD
• GP	\$3.78 per day	NEPOD
• Prison	\$9.26 per day	Warren & Viney, 2004
Costs – dispensing		
• Public	\$1.05	NEPOD
• GP	\$5.00	From State surveys, averaged
• Prison	\$1.05	Assumed same as public – no other data

Use of the Model

We set out to construct a model that could be used by policy makers to explore feasible policy scenarios. We had no intention for the model to generate forecasts of the implications of policy changes. Rather, we intended that the model communicate a particular understanding of the system that could be used as a shared basis for debate on policy issues. As well, the model needed to be able to simulate implications of policy changes, given the current state of the system. Crucial to the calibration of the model was discussion with policy makers to ensure that the model's depiction of the system was sufficiently realistic, without being cumbersome. In that process we learned, for example, it was simpler to assume a system in equilibrium with constant numbers in treatment over the life of the simulation in status quo, rather than being distracted by justifying a constant upward or downward trend in the absence of data.

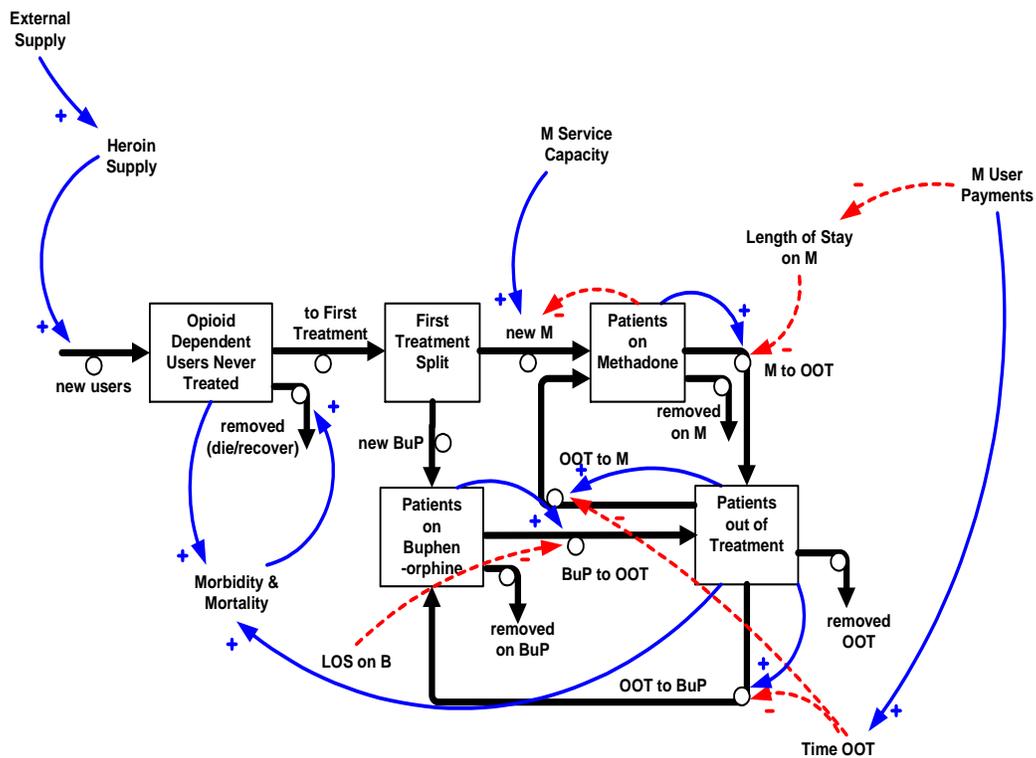
One example of 'triangulating' estimates based on the structure of the model was the ratio between Patients length of time in treatment and out of treatment. Published estimates varied from 0.4 to 1.4. Based on the model structure and related estimates we were able to infer that the figure was around 1.0

