Modelling pharmacotherapy maintenance in Australia

exploring affordability, availability, accessibility and quality using system dynamics
Modelling pharmacotherapy maintenance in Australia: exploring affordability, availability, accessibility and quality using system dynamics

Jenny Chalmers
Alison Ritter
Mark Heffernan
Geoff McDonnell

Drug Policy Modelling Program
University of New South Wales

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Executive summary

The Australian National Council on Drugs (ANCD) commissioned the Drug Policy Modelling Program to investigate the availability, accessibility and affordability of pharmacotherapy treatment for opioid dependence in Australia. The project was conducted in two parts:

- a qualitative review of the issues associated with pharmacotherapy treatment (Ritter and Chalmers, 2009 — ANCD Research Paper 18); and
- the development of a system dynamics model of the service system as a means to explore the implications of policy options designed to address some of the key issues of concern (this report).

The aims of the modelling component of the project were:

1. to develop a system dynamics model of the Australian pharmacotherapy maintenance system
2. to assess the extent to which such a model can inform policy-relevant questions
3. to use the model to explore four policy-relevant issues: affordability, availability, accessibility and quality.

Method

It is difficult to explore the impacts of policy reform ahead of their implementation. Case studies are expensive, difficult and time-consuming to run. In light of the complexity of the pharmacotherapy treatment system, a relatively simple computer model which describes the system in its entirety and explains the machinations of the system is extremely valuable. Because a model abstracts from the remarkable diversity of views among stakeholders, it can be used as a basis for group exploration of plausible outcomes of policy reform.

System dynamics modelling was the chosen modelling approach. Although increasingly commonplace in health research, the use of system dynamics modelling to explore policy options is novel in the drug policy world.
Policy scenarios

The purpose of the model was to explore affordability, availability, accessibility and treatment quality. In order to examine these aspects of the system, we needed to test each of these terms in our model in a way that was consistent with the modelling capabilities.

• Affordability was examined in terms of the dispensing fees debate. This scenario concentrated on a transfer of the responsibility for dispensing fees from patients to the federal government. With no concrete evidence on the impact of dispensing fees on the treatment-seeking and treatment-using behaviour of opioid-dependent people, we used the model to explore the consequences of removing the fees over a range of possible client responses.

• Availability of treatment was characterised as a reduction in the number of available treatment places: initially we reduced the number of general practitioner (GP) treatment places and then reduced the public clinic places.

• Increase in the potential population of opioid users — for example, through increased dependence on pharmaceutical opioids — provided the characterisation of treatment accessibility. Our scenario tapped into only one aspect of accessibility — that of finding a treatment place in the context of increased population prevalence.

• Our final scenario was concerned with treatment quality — and we set out to illustrate the implications of the trade-off between quality of treatment and volume of treatment places. To implement this scenario, we assumed two different types of programs: high-threshold and low-threshold programs where the high-threshold program offers individually tailored, more expensive treatment, while the low-threshold program offers reasonably homogenous treatment at a lower cost. In this highly stylised analysis, we draw attention to the implications of the two models for numbers in treatment, program costs and individual goal attainment of opioid-dependent people.
Results

The model was calibrated to reflect a stable system: that is, a stable number of people entering and leaving the opioid pharmacotherapy system over time. This stability, while not necessarily reflecting current and future trends, enabled us to examine the impacts of the policy scenarios exclusive of population changes.

The base-case results of the model revealed that:

1. The number of people between-treatment (i.e. those who have received at least one episode of treatment but are currently out of treatment) was estimated by the model to be 41,100. This figure represents a reasonable upper bound of unmet treatment.

2. The bulk of prescribing (63%) is undertaken by private medical practitioners and the majority of dispensing (80%) is carried out in community pharmacies: these community-based services form the backbone of the Australian pharmacotherapy maintenance treatment system.

3. The overall cost for the provision of methadone maintenance is $11.73 million per month, as estimated by the model. Forty-three per cent of this cost is borne by State/Territory governments ($5.06m per month), 33 per cent is borne by the patients ($3.90m per month), and the remaining 24 per cent is borne by the federal government ($2.77m per month). The States carry the highest cost burden, followed by the patients.

4. The modelled treatment costs ($11.73m per month) are significantly lower than the costs associated with those people not in treatment (i.e. untreated heroin users), which we estimate to be between $15.8 million and $31.6 million per month. It is clear that the provision of pharmacotherapy maintenance treatment, while costly, is outweighed by the economic benefits accruing to the community through reductions in health care utilisation and crime.

The policy scenario testing revealed that:

5. If the federal government were to pay the methadone dispensing fees for those patients currently fee-paying (around 80% of all patients), the model estimates the costs to be $3.9 million per month.

6. If we make some assumptions about the impact of reduced patient fees on patient behaviour — for example, longer time treatment (50% increase in length of stay) — we have more people in methadone treatment at simulation end ($n = 5549) and an associated increased monthly dispensing cost of $0.8 million per month.

7. While the costs of dispensing currently borne by the patients will represent a financial impost on government, the modelled monthly federal government expenditure compares favourably with the estimated health and crime cost savings as a result of methadone maintenance treatment.
8. If treatment places were to decrease — for example, through a 20 per cent reduction in the number of GP prescribing places — the numbers in treatment fall by 5110 and patients spend longer between treatment waiting to find a prescriber, an increase from 12 months to 15 months spent out of treatment. If public clinics are also constrained and not able to accommodate any of the extra demand, then there are 8322 fewer people in treatment at end-simulation and the time between treatment increases to 20.7 months. Reductions in GP capacity have substantial implications on the time taken to re-enter treatment. Lengthening the time between treatment represents substantial social costs.

9. One area of concern for policy makers is the potential for increased demand for opioid maintenance treatment, flowing from an increase in pharmaceutical opioid dependency. We modelled a 20 per cent increase in opioid dependency (annual inflow into dependency 5400 compared to base-case of 4500). Perhaps surprisingly, the 20 per cent increase produces minimal impacts on the treatment system — at the end of the simulation there are only 1980 more patients in treatment as a whole (a 4% increase). The concern about population changes appears misplaced as the effects of population changes take some years to have an impact on the treatment system.

10. While we find that expansion in the population of newly opioid-dependent people has little impact, the model shows that increased demand for treatment among those currently cycling through the system has more significant repercussions. Reducing the time between treatment for those already in the system (by 20%) increases the numbers in treatment by 11 per cent at simulation end (4995 more patients in treatment). Investing in policies that encourage previous treatment entrants back into treatment has a much greater impact on treatment numbers than focusing on a new population of users.

11. In a highly stylised scenario, we compared a higher quality (patient-focused) but low volume treatment service (named the high-threshold program) with a lower quality but higher volume service (named the low-threshold program). In the simulation, numbers in treatment increased under both models, but more so for the low-threshold model. The extent of individual goal attainment achieved by opioid-dependent people when in treatment increased under both models, but significantly more so under the high-quality model. Yet substantial government investment would be required to achieve the high-quality model. Based on the assumptions that were made, the low-threshold model was more cost-effective.
Conclusions
This is the first system dynamics model of opioid pharmacotherapy treatment in Australia. The policy scenarios presented in this report illustrate that it can be used as:

- a means to explore the potential costs associated with changes in dispensing fee payment, and the implications of possible patient behavioural responses to the costs
- a coherent and justifiable means of estimating the impact of changes in the availability of treatment places on numbers in treatment and numbers between treatment
- a sufficiently robust depiction of the system structure in which we can examine different sources of new treatment demand — that arising from new opioid-dependent people; and that arising from people between treatment, and
- a vehicle for advancing the hotly contested and value-laden debate about the quality of care and volume of treatment places trade-off.

As the first attempt at a system dynamics model of pharmacotherapy maintenance, we see it as the beginning of work in this area.
1. Background and introduction

The Australian National Council on Drugs (ANCD) commissioned the Drug Policy Modelling Program to undertake a project exploring opioid pharmacotherapy treatment in Australia. The aim of the project was to investigate the availability, accessibility and affordability of treatment. The project was conducted in two parts:

- a qualitative review of the issues associated with the Australian pharmacotherapy program (Ritter & Chalmers, 2009 – ANCD Research Paper 18); and
- the development of an interactive quantitative model of the treatment service system in order to explore the implications of policy options designed to address issues of affordability, availability and accessibility of treatment (this report).

Pharmacotherapy maintenance has been demonstrated to be a highly cost-effective intervention for opioid-dependent people (Belenko, Patapis & French, 2005; Connock, Juarez-Garcia, Jowett et al., 2007). In Australia, pharmacotherapy patients receive care from medical practitioners sited in public clinics, private clinics or primary health care services. Dispensing of pharmacotherapy medication occurs in three different settings: public clinics; community pharmacies; and private clinics. The dispensing sites are associated with different patient co-payments. The provision of psychological support can take place within the prescribing service, within the dispensing service or through an allied counselling service. The various elements of the Australian pharmacotherapy service system can operate synergistically or independently. Finally, there are two main forms of opioid maintenance therapy: methadone maintenance and buprenorphine maintenance. In the case of the latter there are two formulations of buprenorphine: buprenorphine alone (Subutex) and buprenorphine–naloxone (Suboxone).

We sought to examine treatment affordability, availability, accessibility and quality through the application of a novel method in pharmacotherapy research: a system dynamics model. A system dynamics model provides a means to explore policy options, through the simulation of specific policy reforms relating to the issues of concerns.

The issues selected for focus were based on those that arose in the qualitative review of the Australian pharmacotherapy treatment program (Ritter & Chalmers, 2009). One of the pressing issues currently facing Australian pharmacotherapy programs is the affordability of dispensing fees incurred by patients. The model is used to examine treatment costs and the bearer of those costs and to explore the ramifications of a transfer of the financial burden of dispensing fees charged by community pharmacies and private clinics from patients to the federal government.

A second issue is the availability of pharmacotherapy maintenance treatment — the extent of unmet demand. We simulate a marked reduction in the number of prescribing places.

Accessibility of services also depends on the numbers of people seeking treatment. One issue of concern is a potential increase in treatment-seeking from a new population of people dependent on pharmaceutical opioids.
Finally, an issue identified in the qualitative review was the potential trade-off between quality of services and availability of services: that is, the balance between more treatment places with lower quality of care versus fewer treatment places but with enhanced care. Put differently, this scenario endeavours to compare the trade-offs between minimising the harms to individuals (quality treatment with restricted treatment places) and the harms to the community (volume of treatment places). This scenario is designed to address concerns about, for example, the advantages of GP prescribing over public clinic prescribing.

This report begins with a discussion of the use of models as a tool to address policy options and an outline of the system dynamics approach. Section 2 provides an overview of the pharmacotherapy model we developed, followed by a presentation of the full details of the model’s parameters and assumptions in section 3. Section 3 is, by its nature, quite technical and detailed. We welcome the reader to skip this section and consult it when, and if, the reader has concerns about assumptions underlying the data used to set up the model. The base-case results from the model are then reviewed (section 4). Section 5 provides the results of the five scenarios on affordability, availability, accessibility and quality. The final section discusses the implications of the work.

Models as a tool to explore policy options

Schultz (1974) defines modelling as ‘the development of a system that is similar in pertinent respects to another existing or hypothesized system, the simuland’. Simulation is ‘the use of that model to perform experiments designed to give results from which implications … can be drawn’ (Schultz, 1974).

The use of modelling spans a wide range of fields including pure mathematics, physical sciences, engineering, computer science, business, military, economics and social science (Robinson, 2002). Some of the areas in which it has been applied include educational gaming; educational administration; health administration; man–machine systems; experimental games; human thought; communication networks; organisations; social systems; civil, political and community systems; regional, national and international systems; war and crisis gaming; operational gaming; management games; queuing systems; and operations research and management science (Barton, 1970).

Models are a preferred approach for many reasons. Models can enable exploration of scenarios in complex environments where the outcomes may not be obvious or intuitive. They can enable group exploration of complex and ambiguous issues, and represent a diversity of views. Modelling provides a ‘common framework and opportunity for fruitful discussion’ (Tsuchiya & Tsuchiya, 1999, p.47). Models are highly relevant tools for policy decision making because case studies in the real world are difficult; simulations can
explore policy options not yet implemented; and they can be inherently fun, creative and interesting. Perhaps more importantly, simulations can be effective and useful aids for decision-making processes, because they represent the complexity and dynamic relationships between important variables in the policy domain (Saunders-Newton, 2000).

So little is understood about social policy, so few of the necessary facts about any policy process can be assembled, so many information sources are subjective and self-serving, that no perturbation of the social system, whether computer-generated or not, can be fully traced and evaluated. It is because social systems are so bewilderingly complex that mathematical models are turned to in the first place. (Meadows & Robinson, 2002)

In light of the complexity of social problems and associated policy, models provide both a tool for handing complexity, but also opportunities for plausible alternatives not confined to a right or wrong answer. Identifying plausible consequences of policies is important as a way of increasing the use of objective information. As put by Levin, models can ‘increase the role of reason over rhetoric’ (Levin, Hirsch & Roberts, 1972).

The assumption is that decision makers benefit from exploring alternatives in a risk-free environment that can represent the issues or framework as a complex system, undergoing rapid and/or constant change and with high inter-relatedness of people, variables and services ‘in a way that is easy to understand’ (Enciso, 2001; Ryan, 2000; Saunders-Newton, 2000).

A model is only a partial representation of reality, and as such is a simplification of the real world. The balance between realism and simplicity is a delicate one (Lehman, 1977). One challenge is to develop the most parsimonious model that represents the key aspects of a system, while leaving sufficient complexity in the model to be relevant to solving an actual problem.

System dynamics as one modelling approach

The creation by Jay Forrester of Massachusetts Institute of Technology in the late 1950s, the system dynamics modelling approach is used both to understand how social systems — in which human actors take decisions which affect events — change over time, and how these changes might best be influenced. System dynamics models portray the flow of information and materials and the associated feedback loops. These closed loops of causal links frequently involve delays and non-linear relationships. Computer simulation of systems of this kind is crucial since humans can conceptualise such complex models but, unassisted, do not have the cognitive capacity to predict the dynamic consequences.
Assisted by modern, icon-based software, system dynamics has provided causal theories for a wide variety of phenomena. Forrester’s pioneering work ranged from the management of growth in a start-up company to the interaction of population and resources on a global scale. Contemporary applications have included, for example, the diffusion of new medical technologies, the dynamics of software development, the long-term management of life insurance companies and the collapse of the Mayan empire.¹

System dynamics modelling represents the structure of service systems as accumulations, or stocks, of service users and potential service users in particular locations, such as ‘in-treatment’ and ‘pre-treatment’. Service users move between the locations and that movement is described as a flow. The rate of flows between stocks is regulated by behaviour patterns.² Continuous time computer simulation displays the behaviour of key variables of interest over time.

The structure of the system relevant to the problem of interest is usually elicited from the mental models of domain experts and the resulting stocks, flows and feedback loops can include computable representations of both quantitative and qualitative variables. The resulting model provides a logical consistent framework for integrating data from multiple, disparate sources. A good model is one that policy makers have the confidence to use to help make important decisions.

There are two recent comprehensive textbooks on system dynamics (Morecroft, 2007; Sterman, 2000) and a growing number of applications of system dynamics to health problems. For instance, it has been used in global vaccination policy, public health, health and drug policy (including tobacco control), chronic disease, service planning, health management, patient flow and body system simulations (Grassly & Garnett, 2003; Homer & Hirsch, 2003; Homer, Hirsch & Milstein, 2007; Homer, Milstein, Wile et al., 2008; Milstein, 2008; Milstein, Jones, Homer et al., 2007; Morecroft, 2007; National Cancer Institute, 2007; Sterman, 2000; Thompson & Tebbens, 2007; Wolstenholme, 2005).

In summary, system dynamics has three key features:

- It approaches modelling from a systems perspective: the relationships between the elements in the model (stocks and flows) are important for system behaviour, and individual elements cannot be separately investigated.
- It uses dynamics in terms of changes over time, and changes in one element brought about by changes in another do not happen instantaneously.
- There is feedback, whereby one element impacts on another and the second element in turn impacts on the first, even though this may come about indirectly through a sequence of causes and effects on a series of other elements.


² In many system dynamics models the behaviour patterns can be affected by what happens elsewhere in the model. For example, the rate of flow of untreated people into treatment might increase as numbers in treatment grow, the view being that people are more likely to enter treatment if they know someone in treatment.
The application of systems dynamics to pharmacotherapy maintenance

This cursory summary of modelling and the system dynamics approach highlights how a model of pharmacotherapy maintenance in Australia may be useful. The important points to note are:

- We designed the model to test some policy options (not as a predictive tool).
- The model is constructed around stocks and flows — that is, states of being out, in and between treatment, and movement between those states.
- The model is a simplification of reality, as discussed below.
- As the first attempt at a system dynamics model of pharmacotherapy maintenance, we see it as the beginning of work in this area.

The aims of this project were:

1. to develop a system dynamics model of the Australian pharmacotherapy maintenance system
2. to assess the extent to which such a model can inform policy-relevant questions, and
3. to use the model to explore four policy-relevant issues: affordability, availability, accessibility and quality.
2. An overview of the pharmacotherapy system dynamics model

The system dynamics model was designed to characterise the Australian pharmacotherapy system as a whole, in the simplest possible way, while being recognisable to the stakeholders and able to depict the repercussions of the various policy scenarios. The simulation model was constructed using the iTHINK software (http://www.iseesystems.com/), a purpose-built software package for system dynamics modelling.3

The model represents the flows into, around and out of treatment. The typical pattern of pharmacotherapy treatment usage in Australia is that of cycling through multiple episodes of care: that is, patients commence, then cease treatment reasonably rapidly, but many return to treatment after a break (Bell, Burrell, Indig & Gilmour, 2006). This cycling behaviour formed the basis of the model. Figure 1 is a representation of the model. It is a simplified depiction but identifies the main features of the model. Firstly, a proportion of non-dependent opioid users become opioid-dependent each year, represented as an annual flow into the opioid-dependent box. After a period of time, some dependent users then flow into one of three first treatment options: treatment from a public clinic; treatment from a GP (this category includes both primary care services and private clinics); or treatment while in prison. We distinguish between prescribing and dispensing because there is not an automatic or default association between the prescriber and the dispenser. (Some patients in public clinics are dispensed in community pharmacies and so on.) The distinction between prescribing and dispensing locations is important because we attach specific treatment costs to both prescribing and dispensing. The costs associated with prescribing the medication, with the medications themselves and with dispensing the medication are calculated for each patient for every day in treatment. (We identify three different bearers of those costs: the federal government; State/Territory governments; and patients — discussed later.)

Patients remain in the treatment stock for an average length of stay. The arrows running between the public prescribing, GP/private prescribing and prison represent the transfer of patients directly from one treatment setting into another. More commonly, however, patients leave treatment and move into the ‘between-treatment’ stock. They remain between treatment for an average length of time before seeking further treatment. The numbers cycling between ‘in treatment’ and ‘between treatment’ depend on the average lengths of time people stay in and out of treatment.

Not all patients cycle like this indefinitely. A proportion leaves the treatment system if they become abstinent or die. The movements out of the treatment system are represented by the three arrows leading to the Death/abstinence box and by the box itself.

In summary, the rectangles represent stocks of opioid-dependent people, before entering pharmacotherapy treatment, when ‘in-treatment’, ‘between-treatment’ and once they have left the system. When ‘in-treatment’, the

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3 The mathematical basis of system dynamics models is differential equations.
model differentiates service providers on the basis of the location of prescribing and location of dispensing. The ‘between-treatment’ stock contains opioid-dependent people not currently in treatment who have experienced at least one episode of care. Patients can move between prescriber and dispenser types in one continuous spell of treatment or exit the model. The flows between the stocks are determined by the time in treatment and the time between treatment. Parameters for each flow have been separately determined, as detailed in Section 3.

Buprenorphine treatment is not represented in Figure 1. The model focuses on methadone treatment. However, we have included a sector for buprenorphine to account for all pharmacotherapy patients in treatment. We did not separate the prescribers and dispensers for buprenorphine, nor did we include treatment costs. Hence the model results, particularly in relation to costs, relate to methadone only. This simplification was necessary given the available data and the project time-lines. We allow some new entrants to treatment to commence with buprenorphine. We assume no net flow between buprenorphine and methadone once treatment is entered.

Figure 1: The model: methadone only
The model needed to be able to simulate implications of policy changes, given the current state of the system. By this we mean that the model reflects the current system in terms of capacity, patterns of accessibility, and so on. 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, that at base-case (before the impact of policy changes) policy makers were more comfortable with a model that simulated relatively constant numbers in treatment over the life of the simulation. We also benefited from discussions about the trade-offs between subtlety in our depiction of patient flows through the treatment system and the information required to build that subtlety. For example, we could not differentiate between the first and subsequent treatment episodes in terms of length of episode because there is no available Australian evidence. Yet there is strong feeling that as patients progress through their treatment career, their treatment episodes lengthen. However, in relation to the time spent in treatment we assume that patients’ experience of treatment is identical, regardless of whether it is the first episode or the 100th episode. Similarly each between-treatment episode is of the same length.

There are some other important limitations to the current model. The systems of treatment delivery (represented as prescriber type and dispenser type) have had the opportunity to develop differently in each of the eight Australian States and Territories, yet we assume an Australia-wide model. It is based on Australia-wide data and assumes that each system of prescribing and dispensing pharmacotherapy is consistent across Australia.

The model does not accommodate take-away dosing. This is an important limitation to consider in light of the costs data produced from the model. Furthermore, although patients do not necessarily present themselves for dispensing every day, we assume full compliance in the current model.

During the building of the model, the structures and parameters were constantly tested for internal consistency. This process is difficult to document, but suffice to say that we checked each of our parameter estimates, which were themselves informed by the literature, for internal consistency given the flow structures of the model and our requirement to maintain relatively constant numbers in treatment, between treatment and entering treatment.

The specifications are logically coherent and internally consistent within the model. For example, we need to keep the number of new patients entering at a rate that will provide stable in-treatment numbers. We have endeavoured to make the documentation as transparent as possible. While readers may disagree with some of the parameters and assumptions, we hope that the scenarios we describe in the results sections will lead to new policy insights.

The purpose of the model is to explore affordability, availability, accessibility and treatment quality. In order to examine these aspects of the system, we needed to test each of these terms in our model in such a way that was consistent with the modelling capabilities.
Scenarios for affordability were tested in terms of the dispensing fees debate. We focus these scenarios on a transfer of the responsibility for dispensing fees in the private sector from patients to the federal government. With no concrete evidence on the impact of dispensing fees on the treatment-seeking and treatment-using behaviour of opioid-dependent people, we use the model to explore the consequences of removing the fees over a range of possible client responses. The repercussions for the costs faced by the federal government are of particular interest. The results regarding affordability are reported in section 5.1.

Availability of treatment was characterised as a reduction in the number of available treatment places: initially we reduce the number of GP treatment places; then we reduce the public clinic places. Attention is drawn to the implications for the numbers in and between treatment. Results are reported in section 5.2.

Increase in the potential population of opioid users — for example, through increased dependence on pharmaceutical opioids — provided the characterisation of treatment accessibility. Our scenario taps into only one aspect of accessibility — that of finding a treatment place in the context of increased population prevalence. We focus on the implications for demand for treatment. Results for accessibility are reported in section 5.3.

Our final scenario was concerned with treatment quality — and we set out to illustrate the implications of the trade-off between quality of treatment and volume of treatment places. To test our model, we assume two different types of programs: high-threshold and low-threshold programs where the high-threshold program offers individually tailored, more expensive treatment, while the low-threshold program offers reasonably homogenous treatment at a lower cost. In this highly stylised analysis, we draw attention to the implications of the two models for numbers in treatment, program costs and individual goal attainment of opioid-dependent people. Results are reported in section 5.4.

The model can produce results in terms of:
- total numbers of people in treatment and between treatment
- the types of treatment providers: prescriber types and dispensing types
- treatment costs: the amounts and who pays
- time between treatment.
3. Establishing the parameters

Following deliberation of the key building blocks in the pharmacotherapy system, the next step was to quantify or establish the parameters for the model: inserting the numbers of people in each stock; and specifying the lengths of stay and the flows between the different system components. Some data are readily available, other data required assumptions and deductive reasoning to establish the parameters. This section details the parameters, showing the information required for the model and setting out the uncertainties around some of the parameter estimates.

3.1 Major stocks of opioid-dependent people

Table 1 sets out the assumed numbers of opioid-dependent people in each of the major stocks, or locations, at commencement of the simulation, and the major flows associated with those stocks. Opioid-dependent people are assumed to be in one of the following states at any point in time: treatment naïve; in treatment; and between treatment. The numbers in pharmacotherapy treatment are based on an official compilation of statistics reported by the Australian Institute of Health and Welfare. The numbers between episodes of treatment are calibrated from the model and consistent with estimates derived from other sources.

Stock of opioid-dependent treatment-naïve people

The size of the opioid-dependent treatment-naïve population is unknown. Our strategy for estimation was to assume that the size of this group remains relatively constant over time, and calculate the number from the estimates we made of inflows and outflows to the group. There is sufficient information available to calculate the annual numbers of newly dependent opioid users (14,000), which represents the inflow to this group. We calculated the annual outflow by combining the annual number of first-time entrants to pharmacotherapy treatment, the time it takes a newly dependent opioid user to enter treatment, and death and recovery rates.

Calculating the inflow to opioid-dependent treatment-naïve population

Our model uses an estimate of 4500 newly dependent heroin users per annum. We turned to recent Australian studies that have estimated trends in the heroin-dependent population. Two studies (Razali, Thein, Bell et al., 2007; and Law, Dore, Bath et al., 2003) estimate the size of the population and both studies accommodate the more recent changes in heroin dependence associated with the ‘heroin drought’. Razali et al. (2007, Table 2) predict that from 2006 onwards the annual number of new injectors, as a proportion of the total using population, will be 5 per cent. Law et al. (2003) assume the same proportionate increase in regular IDU and occasional IDU of 8 per cent net. Based on these studies we assume that annual initiation to dependent injecting occurs at the rate of 5 per cent of the total using population (Caulkins, Dietze & Ritter, 2007; Law et al., 2003; Razali et al., 2007).
Our estimate of the population of heroin-dependent people is the mid-point between 80,000 and 100,000. Razali et al. (2007, p.232) estimate that there were around 80,000 regular injectors and 214,700 regular and occasional injectors in 2005. Law et al. (2003) predict almost 100,000 heroin-dependent people in 2001. An important limitation in using these studies is that they estimate the IDU population, not the heroin-dependent population. However, no other figures exist.

Given a population estimate of 90,000, we set the annual number of entrants to heroin dependency at 5 per cent of 90,000, or 4,500 (see Table 1).

Calculating the outflow from the opioid-dependent treatment-naïve

In our model there are three outflows from the stock of opioid-dependent treatment-naïve: entry to treatment; mortality; and recovery.

New entrants to treatment

We estimate that there are approximately 3,500 new entrants to treatment per year. Our estimate was based on New South Wales and Victorian data, suggesting that there were nearly 2,500 entrants to treatment in 2006 in those two States combined.4 We factored this figure up to an Australia-wide estimate on the basis that 70 per cent of the total treatment population were in Victoria and New South Wales.

Opioid-dependent people do not enter treatment immediately they become dependent. The outflow to treatment from the treatment-naïve stock depends on the time it takes to enter treatment. We use four years as our estimate of the time between becoming opioid-dependent and entering pharmacotherapy treatment. The Victorian arm of the Australian Treatment Outcome Study (ATOS) found that the average age at which the methadone/buprenorphine treatment participants became regular heroin users was 21.4 years and the age at first treatment was 25.0 years.5 This has led us to argue that the time to first methadone treatment was at least 3.6 years (difference between average age at first treatment and average age of regular heroin use) (Holt, Ritter, Swan & Pahoki, 2002).

The New South Wales arm of ATOS found that the average age at which treatment participants became regular heroin users was 20.5 years and the age at first treatment was 23.8 years6 suggesting that the minimum time to treatment was 3.3 years (Ross, Teesson, Darke et al., 2004).