Policy Experiments

The key issues explored in this model were

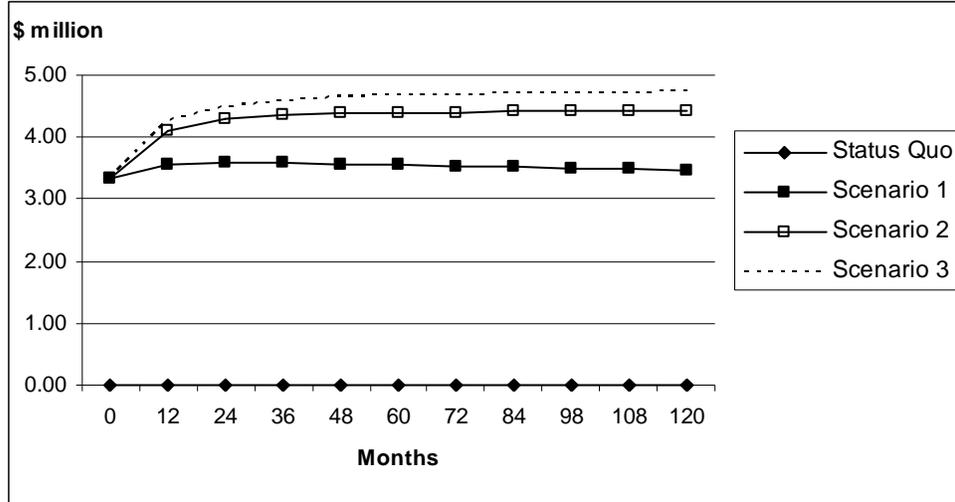
1. Dispensing fees on patients
2. Increasing demand for treatment
3. Decreasing supply of treatment by retirements of prescribing primary care physicians.

A simplified diagram of policy experiments is shown below.



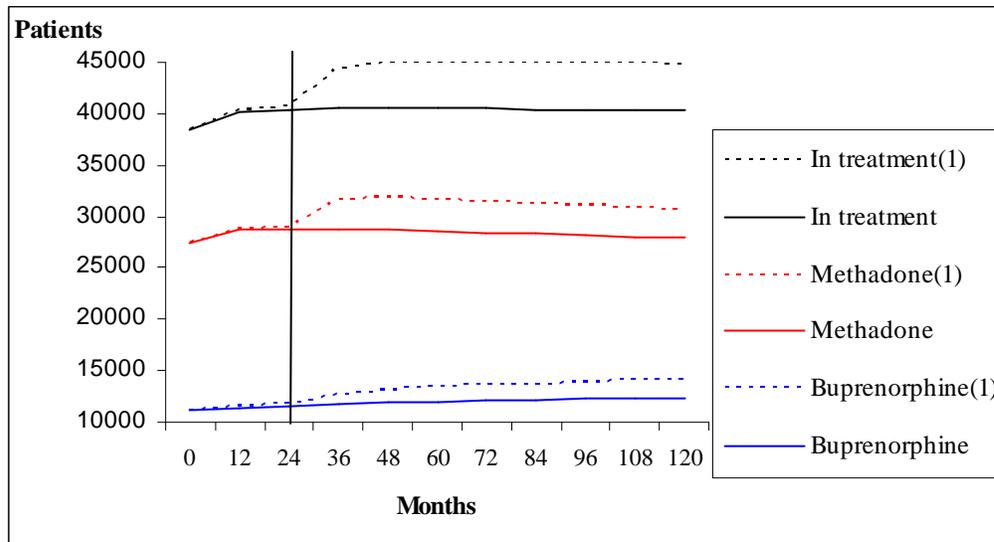
Results of Policy Experiments

Commonwealth Government dispensing and prescribing Costs \$A/month



- Notes:
- Status Quo: Patient pays dispensing fees at pharmacies
 - Scenario 1: Commonwealth pays dispensing fees.
 - Scenario 2: In response the average length of stay in treatment for patients dispensed in pharmacies increases by 50 per cent.
 - Scenario 3: A secondary response is that the time it takes for an opioid dependent person to enter treatment for the first time is halved, on average, from 4 years to 2 years

Patients in treatment on a monthly basis before and after a 20 per cent reduction in the time between treatment



Key

Work in Progress (for Presentation in July)