4 New South Wales and Victoria represented 70 per cent of the stock of patients in 2006 (Australian Institute of Health and Welfare, 2007); n = 2368. Assuming that the number of entrants to treatment is proportional to the stock of patients in treatment in all jurisdictions, then the Australia-wide figure for new entrants is 3,382.

5 Note: For less than half these participants (40%) pharmacotherapy maintenance was their first form of treatment — a limitation with using these data.

6 Again, pharmacotherapy maintenance was not always the first form of treatment sought.
Table 1: Major stocks and flows of opioid-dependent people

<table>
<thead>
<tr>
<th>Major stocks and flows of opioid-dependent people</th>
<th>Number at start of simulation</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>New users p.a.</td>
<td>4500</td>
<td>Unknown. Estimated to be 5% of total IDU population (Razali et al., 2007; Caulkins et al., 2007; Law et al., 2003)</td>
</tr>
<tr>
<td>Treatment naive</td>
<td>14 000</td>
<td>Unknown. To maintain a relatively steady inflow to first treatment of around 3500 per year over the life of the simulation requires a treatment-naïve population of 14 000 over the life of the simulation, i.e. population (14 000)/years to first treatment (4) = annual inflow to treatment (3500) In support of the above estimate we calculate that a population of 12 900 would ensure that the size of the population was constant over the life of the simulation, i.e. equality between the annual inflow and the annual outflow: annual inflow (4500) = annual outflow to treatment (12 900/4) + annual outflow to death and abstinence (10% of 12 900)</td>
</tr>
<tr>
<td>New entrants to treatment p.a.</td>
<td>3500</td>
<td>This fits with information provided by Victoria and New South Wales, which suggested that the annual number of new entrants to pharmacotherapy treatment currently stands at 2500 for the two jurisdictions combined. Since Victoria and New South Wales account for 70 per cent of the Australia-wide treatment population, this suggests an annual Australia-wide inflow figure of around 3500</td>
</tr>
<tr>
<td>Numbers in buprenorphine treatment</td>
<td>11 100</td>
<td>As above (Australian Institute of Health and Welfare, 2007)</td>
</tr>
</tbody>
</table>
Establishing the parameters

The population in treatment

The numbers in treatment are sourced from the annual Australian Institute of Health and Welfare publication on alcohol and drug treatment services in Australia. The latest published report is for 2006–07. However, the model was based on the 2005–06 number of pharmacotherapy patients (both buprenorphine and methadone), which is taken to represent the number of patients on the program on a ‘snapshot/specifed’ day in June 2006. The June 2007 numbers are very similar. As can be seen in Table 1, at the commencement of the simulation we have 27,346 people in methadone maintenance treatment, and 11,100 in buprenorphine maintenance treatment.

Due to time constraints and available information, it was difficult to accommodate both buprenorphine and methadone fully in the model. As a compromise, we elected to include a stock for buprenorphine treatment, but not specify the costs, prescribing and dispensing splits. Effectively, the remainder of the model specifications and discussions concern only methadone. However, in order to derive a reasonable total population from the model and, as accurately as possible, represent inflows into pharmacotherapy maintenance treatment, we included a simple representation of buprenorphine as a single stock. We were also required to specify the differential inflows to methadone and buprenorphine treatment from the treatment-naive group, because the relativity between the inflows to the two treatments is not necessarily the same as the relative proportions in treatment at any point in time. The model uses an inflow split of 36 per cent to buprenorphine and 64 per cent to methadone. These percentages ensured that, in relative terms, the numbers in buprenorphine versus methadone remained more or less stable over the life of simulation.

<table>
<thead>
<tr>
<th>Major stocks and flows of opioid-dependent people</th>
<th>Number at start of simulation</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Numbers between treatment</td>
<td>41,100</td>
<td>To maintain the requirement that numbers in treatment remain relatively constant over the life of the simulation, and given the estimated lengths of stay in treatment and between treatment, the model estimates 41,100 people between treatment.</td>
</tr>
<tr>
<td>Total population of model</td>
<td>93,546</td>
<td>Calculated from model as sum of stocks: $14,000 + 27,346 + 11,100 + 41,100 = 93,546$</td>
</tr>
</tbody>
</table>


8 There are some substantial uncertainties with the data due to inconsistency in the way data items are defined and collected across jurisdictions.
The second assumption in this section of the model is the extent of flow between methadone and buprenorphine. In reality we know that some proportion of people who have received methadone in the past, commence buprenorphine treatment. Likewise a proportion of people previously in buprenorphine treatment, subsequently seek methadone treatment. When buprenorphine was first introduced to Australia, the numbers in buprenorphine treatment progressively grew. Now it appears that the numbers are leveling off and that there is a stable relationship between the numbers in methadone and the numbers in buprenorphine. Therefore, the model assumes a zero net flow between methadone and buprenorphine (that is, while some people may switch from methadone to buprenorphine, a similar number will switch from buprenorphine to methadone).

The population between treatment

Finally, we needed to estimate the number of people between treatment at the commencement of the simulation. The between-treatment population of 41,100 is calibrated from the model and based on the requirement to maintain numbers in treatment relatively constant over the life of the simulation, and with the length of stay in treatment being, on average, slightly shorter than the length of stay between treatment. The end result, 41,100 people between treatment, represents a ratio of between-treatment to in-treatment of around 1:1.

We sought information that might corroborate or refute this ratio. Victorian jurisdictional data were used to examine the ratio of in-treatment to between-treatment through the permit system. The ratio of the number of permits for treatment ever granted to the number of patients in treatment at a point in time can be established. Over two years 28,000 patients were granted permits to receive pharmacotherapy. At the end of that period there were 11,000 patients in treatment providing an upper bound for the ratio of between-treatment to in-treatment of 17,000 to 11,000, i.e. 1.5. It is an upper bound because 17,000 is most probably an over-estimate of the between-treatment group since it includes former patients who may have died or become abstinent.

In their survey of injecting drug users, Dietze, Richards, Rumbold et al. (2003, p.29) found that 63 per cent had been in treatment, 45 per cent had been in treatment in the last 12 months, and 26 per cent were in treatment on the day of the interview. This suggests a ratio of between-treatment to in-treatment ranging from $0.4 = (63-45)/45$ to $1.4 = (63-26)/26$.

From these two sources it is difficult to establish a better estimate of the ratio of in-treatment to between-treatment. The model’s ratio of 1:1 sits roughly in the middle of the ranges provided by other sources.

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9 This assumption of a stable relationship between the numbers in methadone treatment and the numbers in buprenorphine treatment was supported by discussions with the pharmaceutical company and with the Health Departments in Victoria and New South Wales.
The total opioid-dependent population

The total number of people in our model is 93,546 at simulation commencement (14,000 + 27,346 + 11,100 + 41,100 = 93,546). This estimate accords reasonably well with existing estimates: Razali et al. (2007, p.232) arrived at an estimate of around 80,000 regular injectors in 2005. Law et al. (2003) predicted almost 100,000 heroin dependent in 2001.

3.2 Methadone prescribers and dispensers

A feature of the Australian system is that there are different types of prescribers and dispensers. The model differentiates between three types of prescribing medical practitioners: those employed by public treatment clinics; those working in primary health care settings, including those prescribing out of private clinics; and those employed to work in the prison system. It is essential to differentiate prescriber types on this basis because they are associated with different costs and funding sources. Additionally, the settings are associated with different patient pathways and lengths of stay.

Table 2 reports on the model’s allocation of methadone patients to the prescriber types on entry to treatment for the first time, and on re-entering treatment from the between-treatment group. In terms of the stocks of patients in treatment, the Australian Institute of Health and Welfare (AIHW) (2007) tells us that in mid-2006 28 per cent of patients were prescribed in public clinics (public); 62 per cent were prescribed by private medical practitioners (GP);¹⁰ and 8 per cent were prescribed in prisons (prison). According to Bell et al. (2006), the first treatment episode inflow of New South Wales patients in 2000 was 31 per cent, 56 per cent and 9 per cent to public, GP and prison respectively.¹¹ For Australia as a whole we need to place more importance on the inflow to GPs. Victoria, for example, relies almost exclusively on GP prescribing.

We derived our estimates of the inflow allocations in light of the AIHW figures and the Bell research results. We were guided by our decision to maintain, as far as possible, this relative allocation of the stocks in each prescriber type over the life of the simulation. As we describe below, because patients spend different amounts of time in treatment, depending on the location of their prescriber, the first entry and subsequent entry allocations are not the same as the stock allocation.

¹⁰ The datasets used by the federal government do not distinguish between private clinics and GP settings – both are classified as ‘private’ because the prescribing is paid for through Medicare.

¹¹ We assume that 15 per cent of the inflow to the first episode of treatment is via prison prescribing. That might seem high, in light of the fact that some jurisdictions do not prescribe pharmacotherapy drugs to new prisoners who were not in treatment before entering treatment. Our decision was based on the need to maintain numbers in treatment in prisons.
At the commencement of the simulation, with a stock of 27,346 methadone maintenance patients, the split between the prescribers is: public clinics = 7,853; GPs = 17,169; and prison = 2,324 (Australian Institute of Health and Welfare, 2007).

Likewise, the location of dispensing is diverse in Australia – dispensing can occur within the context of a public clinic, a hospital, a community pharmacy, or a private clinic. Again, the funding for dispensing varies depending on the dispensing type. So our model differentiates between the dispensing types. The majority of patients prescribed in a public clinic are dispensed in community pharmacies. All of the patients whose prescriber is a medical practitioner in primary care are dispensed in a community pharmacy. We assume, for the purposes of the model, that all patients prescribed in private clinics are dispensed in community pharmacies. Naturally all patients prescribed in prisons are dispensed in prisons.

Table 3 outlines the allocations of patients by prescriber type into dispenser. The Australian Institute of Health and Welfare (2007, Table 4.3) tells us that in mid-2006 the approximate shares of pharmacy, public and prison dispensing were 78 per cent, 13 per cent and 9 per cent respectively. In making the allocations, we were guided by our decision to largely maintain this relative allocation of the stocks in each dispenser type over the life of the simulation.

Table 2: Flows into prescriber at first episode and subsequent episodes of treatment by prescriber type

<table>
<thead>
<tr>
<th>Prescriber type</th>
<th>Prescriber allocation</th>
</tr>
</thead>
<tbody>
<tr>
<td>First episode of treatment</td>
<td></td>
</tr>
<tr>
<td>• public</td>
<td>25%</td>
</tr>
<tr>
<td>• GP</td>
<td>60%</td>
</tr>
<tr>
<td>• prison</td>
<td>15%</td>
</tr>
<tr>
<td>Subsequent episodes of treatment from between-treatment</td>
<td></td>
</tr>
<tr>
<td>• public</td>
<td>30%</td>
</tr>
<tr>
<td>• GP</td>
<td>50%</td>
</tr>
<tr>
<td>• prison</td>
<td>20%</td>
</tr>
</tbody>
</table>

12 Uncertainties exist with the AIHW data. For example, when pharmacotherapy patients are broken down by dispenser site, Northern Territory is excluded since the relevant data are unavailable. Queensland data exclude patients who were not physically dosed on the snapshot day, thereby excluding those with take-away privileges.
3.3 Flows between and around treatment

The rates of flows between treatment modalities (prescriber types) and into and out of treatment are driven by the lengths of stay in the various ‘states/stocks’.

Table 4 reports the lengths of stay in the key locations; that is, in each of the methadone prescribing locations and when between-treatment. The flows between prescribing locations and between-treatment are also provided in Table 4.

The lengths of stay are ‘averages’ — any one individual may stay for a shorter or longer period. One simplification of the model is that the lengths of stay are the same, regardless of whether it is the first episode of treatment or subsequent episodes. The average length of stay is 7 months in public clinics, 12 months in GP services, and 3 months in prison, while the average length of time between episodes of treatment is 12 months.

We derived the average lengths of stay from a number of sources: the ATOS and NEPOD studies, individual studies (e.g. Bell et al., 2006) and jurisdictional data. The following brief review of Australian analysis on retention shows remarkable consistency of findings. We can expect that roughly half of treatment entrants (be they entering treatment for the first time or subsequently) will have left that episode of treatment after six months. It appears that methadone patients stay longer in treatment than buprenorphine patients and that patients prescribed by private medical practitioners stay longer than those prescribed in public clinics.

Evidence from the Australian Treatment Outcome Study (ATOS) found that 44 per cent of those interviewed 12 months after entering pharmacotherapy treatment (methadone and buprenorphine) had remained in that episode of treatment for the entire 12 months. If those who could not be interviewed were counted as not being in treatment, the retention figure falls to 36 per cent (Ross et al., 2004, p.20). These findings suggest that an entrant to pharmacotherapy treatment, regardless of their location and their prescriber type, could expect to stay continuously in treatment for a period of less than one year. The National Evaluation of Pharmacotherapies for Opioid Dependence (NEPOD) studies suggest that half of the methadone patients stayed in treatment for six months, with just under 40 per cent of buprenorphine patients staying for that amount of time (Mattick, Digiusto, Doran et al., 2001). The ATOS and NEPOD findings are supported by those of a study of New South Wales pharmacotherapy treatment administrative data (Bell et al., 2006). The study found that, of first-time entrants to treatment in February 2000, roughly half remained in treatment for six months continuously. Only 39 per cent were still in that treatment episode after 12 months.
In a study of methadone and buprenorphine implementation, Ritter, Lintzeris, Kutin et al. (2001) found that 71 per cent of patients prescribed in GP settings were still in treatment after one year. Based on survival analysis the mean retention was 312 days, which was substantially higher than the NEPOD average, suggesting that patients prescribed by GPs have longer treatment episodes than public patients. However, the New South Wales study (Bell et al., 2006) had countervailing findings. The study’s comparison of public and private entrants found that 55 per cent of the public prescriber patients remained in treatment after six months, compared with only 46 per cent of the private prescriber patients. The comparable 12-month retention figures were 45 per cent and 29 per cent respectively. We cannot account for the differences between the study findings. In consultations about the model, we did not receive any further information to assist with determining lengths of stay, but respondents were comfortable with the figures we have used.

With no information available on the length of time that patients prescribed in prison remain in treatment, we selected three months. In terms of the stock of patients in treatment at any one time very few are in prison, so this decision has little impact on outcomes. Bell et al. (2006) analysed the length of time it took New South Wales patients to re-enter treatment by following the experience of members of two cohorts of first-time entrants to treatment once they left treatment (the 1990 and 1995 cohorts). At least 50 per cent of both cohorts had re-entered within 12 months (51 per cent and 69 per cent respectively).
Table 4: Lengths of stay in-treatment and between-treatment and flows between prescribers (months)

<table>
<thead>
<tr>
<th>Location</th>
<th>Lengths of stay</th>
</tr>
</thead>
<tbody>
<tr>
<td>Methadone prescriber</td>
<td></td>
</tr>
<tr>
<td>• public</td>
<td>7</td>
</tr>
<tr>
<td>• GP</td>
<td>12</td>
</tr>
<tr>
<td>• prison</td>
<td>3</td>
</tr>
<tr>
<td>Buprenorphine treatment*</td>
<td>6</td>
</tr>
<tr>
<td>Between treatment</td>
<td>12</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Patient flows</th>
<th>Flow probabilities</th>
</tr>
</thead>
<tbody>
<tr>
<td>from GP</td>
<td>to public 10%</td>
</tr>
<tr>
<td></td>
<td>to prison 5%</td>
</tr>
<tr>
<td></td>
<td>to between-treatment 85%</td>
</tr>
<tr>
<td>from public</td>
<td>to GP 10%</td>
</tr>
<tr>
<td></td>
<td>to between-treatment 85%</td>
</tr>
<tr>
<td></td>
<td>to prison 5%</td>
</tr>
<tr>
<td>from out of treatment</td>
<td>to public 30%</td>
</tr>
<tr>
<td></td>
<td>to GP 50%</td>
</tr>
<tr>
<td></td>
<td>to prison 20%</td>
</tr>
</tbody>
</table>

Note * the model does not distinguish buprenorphine prescriber types.
3.4 Exits from the model

There are two ways in which stocks are reduced in the model — through abstinence or through mortality. Table 5 summarises our assumptions about the mortality rates and cessation rates.

Cessation of heroin use can occur before heroin users first access treatment, or at any point in the treatment career. We assume that the pre-treatment cessation rate for dependent heroin users is 5 per cent per annum (i.e. the annual probability of ceasing use). Although not based on research, this accords with the assumptions made by Australian studies (Caulkins et al., 2007; Law et al., 2003).

Cessation while in treatment and between treatment is set at 1.5 per cent per annum. It is lower than the before-treatment rate because spontaneous remission (or natural recovery, as it is known by some) removes from the pool those people who ‘easily’ cease use. There are very little data to inform our cessation rate of 1.5 per cent. Most existing Australian research estimates a cessation (abstinence) rate based on six- or 12-month follow-up information. For example, Darke, Ross, Mills et al. (2007) reported 14 per cent abstinence at 12 months for the ATOS sample. We cannot use these figures because they over-inflate abstinence due to the timeframe of 12 months. Only longer-term follow-up studies (>3 yrs) provide estimates of prolonged abstinence, which then require conversion to an annual rate.

In the United States, Hser, Hoffman, Grella & Anglin (2001) report a rate of 2.86 per cent per annum at 10 years; 1.25 per cent per annum at 20 years; and 0.7 per cent per annum at 33 years. The Drug Abuse Treatment Outcome Study (DATOS) found a rate of 3.6 per cent per annum over five years (Hser, 2003). For the methadone treatment group in the United Kingdom National Treatment Outcome Research Study (NTORS), Gossop, Marsden, Stewart & Kidd (2003) reported an average of 5.8 per cent abstinent per annum.13 Turning to the limited Australian data, Byrne (2000) reported a 3.6 per cent annual ‘recovery’ in methadone maintenance.14 Darke, Ross et al. (2007) in the 36-month follow-up of the New South Wales ATOS sample, report 8 per cent sustained abstinence, which converts to an annual rate of 2.6 per cent per annum.

These sources give us the following estimates: percentages of 0.7, 1.25, 2.6, 2.86, 3.6 and 5.8 respectively. Our estimate is for both in-treatment and between-treatment. The estimate used in the model — 1.5 per cent — is conservative.

There is substantial international and Australian research evidence supporting the claim that treatment reduces mortality rates (see Darke, Degenhardt & Mattick, 2007; Denis, Roscop, Lavie et al., 2008; for a review of the literature). We set the pre-treatment death rate at 2 per cent per annum. There was no Australian research to inform us, but a recent international systematic review found that the number of deaths per 1000 person years ranged from 20.0 to 83.8 (Denis et al., 2008). Our estimate is at the lower end of this range.15

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13 Gossop et al., 2003: meth group 25.7 per cent abstinent from all drugs at 4–5 years (av 4.4 yrs) = 5.8 per cent per annum; abstinent from heroin = 39.1 per cent = 8.89 per cent per annum.

14 Sample size of 31 patients over 8.6 years prolonged abstinence.

15 Note that much of the literature on mortality rates reports the mortality rate per 1000 person years. Translating this to an annual mortality rate is not as simple as dividing by 10, but this is a reasonable approximation and one that we have used for the purposes of this study.
Three Australian studies have investigated the mortality rates of cohorts of entrants to pharmacotherapy treatment (Gibson, Degenhardt, Mattick et al., 2008; Byrne, 2000; Caplehorn, Dalton, Cluff & Petrenas, 1994). They found annual mortality rates for these cohorts of around 1 per cent per annum. Gibson et al. (2008) found no difference between the mortality rates of buprenorphine and methadone patients in treatment, so we assume identical mortality rates for these two groups. This study found a remarkably low 0.1 per cent per annum mortality rate for members of the in-treatment group. We set our rate at 0.8 per cent, which sits at the low end of the range of deaths per 1000 person years (5.0 to 25.0) reported in international review studies (Denis et al., 2008; Darke, Degenhardt & Mattick, 2007). According to Caplehorn et al. (2004) and Gibson et al. (2007), those between treatment were at least three times as likely to die as those in treatment. We set our between-treatment mortality rate at 2 per cent per annum, somewhat less than three times the in-treatment rate, but again more in line with the findings of international studies which saw deaths per 1000 person years ranging from 16.5 to 82.0 (Denis et al., 2008).

Table 5: Mortality and abstinence rates

<table>
<thead>
<tr>
<th>Death rate</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-treatment</td>
<td>2%/annum</td>
</tr>
<tr>
<td>In treatment</td>
<td>0.8%/annum</td>
</tr>
<tr>
<td>Between treatment</td>
<td>2%/annum</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Abstinence/cessation rate</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-treatment ceasing use rate</td>
<td>5%/annum</td>
</tr>
<tr>
<td>In and between treatment</td>
<td>1.5%/annum</td>
</tr>
</tbody>
</table>
3.5 Funding as represented in the model

Currently federal, State and Territory governments, as well as patients, all contribute to the funding of opioid pharmacotherapy treatment. The model includes treatment costs and estimates the contribution to costs of each of the three funders (henceforth State governments, federal government and patients).

We distinguish between the prescribing and dispensing costs. We are interested in the direct costs of treatment, so we do not include the costs borne by patients associated with travel, for example.

In constructing the costs, we relied largely on published research — and each piece of research had idiosyncratic costing methods. For this reason there are likely to be uncertainties around the cost components used in the model.

Ideally the costs we use would approximate ‘marginal cost’, or the change in cost that arises when the quantity of services increases by one unit. We used NEPOD and other cost data which were documented as marginal costs. However, a limitation of using these estimates is that our scenarios involve changes to service capacity, whereas these studies did not accommodate capacity expansion associated with expanding infrastructure. This means that our cost estimates may underestimate the impact of increased treatment numbers. That is, when considering capacity changes it is important to differentiate between capacity increases that can be absorbed with the current infrastructure and those associated with expanding the infrastructure, that is physical capacity (through, for example, expanding the premises or building new clinics) and/or staffing capacity (through, for example, staff training or hiring of new staff). It is unlikely that any of the cost estimates used in our model fully accommodate infrastructure expansion.

Prescribing

In public clinics the prescribing is funded entirely by the State/Territory governments.\textsuperscript{16} We estimate the cost of prescribing in public clinics, from the NEPOD data, as $14.58 per day. The NEPOD report does not provide details of what is included within this public clinic cost but we take it to be inclusive of medical services and any case management/counselling support that is provided.

In the GP and private sector the costs of medical consultations and pathology tests for methadone and buprenorphine patients are covered by the Australian Government under Medicare, as long as the doctor charges no more than the Medicare benefit; patients receive the rebate from the federal government. We presume that the large majority of medical practitioners charge pharmacotherapy patients no more than the Medicare benefit, but there is no evidence either way.\textsuperscript{17}

Medicare-funded services associated with pharmacotherapy maintenance are not distinguishable from other visits to medical practitioners in the Medicare Benefits Schedule (MBS) statistics\textsuperscript{18} and the frequency of service

\textsuperscript{16} These funds come out of State spending on health funded through State general taxation revenue via transfers from the federal government.

\textsuperscript{17} The majority of patients rely on income support as their primary source of income, so one would expect that this would be the norm. Patients would, however, need to cover any gap between the Medicare benefit and actual fees for visits to medical practitioners for prescribing.

\textsuperscript{18} \url{http://www.medicareaustralia.gov.au/statistics/dyn_mbs/forms/mbsgtab4.shtml}. 
provision is left largely to the practitioner’s judgement. Two attempts at estimating the frequency of service provision, one based on analysis of patient visits to medical practitioners from the MBS statistics (Ward & Mattick, 2005) and the other on observation of patient visits to medical practitioners in the NEPOD study (Mattick et al., 2001), result in markedly different estimates. Ward and Mattick (2005) constructed two estimates. The first consisted of an average of 24.2 consultations with any methadone-prescribing doctor. Their more conservative estimate was to limit consultations to only those consultations provided by the patient’s registered doctor, which reduced the annual consultations to 19.7. According to our calculations of the NEPOD data, the comparable annual figure for doctor consultations is about 12.

We base our GP cost figure on the raw NEPOD data, i.e. $3.78 per day. In their published form, they do not distinguish between all the costs as thoroughly as we would like (Mattick et al., 2001). But we assume it includes the prescribing costs and any additional services that the medical practitioner provides as part of each individual consultation.

The prescribing costs for prison are set at $9.26 per day, based on an analysis of opioid pharmacotherapy treatment in the New South Wales prison system (Warren & Viney, 2004).

The pharmacotherapy drugs

The Australian Government has the financial responsibility for providing pharmaceutical services through the Pharmaceutical Benefits Scheme (PBS). The drugs methadone and buprenorphine are listed as Schedule 8 (Controlled) drugs in Australia, meaning there are strict regulatory controls associated with their use. The Australian Government funds the cost of both drugs for treatment of opioid dependence supplied under the PBS. Both drugs are supplied through the PBS under a particular program (the opiate dependence treatment program, provided for under section 100 of the National Health Act 1953). The Australian Government provides the drugs free of charge to the body responsible for dispensing (be it a public clinic, community pharmacy, prison or hospital).

Based on studies of the dose level in New South Wales and Victoria, we assume an average dose of 70mg (Winstock, 2008; Lintzeris, Pritchard & Sciacchitano, 2007). According to the PBS, the cost of 1 litre of methadone is $36 per litre19 or 3.6 cents per ml or 0.72 cents per 1 mg. Therefore the cost per dose is 50.4 cents.

---

Dispensing

In the community pharmacies and private clinics, the patients themselves tend to cover the cost of dispensing. There are a number of exemptions and special arrangements affecting a minority of patients: for example, free dispensing for juveniles in Victoria; prison releasees receive dispensing fee relief in a number of jurisdictions; the Northern Territory Government pays the dispensing fees for mothers and pregnant women. There are significant differences in fees paid by patients both between and within jurisdictions. For example, Muhleisen, Clark, Teo & Brogan (2005) noted weekly fees ranging from $9 to $53 in New South Wales, and from $15 to $30 in Victoria. A number of pharmacies charge the same weekly fees, regardless of the number of take-away doses. We use a dispensing fee figure of $5 per day for community pharmacies.

In the public clinics in New South Wales, Queensland, the Northern Territory, South Australia and Western Australia, each State/Territory government covers the dispensing fee. In the other jurisdictions (Tasmania, Victoria and the Australian Capital Territory) the patients pay some proportion of the dispensing costs. Nonetheless, we assume that all public clinic patients are dispensed free of charge and, on the basis of the NEPOD data, calculate the daily dispensing cost covered by the State/Territory government as $1.05.

Prison dispensing is covered entirely by State/Territory governments. There are no available estimates, so we used the public clinic dispensing cost.

Case management, counselling and psychosocial support

We had some difficulty accurately accommodating case management and counselling costs in our model. The main reason is that it is likely, but unclear, as to whether these costs are included in the NEPOD costs, especially for the public clinic costs. Thus the daily cost of prescribing in public clinics of $14.58 is assumed to include additional psychosocial services.

In the GP settings, we do not have any record of case management or counselling costs. Until 2006, this may have been trivial in any case. But since 2006, the Australian Government has invested in new programs to provide better access to case management, mental health professionals and team-based mental health care under the Better Access to Psychiatrists, Psychologists and General Practitioners through the Medicare Benefits Schedule (MBS) initiative. The initiative includes three new Medicare items for GPs providing mental health care: the preparation of a GP mental health care plan; the review of a GP mental health care plan; and GP mental health care consultation. It also provides GPs with new referral pathways by introducing Medicare items for psychological assessment and therapy services provided by clinical psychologists and the provision of psychological strategies by allied mental health professionals (see Appendix A for details).
In theory, these costs should be included in the model. However, we lack essential pieces of information, specifically the extent to which GPs are taking up these options and referring patients to psychological services; the availability of the psychological services; and the numbers of patients per annum who receive these services. Given the substantial uncertainties, we have excluded these costs from the model, but note that this therefore underestimates federal government costs.

### Other points

State/Territory governments also subsidise service providers in some instances. For example, the New South Wales Government pays a once-only incentive payment to pharmacies new to dispensing and ongoing incentives for continuous patients. The Australian Capital Territory Government subsidises community pharmacies to the value of $15 per week per patient. Tasmania also provides incentive payments to pharmacists. We do not take these idiosyncratic payments into account in the model; hence State government investment is under-estimated.