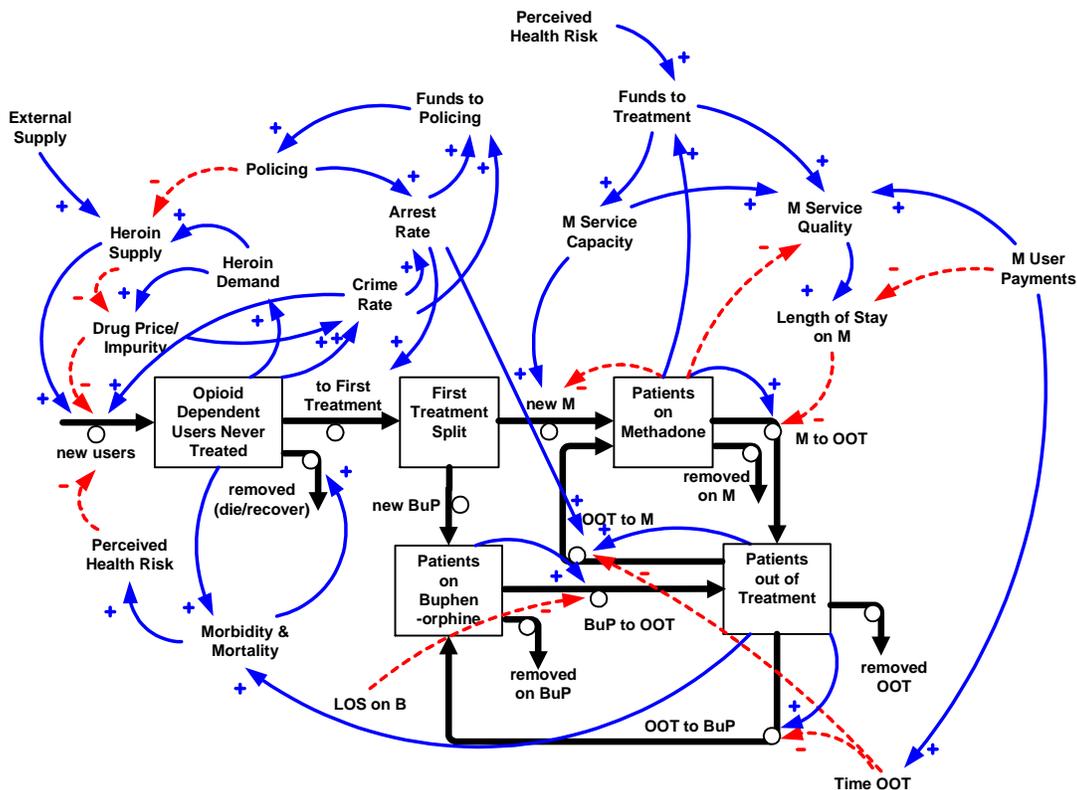
We are planning some extensions to this work to further quantify the benefits of various policies. Key indicators include the benefits in treatment, including reduction in crime rate, policing and criminal justice costs and the morbidity and mortality avoided, including heroin overdoses and HIV/AIDS reduction.

Further Policy Experiments (in Progress)

Phase Plots including the difference between abrupt and gradual changes in supply and demand parameters

Expanding the scope to include related System Dynamics Work

Once the project team has successfully built and demonstrated simple models we are exploring the possibility of extending the scope of the work to progressively include additional feedback interactions. An example of some of the possibilities is shown below. This addresses the perennial issues of interactions between criminal and health interventions and the vexed question of relative direct and indirect contributions of different intervention mixes to reduce crime and health risks on changing the rate of new opioid dependent users.



Conclusion

This project demonstrates the successful development of a useful stock and flow model to assist policy makers in considering the impacts of various policy experiments. It offers a firm foundation of a simple well-calibrated model which has the capability to be progressively expanded to challenge the current boundaries of analysis used in this area. It has the potential to more successfully spread the understanding of feedback interactions among health and policing policies by carefully building on earlier system dynamics work in this area.

References

Australian Institute of Health and Welfare (AIHW) (2007) *Alcohol and other drug treatment services in Australia 2005-06: Report on the National Minimum Data Set Drug Treatment Series no. 7*. Cat. no. HSE 53 Canberra, AIHW.

Bell

Caulkins

Chalmers, J., Ritter A., Faes, C. with input from the expert advisory group (Nick Lintzeris, Tamara Speed, Bob Batey and Alex Wodak) (2008) "Opioid Pharmacotherapy Maintenance in Australia – A background issues paper"

Dietze

Hirsch GB 2007 Personal communication

Homer JB Why we iterate: scientific modeling in theory and practice

Sys.Dyn.Rev. 1996 12 1 p1-19

Levin G Roberts EB Hirsch GB *The Persistent Poppy: A Computer-Aided Search for Heroin Policy* Ballinger Cambridge MA 1975 ISBN 0-88410-031-6