<table>
<thead>
<tr>
<th>Cost type</th>
<th>Costs</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medication cost (per dose)</td>
<td>50.4 cents</td>
<td>PBS $36 per litre; 1mg = $0.72 Av. meth. dose 70mg</td>
</tr>
<tr>
<td><strong>Costs — prescribing</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>public</td>
<td>$14.58 per day</td>
<td>Our calculations from NEPOD data</td>
</tr>
<tr>
<td>GP</td>
<td>$3.78 per day</td>
<td>Our calculations from NEPOD data</td>
</tr>
<tr>
<td>prison</td>
<td>$9.26 per day</td>
<td>Warren &amp; Viney, 2004</td>
</tr>
<tr>
<td><strong>Costs — dispensing</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>public</td>
<td>$1.05</td>
<td>Our calculations from NEPOD data</td>
</tr>
<tr>
<td>pharmacy</td>
<td>$5.00</td>
<td>Averaged from New South Wales, Victorian &amp; Australian Capital Territory surveys</td>
</tr>
<tr>
<td>prison</td>
<td>$1.05</td>
<td>Assumed same as public — no other data</td>
</tr>
</tbody>
</table>
Table 7 summarises the current service delivery systems and the proportion of patients prescribed and dispensed in each of the models. The bearer of the costs depends on the location of the prescribing and dispensing. The table also shows our assumptions about the primary bearer of costs in each of the systems. Our cost sharing is stylised, i.e. the State covers 100 per cent of dispensing costs in public clinics, even though we are aware of some public clinics that charge dispensing fees to patients. Likewise, we assume that patients cover 100 per cent of dispensing costs in pharmacies even though some governments offset the costs to pharmacies through incentive payments.

Table 7: Proportion of pharmacotherapy patients by prescriber and dispenser type in 2006, and bearer of costs of treatment for prescriber and dispenser

<table>
<thead>
<tr>
<th>Prescriber type</th>
<th>Proportion of patients (%)</th>
<th>Bearer of costs of treatment (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Patient</td>
<td>Federal</td>
</tr>
<tr>
<td>Public clinic</td>
<td>28</td>
<td>0</td>
</tr>
<tr>
<td>GP(^b)</td>
<td>64</td>
<td>0</td>
</tr>
<tr>
<td>Prison</td>
<td>7</td>
<td>0</td>
</tr>
<tr>
<td>Dispenser type</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Public clinic</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>Community pharmacy(^c)</td>
<td>79</td>
<td>100</td>
</tr>
<tr>
<td>Prison</td>
<td>7</td>
<td>0</td>
</tr>
<tr>
<td>The drug</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Public clinic</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>Community pharmacy(^c)</td>
<td>79</td>
<td>0</td>
</tr>
<tr>
<td>Prison</td>
<td>7</td>
<td>0</td>
</tr>
</tbody>
</table>

Source: Australian Institute of Health and Welfare, 2007, Tables 6.3 and 6.4

\(^a\) Proportions do not add to 100 per cent because some treatment centres cannot be classified along these lines.

\(^b\) Includes those prescribed in private clinics.

\(^c\) Includes those dispensed in private clinics.
3.6 Sensitivity analyses

As with any model, there is uncertainty surrounding parameter assumptions and the construct of the model. So, how trustworthy are policy recommendations arising from the model? And, how important is each of the parameter assumptions to the behaviour of the model? We conducted some limited sensitivity analyses on the model parameters. These are reported in Appendix B. The variables we chose were: mortality rates; and lengths of stay in treatment and between treatment, as these have the potential to be key drivers of numbers in treatment and between treatment.

Since the goal of the model is to inform policy recommendations, it is arguably more important to explore the sensitivity of policy recommendations to parameter assumptions and the construct of the model. Effectively that is what we do when exploring each of the policy scenarios. For example, when uncertain about behavioural responses, as we are in relation to the impact of dispensing fees on retention in and entry to treatment, we allow for a range of behavioural responses.
4. Model results at base case

Prior to conducting scenario testing – which is the primary purpose of the model – we examine some basic descriptive results from the model, using the base-case parameters and assumptions set out in section 3. The model simulates a 10-year period, one month at a time. The descriptive results reveal how the following key model outcomes evolve over the simulation period: numbers of patients in treatment and between treatment; prescribing and dispensing location of patients in treatment; and the costs faced by each of the three funders.

In Figure 2 we have charted the simulated numbers of those in treatment and between treatment over the 10 years. As can be seen, the model depicts a relatively stable number of patients in treatment over the 10-year period, with just under 40 000 at the start of the simulation and closer to 45 000 at simulation end. The majority of these patients receive methadone. The number between treatment is also (deliberately) relatively stable across time, commencing at just over 40 000 and stabilising around 44 000 at simulation end. The numbers are provided in Appendix C.

Figure 2: Numbers of patients in pharmacotherapy treatment (methadone and buprenorphine) and between pharmacotherapy treatment over a simulation of 120 months
Figures 3 and 4 set out the numbers in methadone treatment by prescriber and dispenser types respectively. They serve to remind us that Australia-wide the bulk of prescribing is undertaken by private medical practitioners (63%) and the burden of dispensing is largely borne by community pharmacists (80%). The numbers are reported in Appendix D.

The base-case model estimates the numbers of people between treatment at the commencement of simulation, which is 41 100. This represents people who have previously sought pharmacotherapy maintenance treatment but are not in treatment at that point in time. This is an approximation of the potential unmet demand for treatment. While the number was calibrated from a stable system — and so is not necessarily an independent indicator of unmet demand, it is certainly one reasonable indicator.

Figure 3: Methadone patients by prescriber type over a simulation of 120 months
Given the parameters described in section 3.5 above, our model demonstrates the costs associated with providing methadone maintenance and who bears those costs. As can be seen in Figure 5, the monthly cost to the State and Territory governments (henceforth State governments) combined at simulation end is estimated to be 5.06 million, the monthly cost to the Australian Government is $2.77 million and the costs covered by patients total $3.90 million per month. The States carry the highest cost burden, followed by the patient. According to our model, the overall total cost per month for the provision of methadone maintenance is $11.73 million.

As noted in the earlier section, there are caveats for these data: the NEPOD data were used to estimate both the public clinic and GP costs; and the patient dispensing fee in community pharmacies was set at $5 per day.

How do the costs associated with providing the treatment (as estimated from our model) compare with the economic benefits of providing treatment? In order to conduct such analyses, one requires estimates of the social cost of heroin use. This project did not include a cost–benefit component, but we use existing published data to derive approximate estimates of the social costs associated with heroin use (i.e. incurred in the out-of-treatment State). Ideally, a social cost estimate of the burden of heroin use would include the costs associated with health care utilisation, criminal activity, welfare payments, family disruption,
poor public amenity and private costs. In reality, we could source data only for estimates of health care utilisation and criminal activity associated with ongoing heroin use. The estimated cost of health care utilisation plus criminal activity per heroin user ranged from a low figure of $6000 to a high figure of $12 000 per annum. The full details are provided in Appendix E. Therefore treatment for one year for one person saves the community between $6000 and $12 000. Expressed as a monthly figure, cost savings associated with one month of pharmacotherapy maintenance treatment range from a low of $500 to a high of $1000.

We can then apply these figures to the numbers in treatment in our model and compare them to the modelled treatment costs. The cost of providing methadone maintenance is $11.73 million per month (see Figure 5). The cost savings per month, given that 31 568 people are in treatment in that month are between $15.8m and $31.6 million per month.\textsuperscript{20} It is clear that the provision of pharmacotherapy maintenance treatment, while costly, is outweighed by the economic benefits accruing to the community through reductions in health care utilisation and crime.

\textsuperscript{20} 31 568 people in treatment in month 120 of the model multiplied by $500 per month (low estimate) = $15 784 000 cost savings; high estimate $1000 per month cost savings of $31 568 000.
5. Scenario exploration

We explore four different policy scenarios:

- affordability — government pays dispensing fees
- availability — reducing treatment places
- accessibility — increased demand for treatment
- quality — quality versus volume trade-offs.

5.1 Affordability: government pays dispensing fees

Probably the most talked-about issue for Australian pharmacotherapy programs is that of patient dispensing fees. While the cost of methadone and buprenorphine medication is funded by the Australian Government, the cost associated with dispensing the drug is not. In public-funded clinics, the cost of dispensing the medication is generally paid for by the State government, but sometimes by the patient. All patients who receive their medication in community pharmacies (and private clinics) pay a dispensing fee. Based on official figures of the location of dispensing, we estimate that over 80 per cent of pharmacotherapy patients pay something for dispensing (Australian Institute of Health and Welfare, 2007, Table 6.4).

The most obvious concern with dispensing fees is that patients simply cannot afford them. Another concern with patient dispensing fees is the inherent inequity. The Australian Government has financial responsibility for providing pharmaceutical services through the Pharmaceutical Benefits Scheme (PBS), a scheme that is designed to provide equity of access to PBS-approved prescription drugs. It achieves equity of access through subsidising the price of prescription drugs, the price incorporating both the cost of the drug and dispensing costs. Methadone and buprenorphine are both PBS-approved drugs, yet the Australian Government does not subsidise the dispensing costs. The dispensing fee arrangements also introduce inequities within the patient population. For a discussion of these issues, see Ritter and Chalmers (2009).

In the first policy scenario we explore the implications of the federal government subsidising the dispensing costs of methadone for patients dispensed in pharmacies (and private clinics). This is not to say that were dispensing fees transferred from the patient to the public purse, they should automatically be seen as the responsibility of the federal government. The other jurisdictions could equally take responsibility for the dispensing fees.

To commence, we simply estimate the costs to the Australian Government should they fund dispensing for those not dispensed in public clinics. This simple accounting exercise, illustrated in Figure 6 (scenario 1), reveals that the monthly cost to the federal government would be $3.9 million. We discuss the implications of this below. The assumption behind such a simplistic accounting exercise is that people do not change their behaviour in response to an alteration in the cost of services. This is unlikely to be true — for example, patients may stay longer in treatment and/or more may be encouraged into treatment. The model allows us to accommodate these potential behavioural changes in our costing estimate.
There is surprisingly little research that investigates quantifying the impact of fees (dispensing or otherwise) on those in pharmacotherapy treatment and on those thinking of entering treatment. While it seems self-evident that cost of treatment must impact on entry to treatment and retention in some way, the evidence base for the extent of the impact is lacking (see Ritter and Chalmers, 2009, for a review of the literature). Given this uncertainty we use the model to explore the implications of a range of possible behavioural responses in terms of time spent in treatment and time taken to enter treatment:

- Under scenario 2, the length of stay of patients whose fees are now covered increases by 50 per cent, i.e. from 12 months to 18 months for GP patients (since all are dispensed in pharmacies); and from 7 months to 10.5 months for public clinic patients dispensed in pharmacies.

- Under scenario 3, the average time to initial treatment entry from the treatment-naïve group is reduced from four years to two years (in addition to the increase in length of stay) (i.e. cumulative impact).

In Figure 6, the line entitled ‘Status quo’ shows that, under the current arrangement, the Australian Government does not contribute to dispensing fees. Under scenario 1, there is a simple transfer of dispensing fees from patients to the government amounting to almost $3.9 million per month at the end of the simulation period. Under scenario 2, numbers in treatment increase by 5549 by end of simulation, an almost 18 per cent increase. This further increases the government’s costs of dispensing by $0.8 million per month to $4.7 million per month at end of simulation. Under scenario 3, a further 3068 opioid-dependent people are in treatment at simulation end with government spending on dispensing increasing by another $0.4 million per month to $5.1 million. These additional patients also incur medication and prescribing costs: government funding of the medication (methadone) and prescribing (GP fees) increases by almost $1 million per month from the base case.
Status quo: Patient pays dispensing fees at pharmacies

Scenario 1: Federal government pays dispensing fees at pharmacies

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 four years to two years
### Table 8: Methadone patients and federal government dispensing costs at end of simulation under various scenarios

<table>
<thead>
<tr>
<th>Scenario Description</th>
<th>Methadone Patients</th>
<th>Federal government dispensing costs ($million/month)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base case</td>
<td>31 568</td>
<td>$0.0</td>
</tr>
<tr>
<td>Government pays dispensing fees for patients currently paying</td>
<td>31 568</td>
<td>$3.9m</td>
</tr>
<tr>
<td>+ patients stay longer in treatment</td>
<td>37 117</td>
<td>$4.7m</td>
</tr>
<tr>
<td>+ treatment-naïve enter treatment sooner</td>
<td>40 185</td>
<td>$5.1m</td>
</tr>
</tbody>
</table>

**Figure 7:** Federal government monthly dispensing costs at end of simulation under various scenarios
If both hypothesised behaviour changes were to be effected by the removal of dispensing fees, the federal government’s total annual expenditure for both the drug (methadone) and the dispensing costs would be $68.5 million, at simulation end (10 years hence). This reflects the cost of the medication (methadone) at $7.3 million, plus the cost of dispensing in pharmacies and private clinics of $61.2 million (12 times $5.1 million).

In comparison with total expenditure on individual PBS drugs, the modelled estimate of expenditure on methadone (dispensing + medication = $68.5m) would have ranked it 14th for the year ended June 2007.21 We could also approach this comparison from the perspective of methadone as a treatment for a chronic relapsing condition. Then comparison could be made with the cost of medications for an analogous condition such as diabetes or asthma. The total cost of medications used in diabetes was $272.9 million for the year ended June 2007 and the similar cost for asthma (medications for obstructive airway diseases) was $427.0 million (DOHA, undated, Table 10a). At $68.5 million, methadone compares favourably.

Fourthly, while the strength of the modelling approach is that it allows us to incorporate a range of behavioural changes to policy, the research literature does not provide unambiguous support for the behaviour changes modelled. It appears likely that treatment fees discourage entry to treatment but that they have an impact on retention in treatment is more uncertain.

Finally, there is the issue of the level of responsibility the federal government would actually assume for patient fees. Under the current PBS system, pharmacotherapy patients reliant on income support pay $5 per prescription, per calendar year, until they reach the safety net (i.e. approximately 50 prescriptions). From then on they receive prescriptions for free. Hence, we present in this scenario what the government would pay if every pharmacotherapy patient qualified for the subsidised PBS system and every patient

21 Table 12a of Australian Government Department of Health and Ageing (DOHA) (undated).

22 Since the early 1990s the Australian Government has negotiated a series of five-year agreements with the Pharmacy Guild of Australia, including the formula for the pharmacy mark-up on the cost of PBS drugs and the pharmacist’s dispensing fee.
had reached his or her safety net before entering treatment. There is no information available on the proportion of patients that have already met their safety net conditions before they start pharmacotherapy maintenance treatment.

Hence our estimate of federal government costs represents an upper bound due to daily dispensing, 100 per cent compliance assumptions, our assumptions about behavioural responses to dispensing fees, and the assumption that patients do not need to make co-payments. Appendix F provides some further estimates of the costs to the government of paying dispensing fees, when we vary some of the assumptions listed above.

Is payment of dispensing fees a worthwhile investment?

Monthly federal government expenditure compares favourably with the estimated health and crime cost savings as a result of methadone maintenance treatment.23 With an extra 8617 patients in treatment by simulation end, the health and crime cost savings range from $4.3 million to $8.6 million per month for these extra patients. These cost savings are commensurate with the modelled dispensing costs ($5.1m).

5.2 Availability: service system changes

The second policy scenario explores the implications of a shock to the system that markedly reduces the places in GP prescribers, perhaps through GP retirement in locations not serviced by other GPs willing to take on pharmacotherapy patients or to take on more patients. The only prescribing alternative is public clinics. However, there are also constraints on the public clinic places (see, for example, Winstock, 2007). With this in mind, we explore the implications of constraining entry to public clinics on top of the reduction of GP prescribing places. When the reduction of prescribing places comes into play, patients are not forced out of treatment. Rather, those who are between treatment find difficulty in re-entering treatment. Although still interesting to explore the implications for numbers in treatment, it is perhaps more worthwhile to determine the impact on the time taken to return to treatment. This is when the costs of opioid dependence accrue most rapidly and it is possible delays in entering treatment might weaken the desire to undertake treatment.

Scenario 1 constrains GP methadone places to 80 per cent of the initial number in treatment. This limiting takes place two years into the simulation. Scenario 2 also constrains public clinic places to 80 per cent of initial numbers. Again the limiting commences two years into the simulation.

Figure 8 illustrates the impact of these capacity limits. As a consequence of limiting entry to methadone places with GPs, the end-of-simulation numbers of people between treatment increase by 4724. The number of patients in treatment falls by 5110. The reduction of 7247 patients prescribed by GPs is partially offset by increased access to public clinics, with an increase of 1684 in publicly prescribed patients. The impact on the length of time between episodes of treatment is an increase from 12 to 15 months at simulation end.

23 See Appendix E for details.
When we introduce the further constraint that public clinics cannot accommodate the extra patients, we see more dramatic responses. The time between treatment at the end of the simulation increases to 20.7 months under scenario 2. There are 8322 fewer people in treatment compared to the base-case simulation.

The lesson of this simulation is that a 20 per cent reduction in GP capacity has substantial implications on the time taken to re-enter treatment. This might have the secondary effect of reducing a person’s tendency to re-enter treatment. It might also discourage patients from leaving treatment in the first place. An important assumption underlying this policy experiment is that there is no spare capacity in the system. There is conflicting anecdotal evidence about the existence of spare capacity, perhaps due to geographical issues and/or system differences across jurisdictions.

![Figure 8: Impact of capacity limits on numbers between and in methadone treatment by prescriber](image)

Note: Scenario 1: limiting of GP methadone places to 80 per cent of the initial number in treatment
We can assess the social cost implications of such a limit on service delivery. If we assume the social costs associated with health care utilisation and criminal activity of a dependent heroin user are between $500 and $1000 per month (see Appendix E), extending the between-treatment time by an additional eight months costs between $4000 and $8000 per person. Given that about 8000 people are affected by the reduced service delivery, this represents social costs of between $32m and $64m incurred by the community in relation to those people out of treatment.

5.3 Accessibility: increased demand for treatment

In this policy scenario we assess the implications of increased demand for treatment stemming from an expansion of the non-heroin opioid-dependent population, those dependent on pharmaceutical opioids. The increase in the pharmaceutical opioid-dependent population is characterised as a 20 per cent increase in the annual inflow into dependency (4500 to 5400) two years into the simulation. We contextualise this source of increased demand by comparing the implications with increased demand sourced from a reduction in the time taken to return to treatment from the between-treatment group, and increased demand arising from a

Figure 9: Patients in treatment on a monthly basis before and after a 20% increase in inflow to the pre-treatment opioid-dependent group

Note: Scenario 1: 20 per cent increase in the annual inflow into the population of pre-treatment opioid-dependent people two years into simulation
reduction in the time taken by newly heroin-dependent people to enter treatment. The two comparison behaviour changes may be initiated by reduced availability of heroin. They may also be encouraged through policy intervention directed at the specific groups.

Figure 9 illustrates the results from a 20 per cent increase in the annual inflow to dependency. As can be seen, there is little impact on numbers in treatment.

At the end of simulation there are only 1980 more patients in treatment as a whole (a 4 per cent increase): 1240 more in methadone treatment and 740 more in buprenorphine. The impact on government expenditure for methadone maintenance over the simulation period is likewise minimal, as Figure 10 reveals. At simulation end the increased costs faced by the federal government come to $109 500 per month while the combined State governments face increased monthly costs of $195 000.

Why does the response to a 20 per cent increase in the inflow to the opioid-dependent population seem so small? While 900 extra people become opioid-dependent every year, the annual increase in the flow from the opioid-dependent group into treatment is only 650, at simulation end. It takes four years, on average, for a newly opioid-dependent person to enter treatment and in that time there is a significant risk of death, i.e. 5 per cent per year. Furthermore, not everyone who becomes dependent requires treatment; 5 per cent per annum become

![Figure 10: State and federal government costs associated with the increased ‘demand’](image-url)
abstinent before entering treatment. Finally, even those who enter treatment cycle in and out of treatment. At simulation end there are over 1500 more opioid-dependent people in the between-treatment population.

For those concerned about whether the treatment system could deal with a 20 per cent increase in opioid dependency, the modelling shows that there is a slow build-up to the increased patient numbers. Our depiction in system form shows that changes do not necessarily occur instantaneously. The population increase commences in year two of the simulation, and it takes four years for that increase to work its way through to the numbers in treatment.

We compare these findings with the implications of a 20 per cent reduction in the time that it takes newly opioid-dependent people to enter treatment from four years to 3.2 years. Again this takes place two years into the simulation. Such a policy intervention might be initiated through increased efforts at needle and syringe programs to facilitate more rapid referral into treatment. As a consequence numbers in treatment at simulation-end would increase by only 3 per cent to 46,986 (see Table 9).

As a further point of comparison we also simulate the impact of a policy intervention characterised by a 20 per cent reduction in the time it takes to return to another episode of treatment after leaving an episode (Figure 11). Such a policy intervention might be seen as

Figure 11: Patients in treatment on a monthly basis before and after a 20% reduction in the time between treatment

Note: Scenario: 20 per cent reduction in time between treatment from two years into simulation
the decision to contact anyone who has ever been a patient to encourage and/or facilitate their re-entry to treatment, perhaps through phone calls or outreach workers. Again the reduction takes place two years into the simulation. At that point the time between spells of methadone treatment is reduced from 12 months to 9.6 months, and the time between spells of buprenorphine treatment is reduced from 6 months to 4.8 months.

The results are displayed in Figure 11 and Table 9. We find that there are 4995 (or 11%) more patients in treatment at the end of the simulation, almost three-fold the increase consequent on a 20 per cent reduction in time to first treatment entry. There are 3489 more patients in methadone treatment and 1506 more patients in buprenorphine treatment. Furthermore the increased inflow of patients is almost instantaneous, so that within two years we have seen the maximum response. Indeed, to manufacture this increase in patients in treatment from expansion in the opioid-dependent population alone requires a 50 per cent increase in the flow into the treatment-naive opioid-dependent group (2250 extra newly opioid-dependent people per year).

This exploration informs policy makers of the implications of increased demand, but it also provides guidance into the potential returns from strategies designed to encourage treatment entry or re-entry. In our example it is clear that investing in policies that encourage previous treatment entrants back into treatment has a much greater impact on treatment numbers than focusing on a new population of users. Even though a 20 per cent rise in the opioid-dependency rate would be newsworthy, potentially resulting in calls for all sorts of new interventions, our model suggests that continuing to invest in the existing population is likely to be a more effective approach to increasing numbers in treatment.

### Table 9: Methadone and buprenorphine patients at end of simulation under various scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Methadone + buprenorphine patients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base case</td>
<td>45 600</td>
</tr>
<tr>
<td>20% increase in inflow to opioid-dependent treatment-naive</td>
<td>47 580 (+4.3%)</td>
</tr>
<tr>
<td>20% reduction in time to enter treatment for treatment-naive</td>
<td>46 986 (+3.0%)</td>
</tr>
<tr>
<td>20% reduction in time between treatment</td>
<td>50 595 (+11.0%)</td>
</tr>
</tbody>
</table>
5.4 Quality: quality versus volume trade-offs

One of the common trade-offs in health service delivery is between a high-quality but low-volume service versus a lower-quality and high-volume service. In drug treatment, this sometimes translates to a trade-off between minimising the harms to individuals (quality of treatment) and the harms to the community (volume of treatment). We endeavour to explore the relative merits of what we call the volume versus quality trade-off in our final policy simulation. This scenario demonstrates the capacity of a model to depict trade-offs between quality of care, the cost of providing the care, and numbers in treatment.

This policy simulation is the most abstracted from reality. The advantage of such an abstraction is that it enables the reader to generalise the findings to a range of scenarios, such as

- the comparison of a system based entirely on GP prescribing with one reliant on public clinic prescribing with individually focused care
- the comparison within a jurisdiction of public clinics providing patient-focused care versus public clinics providing high-volume care.

In the case of high quality (henceforth, the high-threshold program), the program places great emphasis upon individual goal attainment for patients within the program and makes resources available for any one individual, such that they have access to a variety of different support services, including counselling, employment retraining, housing support, financial counselling and so on. In general, individually focused programs are more resource-intensive. At the other end of the spectrum is the low-threshold program. This program is largely reliant on the medication as the primary mechanism of behaviour change, and encourages as many patients as possible to enter the program, irrespective of level of individual motivation or willingness to engage with the variety of support services. Patients are not given free access to support services. In general, this latter public health approach sees many more people in the treatment system, each with a lesser chance of attaining their own particular treatment goal.

The rationale for using the system dynamics model to compare the outcomes of the low-threshold and high-threshold programs is to illustrate the trade-offs under the different programs. The modelling exercise enables consideration of the trade-offs in costs borne by government and patients, and individual goal attainment, an artificial variable constructed specifically for this scenario to depict the outcome for each opioid-dependent person, whether he/she is in treatment or between treatment. For the purposes of the discussion we assume no constraints on treatment capacity, so that numbers in treatment can increase to whatever level is suggested by our depiction of the two models of care. Underlying the aggregated patient outcomes and costs of treatment are two other variables of interest: the time spent in treatment; and quality of care. We reiterate that the relationships between these variables are by no means evidence-based.

The two programs (high-threshold and low-threshold) are depicted, in comparison with the base-case model, in Table 10. They are described by the five variables we consider key in this analysis: average cost of treatment per patient; average length of stay in treatment; average length of stay between treatment; average level of between-treatment goal attainment; and average within-treatment goal attainment. We represent the two programs in terms of multipliers applied to the base-case
values of each of the five variables. It is not important for the purpose of this exercise to provide the value of each variable at base case. At base case the multiplier attached to each variable is 1.

We allow the variables to have a range of values under the low- and high-threshold models, i.e. for both models there is both a low-impact and a high-impact version. The variation in impact allows for uncertainty in the degree of goal attainment achieved. Under the high-impact version of the high-threshold model, for example, individuals are twice as likely to achieve their goals when in treatment relative to the base case, whereas under the low-impact version of the high-threshold model they are half as likely to achieve their goals.

In articulating the models below, we have used the following sets of multipliers. These are just one alternative. Any multipliers can be substituted for the ones we have used.

**High-threshold model**
- The costs increase by 50 per cent, compared with the base case. These costs are taken to represent the additional counselling and social support costs that we assume are associated with the high-threshold program.\(^{24}\)
- The extent of in-treatment individual goal attainment increases by 50 per cent to 100 per cent (i.e. multiplier of 1.5–2.0), reflecting the advantages of individually tailored treatment.
- Individual goal attainment among the between-treatment group is unchanged from its base-case value. Note that the model makes no value judgement about the difference between a patient’s goal attainments in treatment versus the extent of goal attainment between treatment at base case.
- We hypothesise that the lengths of stay in treatment and between treatment will increase by 10 per cent to 50 per cent (1.1–1.5). The between-treatment lengths of stay will be extended due to the more stringent entry criteria attached to accessing treatment, while we assume that patients stay in treatment longer because treatment is more personalised.

**Low-threshold model**
- The costs are 10 per cent lower than base case. This represents the reduction in counselling and social support services.
- The extent of in-treatment individual goal attainment increases by 20 per cent to 50 per cent (i.e. multiplier of 1.2–1.5). Although it seems logical that the extent of individual goal attainment should be lower than under the high-threshold program, the degree of the improvement is arbitrary.\(^{25}\)
- Individual goal attainment among the between-treatment group is unchanged from its base-case value.

---

\(^{24}\) In practice, we apply the cost multipliers to the prescribing costs from the base-case model.

\(^{25}\) The multipliers have been arbitrarily set, but our preference was to remain conservative with the multipliers rather than producing dramatically different results.
Under the low-threshold program the in-treatment and between-treatment lengths of stay will decrease by between 10 per cent and 25 per cent (i.e. multiplier of 0.9–0.75). It is easier for patients to re-enter treatment, due to less stringent entry criteria, and with less personalised treatment we assume that patients will not want to stay in treatment as long. The model has the ability to inform stakeholders of the likely impact on numbers in treatment and between treatment of each of the programs. For this reason we do not constrain the numbers in treatment. It is assumed that were a policy endorsed, the resources required to implement the policy would be available.

Table 10: Scenarios for exploration of low-threshold and high-threshold programs

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Multipliers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Goal attainment between treatment</td>
</tr>
<tr>
<td>Base case</td>
<td>1.0</td>
</tr>
<tr>
<td>High threshold</td>
<td>High impact</td>
</tr>
<tr>
<td></td>
<td>Low impact</td>
</tr>
<tr>
<td>Low threshold</td>
<td>High impact</td>
</tr>
<tr>
<td></td>
<td>Low impact</td>
</tr>
</tbody>
</table>
First we describe the results for in-treatment numbers and then between-treatment numbers. Figures 12 and 13 illustrate the numbers in treatment and between treatment for both of the program scenarios. Notice that there are two series for both the low and high thresholds, representing the range of possibilities reflected in our low- and high-impact outcomes.

As can be seen in Figure 12, the numbers in-treatment are higher than the base case under both versions of the low-threshold model and lower than base case under both versions of the high-threshold model. This is what we would expect: the high-threshold program treats fewer individuals than the low-threshold program.

Figure 13 examines between-treatment numbers. There would be fewer people between treatment than in the base case under the low-threshold program and more people between treatment under the high-threshold program.

Considered together, the numbers in treatment and between treatment under the two models of care represent countervailing forces. The low-threshold program produces the highest numbers of people in treatment (easy entry, easy exit). The lowest numbers in treatment are produced under the high-threshold, high-impact model. At the same time as numbers in treatment are highest in the low-threshold model, the numbers between treatment are also lower. Patients

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26 The differences between the scenarios in terms of numbers in treatment and between treatment are relatively small because we keep the changes in length of stay in and between treatment identical — and these have countervailing effects.
cycle in and out of treatment more quickly under the low-threshold model of care. These findings are more or less predictable, indicating the intent of the two scenarios: the low threshold makes it easier for people to enter treatment so they spend less time between treatment. In contrast, under the high-threshold model it is more difficult to access treatment but patients stay in treatment longer in response to receiving more attractive individualised treatment and/or in response to the increased anxiety that they will not be able to access treatment easily if they choose to leave for a time. Put differently, under the high-threshold model it is more difficult to access treatment, but once in treatment each patient stays longer in response to the highly personalised treatment. Under the low-threshold model it is easier to access treatment and patients have shorter episodes of care. The net effect of these various influences on treatment numbers is that more patients are in treatment than at base case for the low-threshold program.

Where the model provides further insight is in its illustration of the trade-off between changes to the level of individual goal attainment measured over both the in-treatment and between-treatment populations. Table 11 compares the goal attainment with the associated costs at the end of the simulation. It shows that, just as we assumed, individual goal attainment increases with both models. It is highest under the high-impact version of the high-threshold model. To achieve the 50 per cent increase in individual goal attainment (i.e. 93 982/62 448) would involve a 31 per cent increase in costs. In stark contrast the modelling suggests that a gain of around 25 per cent in

![Figure 13: Numbers between treatment depending on model of care](image-url)
Modelling pharmacotherapy maintenance in Australia

opioid-dependent population-wide individual goal attainment could be achieved by the high-impact version of the low-threshold model (i.e. 78 341/62 448), with an accompanying reduction in costs of around $0.7 million (a 6 per cent reduction).

This sort of analysis can be instructive. It depicts the trade-offs between two markedly different approaches to treatment provision in simple but compelling terms. Given our assumptions, a 25 per cent increase in the degree of individual goal attainment of all opioid-dependent people could be achieved with reduced costs with the low-threshold model. In contrast, it would take around a 15 per cent increase in costs to achieve a 25 per cent increase in individual goal attainment under the high-threshold model. The model shows that a 50 per cent increase would be achieved through expanding costs by 31 per cent.

Comparison of these two approaches to treatment provision is often considered value-laden. The evidence base is lacking. The modelling process reduces the comparison to a trade-off between aggregated costs of treatment and individual goal attainment and surfaces the assumptions underlying the magnitude of those trade-offs. The size of the achievable individual goal attainment outcomes and the associated costs under each approach are debatable, but framed in the terms of this scenario, policy makers are able to focus on the likely trade-offs, independently from the values debate.

Table 11: Outcomes at end of simulation

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Number in methadone treatment</th>
<th>Number between methadone treatment</th>
<th>Total in system</th>
<th>Individual goal attainment</th>
<th>Total cost ($ million)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base case</td>
<td>31 568</td>
<td>30 880</td>
<td>62 448</td>
<td>62 448</td>
<td>11.7</td>
</tr>
<tr>
<td><strong>High threshold</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High impact</td>
<td>31 541</td>
<td>30 900</td>
<td>62 441</td>
<td>93 982</td>
<td>15.327</td>
</tr>
<tr>
<td>Low impact</td>
<td>31 538</td>
<td>30 906</td>
<td>62 444</td>
<td>78 213</td>
<td>15.3</td>
</tr>
<tr>
<td><strong>Low threshold</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High impact</td>
<td>31 751</td>
<td>30 715</td>
<td>62 466</td>
<td>78 341</td>
<td>11.0</td>
</tr>
<tr>
<td>Low impact</td>
<td>31 619</td>
<td>30 834</td>
<td>62 453</td>
<td>68 776</td>
<td>11.0</td>
</tr>
</tbody>
</table>

27 Given that there are only three more people in treatment between the high impact and low impact scenarios, the cost differential is trivial.
6. Discussion and conclusions

The aims of this project were:

1. to develop a system dynamics model of the Australian pharmacotherapy maintenance system
2. to assess the extent to which such a model can inform policy-relevant questions
3. to use the model to explore four policy-relevant issues: affordability; availability; accessibility; and quality.

In relation to the first aim, we have developed and documented a model of the Australian pharmacotherapy maintenance system. This is the first system dynamics model of opioid pharmacotherapy treatment in Australia. The model development process itself has highlighted some substantial gaps in knowledge and data. Further research addressing these gaps in information will increase the precision and usefulness of future models. The following important gaps in knowledge were identified:

- There is much to learn about the average length of stay within a treatment episode. We do not have unambiguous evidence that the lengths of stay differ between patients prescribed in public clinics and patients prescribed within the private sector. Nor do we know whether length of stay increases with each episode of care. Likewise, we do not have accurate data on the length of time users spend between treatment episodes. These pieces of information form the basis of our estimate of the base-case numbers between treatment. They are also crucial to a realistic representation of the implications of policy reform designed to affect, for example, retention in treatment, especially if it is directed at only one of the treatment modalities.

- A thorough-going analysis of policy options requires adequate cost data. There are substantial uncertainties around some of the cost data. Research that includes comprehensive documentation of the inclusions and exclusions for the cost data would be of benefit. In addition, the available Australian cost data can be taken to represent the costs associated with changes in treatment numbers that do not require expansions in capacity.

- Many of the policy options that we explore result in substantial increases in numbers in treatment. There is no publicly available information on whether the service systems are at capacity. If a service system is at capacity we need estimates of the costs associated with expanding the available treatment places (as opposed to marginal unit costs).

- The modelling process allowed us to explore the implications of a range of patient responses to policy reforms, such as reductions in the cost of dispensing faced by patients. However, our findings would have been more powerful if they had been based on estimates of patient behavioural responses to key parameters, such as the costs of treatment.

- Epidemiology data about the size of the opioid-dependent population, its annual growth rate and mortality, and spontaneous recovery rates were all approximated from limited existing research. As these numbers form an important basis for estimating the treatment system, they require greater precision.
Despite these data uncertainties, which are a common feature of any modelling approach, the system dynamics model is robust and internally consistent. The purpose of the model was to test policy-relevant scenarios, given the current state of the treatment system, current estimates of the opioid-dependent population, current treatment alternatives, and so on. The policy scenarios presented in this report illustrate that it can be used as:

- a means with which to explore the implications of possible patient behavioural responses to the removal of dispensing fees
- a coherent and justifiable means of estimating ‘hidden’ sub-populations within the opioid-dependent population, in this case numbers between treatment
- a sufficiently robust depiction of the system structure that we were able to model the likely implications of policy options on the time between treatment, even though estimates of time between treatment had been used to create the structure of the system, and
- a vehicle for advancing the hotly contested and value-laden debate about the quality of care versus volume of treatment places trade-off.

A number of important policy insights have been generated from the work. For example, we estimated that the base-case number of people between treatment in our model was 41,100 — one reasonable indicator of unmet demand. Patients bear a significant proportion of the costs of pharmacotherapy maintenance treatment, which we estimated as $11.7 million per month. Indeed, our model estimated that patients bear one-third of the total cost of the program, State governments 43 per cent, and the federal government 24 per cent (see Figure 5). This is an unusual state of affairs — the patient co-payment for a chronic relapsing medical condition is high.

On affordability, if we simulate alternate payment systems, such as government funding the dispensing costs, the treatment becomes relatively expensive for government. For example, if the federal government were to subsidise the cost of methadone dispensing, we estimate that methadone would be in the top 20 most costly medications funded by the government under the PBS. However, there are substantial cost benefits of treatment — taking the social costs associated with savings from reduced health care utilisation and crime, the cost of providing methadone maintenance per month is estimated by the model to be $11.7 million compared to a cost saving of between $15.8m and $31.6 million per month. It is clear that the provision of pharmacotherapy maintenance treatment, while costly, is outweighed by the economic benefits accruing to the community through reductions in health care utilisation and crime.

Availability of treatment was evaluated through a scenario of reductions in the supply of treatment. A 20 per cent reduction in GP places can have long-term implications. Our model suggests that such a reduction, coupled with a similar reduction in public clinic places, leads to a fall in numbers in treatment of over 25 per cent (8322 people) (Figure 8). What is perhaps more instructive is that the reduction in supply of treatment places forces opioid-
dependent people to spend longer between treatment, placing them at risk of ongoing injecting drug use, overdose and other harms associated with heroin use.

Accessibility of treatment was examined through changing the source of demand for treatment. We compared a 20 per cent increase in the new opioid-dependent population with a 20 per cent reduction in the length of time people were between treatment and found dramatic differences. The 20 per cent increase in the total population may cause public concern, but from the perspective of the impact on numbers in treatment it is likely to be trivial, even many years after the increase. In contrast, encouraging people who have previously been in treatment back into treatment would result in a significant and immediate increase in demand. This contextualises the relative merits of efforts directed towards existing opioid-dependent people versus those directed towards dealing with future opioid-dependent populations. Indeed, the modelling suggests that it would take a 50 per cent increase in the rate of inflow to opioid dependence to match the impact on in-treatment numbers of a 20 per cent decrease in the length of stay between treatment.

Finally we examine quality of care versus volume of care trade-offs. One of the more contentious issues in this field is the relative worth of a program that provides quality individually focused care versus a low-threshold program focused on the benefits of the pharmacotherapy medication in and of itself. The findings from our analysis were informative. Whereas a 25 per cent increase in the individual goal attainment of all opioid-dependent people (in- and between-treatment) could be achieved with a small cost-saving to the government (prescribing costs alone) with the low-threshold model, it would take a 31 per cent increase in such costs to achieve a 50 per cent increase in overall individual goal attainment under the high-threshold model.

An important limitation to all the results presented above is that the model represents Australia rather than any one jurisdiction. The substantial variations in jurisdictional policies and treatment systems were not built into the model. Nonetheless, the model was built in such a way that it could be relatively easily modified to represent a particular State or Territory, both in terms of the particularities of its treatment system and the policy options specific to the jurisdiction.
7. References


8. Appendices

8.1 Appendix A: Case management and counselling services: federal government items

Since the introduction in 2006 of the Better Access to Psychiatrists, Psychologists and General Practitioners through the Medicare Benefits Schedule (MBS) initiative, GPs can provide case management through Medicare-specific items. There are two forms of case management in the Medicare system: through the GP Mental Health Care Plan (introduced on 1 November 2006); or through a referred psychiatrist assessment and management plan. Drug use disorders are considered to be a mental health disorder for the purpose of these items.

Once a care plan is prepared under either the GP Mental Health Care Plan or a referred psychiatrist assessment and management plan, the patient is eligible to be referred by their GP for allied mental health services. Pharmacotherapy patients have always been able to attend psychiatrists and been covered by the Medicare system, but in 2006 the federal government also extended fees to cover psychologists and some other allied health professionals for psychological therapy through the Medicare system.

Allied mental health services under this initiative include psychological assessment and therapy provided by eligible clinical psychologists, and focused psychological strategies provided by eligible psychologists, social workers and occupational therapists. These service providers must be registered with Medicare Australia. Patients are eligible for up to 12 individual and 12 group sessions per year. In addition, those patients in public clinics who may wish to receive additional counselling support can do so through these new Medicare arrangements. Patients would, however, need to cover any gap between the Medicare schedule fee and the fee charged for psychological therapy.

Table A1 sets out the services covered under the Better Access to Psychiatrists, Psychologists and General Practitioners through the MBS initiative.
Table A1: Services covered under the Better Access to Psychiatrists, Psychologists and General Practitioners through the MBS initiative

<table>
<thead>
<tr>
<th>Item</th>
<th>Content</th>
<th>Rebates at November 2007</th>
<th>Restrictions on number per year</th>
</tr>
</thead>
<tbody>
<tr>
<td>GP Mental Health Care Plan</td>
<td>These items are intended to provide a structured framework for GPs to undertake early intervention, assessment and management of patients with mental disorders. They will also provide new referral pathways to clinical psychologists and allied mental health service providers</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Item 2710</td>
<td>Preparation of plan</td>
<td>$153.30</td>
<td>1</td>
</tr>
<tr>
<td>Item 2712</td>
<td>Review of plan</td>
<td>$102.20</td>
<td>2</td>
</tr>
<tr>
<td>Item 2713</td>
<td>Consultation involving taking relevant history, identifying presenting problem(s), providing treatment, advice and/or referral for other services or treatments, and documenting the outcomes of the consultation, on a patient in relation to a mental disorder and lasting at least 20 minutes</td>
<td>$67.45</td>
<td>No restrictions</td>
</tr>
<tr>
<td>Associated services</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual services</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>80000, 80005, 80010, 80015</td>
<td>Psychological therapy services provided by clinical psychologist</td>
<td>&lt;50 mins  80000: $90.15  80005: $112.60 (not in surgery)  50+ mins  80010: $132.25  80015: $154.75 (not in surgery)</td>
<td>12</td>
</tr>
<tr>
<td>Item</td>
<td>Content</td>
<td>Rebates at November 2007</td>
<td>Restrictions on number per year</td>
</tr>
<tr>
<td>-----------------</td>
<td>--------------------------------------------------------------------------</td>
<td>--------------------------</td>
<td>---------------------------------</td>
</tr>
</tbody>
</table>
| 80100, 80105, 80110, 80115 | Individually focused psychological strategies services provided by a psychologist | <50 mins  
80100: $63.85  
80105: $86.80 (not in surgery)  
50+ mins  
80110: $90.15  
80115: $113.15 (not in surgery) | |
| 80125, 80130, 80135, 80140 | Individually focused psychological strategies services provided by an occupational therapist | <50 mins  
80125: $56.25  
80130: $79.20 (not in surgery)  
50+ mins  
80135: $79.40  
80140: $102.35 (not in surgery) | |
| 80150, 80155, 80160, 80165 | Individually focused psychological strategies services provided by a social worker | As for OT | |
| 2721, 2723, 2725, 2727 | Individually focused psychological strategies services provided by a GP | ? | |
| **Group services** | | | 12 |
| 80020 | Group psychological therapy services provided by a clinical psychologist | $33.60 | |
| 80120 | Group-focused psychological strategies services provided by a psychologist | $22.95 | |
| 80145, 80170 | Group-focused psychological strategies services provided by OTs or social workers | $20.20 | |
8.2 Appendix B: Sensitivity analysis

Discussion of the setting of parameters for the model in section 3 revealed the uncertainty associated with estimates of many of the base-case parameters. A sensitivity analysis is designed to show how the model’s output varies with changes in the parameters and in key model assumptions. Identification of the extent to which each source of uncertainty weighs on the model’s conclusions then acts as a tool for assessing the robustness and credibility of the model’s findings.

Here we present the sensitivity of numbers in treatment and between treatment to the mortality rates and lengths of stay in treatment and between treatment. This is not to say that we have undertaken sensitivity analyses only on these parameters. During the model building process we undertook many sensitivity analyses to ensure that the structure of the model was not sensitive to particular parameters. This is a crucial element of the model building exercise. We chose to present the sensitivity analysis of the mortality rates because there is some argument that we have set the rates too high. We present a sensitivity analysis of the lengths of stay in treatment and between treatment because these parameters were integral to determining the size of the between-treatment population.

The first sensitivity analysis was conducted on mortality rates, as presented in Table B1. As detailed in section 3.4, the variation in death rates observed in the international literature is marked. While many would argue that this variation is due largely to factors related to the location of the cohorts studied, and rests predominantly with differences in the prevalence of HIV (human immunodeficiency virus), the variation might also be related to variations in study design and representativeness of cohorts. With Australia’s relatively low prevalence of HIV within the opioid-dependent population, it could be argued that the death rates we have used are on the high side. However, the treatment population is ageing. Our reliance on studies of past outcomes means that ageing has not been factored into the estimates of mortality rates. In Table B1 we report the outcomes resultant on varying the death rates between the upper and lower bounds of the international literature (Darke, Degenhardt & Mattick, 2007; Denis et al., 2008).

The base-case treatment-naïve mortality rate is 2 per cent per annum. If it were to increase to 10 per cent per annum, the number in treatment would fall by 5.6 per cent by end of simulation (to 43 038) and the number between treatment would fall by less than 5 per cent. A halving of the death rate to 1 per cent per annum would see an increase in the numbers in treatment and between treatment of only less than 1 per cent.

The base-case in-treatment mortality rate is 0.8 per cent per annum, although some Australian studies found even lower rates. Even if we did not allow for any deaths in treatment, the repercussions would be remarkably small, with increases of a little over 3 per cent in numbers both in treatment and between treatment. A tripling of this rate to 2.4 per cent per annum, results in a less than 10 per cent reduction in both the between-treatment and in-treatment populations.

The base-case between-treatment mortality rate is 2 per cent. Halving this rate would increase numbers in treatment and between treatment by around 4 per cent. In contrast a fourfold increase in this rate would see numbers in treatment fall by around 20 per cent.
It is somewhat disingenuous to vary the three death rates separately. Even if we were to alter the three death rates simultaneously, the implications would not be large. We would be far more likely to lower the death rates, since the Australian estimates are at the low end of the international range. As a result numbers in treatment and between treatment would increase by less than 10 per cent.

Table B1: Sensitivity analysis on mortality rates per annum

<table>
<thead>
<tr>
<th>Mortality rate per annum</th>
<th>Treatment naive</th>
<th>In treatment</th>
<th>Variation from base line</th>
<th>Between treatment</th>
<th>Variation from base line</th>
</tr>
</thead>
<tbody>
<tr>
<td>1%</td>
<td>45 982</td>
<td>+0.8%</td>
<td>44 751</td>
<td>+0.7%</td>
<td></td>
</tr>
<tr>
<td>2%</td>
<td>45 600</td>
<td>-5.6%</td>
<td>42 292</td>
<td>-4.8%</td>
<td></td>
</tr>
<tr>
<td>10%</td>
<td>43 038</td>
<td>-5.6%</td>
<td>42 292</td>
<td>-4.8%</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>In treatment</th>
</tr>
</thead>
<tbody>
<tr>
<td>0%</td>
</tr>
<tr>
<td>0.8%</td>
</tr>
<tr>
<td>2.4%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Between treatment</th>
</tr>
</thead>
<tbody>
<tr>
<td>1%</td>
</tr>
<tr>
<td>2%</td>
</tr>
<tr>
<td>8%</td>
</tr>
</tbody>
</table>
The second sensitivity analysis was conducted on length of stay, both in and between treatment. The findings are set out in Table B2. Our length-of-stay parameters were based on research findings from the small number of available Australian studies. The findings of the Australian studies were remarkably consistent, so we arbitrarily doubled and halved the lengths of stay.

The results are more sensitive to the length-of-stay parameters than to the mortality rates. Since the average length of stay in treatment and between treatment is very similar, as are the numbers in treatment and between treatment, the implications of their variation are much the same. A doubling has much the same impact as a halving. The numbers between treatment are more sensitive than the numbers in treatment.

Table B2: Sensitivity analysis on lengths of stay in treatment and between treatment

<table>
<thead>
<tr>
<th>Length of stay</th>
<th>In treatment</th>
<th>Variation from base line</th>
<th>Between treatment</th>
<th>Variation from base line</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>In treatment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>+100%</td>
<td>58 475</td>
<td>+28.2%</td>
<td>28 426</td>
<td>–36.0%</td>
</tr>
<tr>
<td>At base line</td>
<td>45 600</td>
<td></td>
<td>44 433</td>
<td></td>
</tr>
<tr>
<td>–50%</td>
<td>32 879</td>
<td>–27.9%</td>
<td>64 450</td>
<td>+45.0%</td>
</tr>
<tr>
<td><strong>Between treatment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>+100%</td>
<td>33 458</td>
<td>–26.6%</td>
<td>63 948</td>
<td>+43.9%</td>
</tr>
<tr>
<td>At base line</td>
<td>45 600</td>
<td></td>
<td>44 433</td>
<td></td>
</tr>
<tr>
<td>–50%</td>
<td>58 140</td>
<td>+27.5%</td>
<td>28 766</td>
<td>–35.3%</td>
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</tbody>
</table>
### 8.3 Appendix C: Modelled base-case numbers between-treatment and in-treatment, and methadone patients by prescriber type over life of simulation

<table>
<thead>
<tr>
<th>Months</th>
<th>Between treatment</th>
<th>In treatment</th>
<th>Between methadone treatment</th>
<th>Methadone patients</th>
<th>Private practitioner</th>
<th>Public clinic</th>
<th>Prison</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>41 100</td>
<td>38 446</td>
<td>30 000</td>
<td>27 346</td>
<td>17 169</td>
<td>7853</td>
<td>2324</td>
</tr>
<tr>
<td>12</td>
<td>40 014</td>
<td>40 706</td>
<td>28 803</td>
<td>29 109</td>
<td>18 174</td>
<td>8996</td>
<td>1940</td>
</tr>
<tr>
<td>24</td>
<td>40 359</td>
<td>41 513</td>
<td>28 917</td>
<td>29 555</td>
<td>18 532</td>
<td>9081</td>
<td>1942</td>
</tr>
<tr>
<td>36</td>
<td>40 874</td>
<td>42 121</td>
<td>29 162</td>
<td>29 855</td>
<td>18 750</td>
<td>9148</td>
<td>1957</td>
</tr>
<tr>
<td>48</td>
<td>41 413</td>
<td>42 674</td>
<td>29 423</td>
<td>30 126</td>
<td>18 929</td>
<td>9223</td>
<td>1974</td>
</tr>
<tr>
<td>60</td>
<td>41 949</td>
<td>43 201</td>
<td>29 682</td>
<td>30 385</td>
<td>19 094</td>
<td>9301</td>
<td>1991</td>
</tr>
<tr>
<td>72</td>
<td>42 473</td>
<td>43 710</td>
<td>29 935</td>
<td>30 636</td>
<td>19 251</td>
<td>9377</td>
<td>2007</td>
</tr>
<tr>
<td>84</td>
<td>42 984</td>
<td>44 203</td>
<td>30 181</td>
<td>30 879</td>
<td>19 404</td>
<td>9452</td>
<td>2023</td>
</tr>
<tr>
<td>96</td>
<td>43 480</td>
<td>44 682</td>
<td>30 420</td>
<td>31 115</td>
<td>19 552</td>
<td>9525</td>
<td>2038</td>
</tr>
<tr>
<td>108</td>
<td>43 963</td>
<td>45 148</td>
<td>30 653</td>
<td>31 345</td>
<td>19 696</td>
<td>9595</td>
<td>2053</td>
</tr>
<tr>
<td>120</td>
<td>44 433</td>
<td>45 600</td>
<td>30 880</td>
<td>31 568</td>
<td>19 836</td>
<td>9664</td>
<td>2068</td>
</tr>
</tbody>
</table>
### Appendix D: Modelled base-case numbers in methadone treatment by dispenser type over life of simulation

<table>
<thead>
<tr>
<th>Months</th>
<th>Pharmacy</th>
<th>Prison</th>
<th>Public clinic</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>21 881</td>
<td>2324</td>
<td>3141</td>
</tr>
<tr>
<td>12</td>
<td>23 571</td>
<td>1940</td>
<td>3598</td>
</tr>
<tr>
<td>24</td>
<td>23 981</td>
<td>1942</td>
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<tr>
<td>36</td>
<td>24 239</td>
<td>1957</td>
<td>3659</td>
</tr>
<tr>
<td>48</td>
<td>24 463</td>
<td>1974</td>
<td>3689</td>
</tr>
<tr>
<td>60</td>
<td>24 674</td>
<td>1991</td>
<td>3720</td>
</tr>
<tr>
<td>72</td>
<td>24 878</td>
<td>2007</td>
<td>3751</td>
</tr>
<tr>
<td>84</td>
<td>25 075</td>
<td>2023</td>
<td>3781</td>
</tr>
<tr>
<td>96</td>
<td>25 267</td>
<td>2038</td>
<td>3810</td>
</tr>
<tr>
<td>108</td>
<td>25 453</td>
<td>2053</td>
<td>3838</td>
</tr>
<tr>
<td>120</td>
<td>25 634</td>
<td>2068</td>
<td>3866</td>
</tr>
</tbody>
</table>
8.5 Appendix E: Social costs associated with ongoing heroin use

Our purpose was to establish the cost burden per heroin users per day/month, i.e. what are the social costs associated with untreated heroin users. We then use this figure to show putative cost savings per numbers in treatment in any one month.

We also use this figure against the cost of providing treatment, as defined for the purposes of the model (unit cost per day, see specifications table).

Thus, we aim to estimate a number that represents the ‘cost burden’ of heroin use per user. In theory, it should include all the costs associated with using heroin:

- health care costs (blood-borne viruses, accidents, trauma, overdose)
- crime (associated with heroin)
- welfare payments
- family disruption, domestic violence, impact on children
- public amenity (perceptions of public safety, use of public space)
- private costs (e.g. insurance premiums).

The reality is that no one has fully estimated each of these costs associated with the use of heroin. Rarely are the costs collected in relation to only dependent users (which is what we need), and the economic/accounting methods differ enormously between studies. Only two costs have been estimated: health and crime, so we confine ourselves to these.

The two largest studies conducted in Australia that included a cost component were the NEPOD series of studies, and the subsequent ATOS study. In both cases, the economic perspective taken was only of the treatment resources in the health sector, and effectiveness was measured in treatment outcome terms (such as heroin-free days). Thus these studies report a cost per additional heroin-free day. However, these data cannot be used for our purposes — we require a cost per heroin-using day. Instead, we have turned to other treatment studies that either report the social costs associated with heroin use at baseline (prior to entry to treatment), or report on reductions in health or crime associated with treatment, which can then be translated into costs.

There are three studies that have estimated the costs of health and crime prior to entry into treatment. It is these estimates that can provide us with approximate costs of untreated heroin use, which can then be compared to the treatment costs in our modelling exercise.

The Buprenorphine Implementation Trial (Harris, Gospodarevskaya & Ritter, 2003; Harris, Gospodarevskaya & Ritter, 2005; Ritter et al., 2001) took a societal perspective, with the main outcome being cost per heroin-free day per quality-adjusted life year. The technical report provides detailed cost estimates of resource utilisation in the month prior to treatment entry (Ritter et al., 2001). In this study, costs estimates were:

- health care costs $3506
- crime costs $15 856 (but note that there were wide variations between individuals).

The total cost per heroin user per annum was $19 362.
Clark, Gospodarevskaja, Harris and Ritter (2003)\textsuperscript{28} reported the costs per annum for untreated heroin users based on a number of clinical trials conducted in Victoria, taking the baseline reporting of health services utilisation, crime as well as social security costs and lost tax revenue.

- Health costs $1848
- Crime costs $13 620
- Social security $8400
- Lost tax revenue $5940

TOTAL = $29 808 per heroin user, per annum

The third estimate comes from Moore (2007). The health costs associated with heroin use were calculated using Disability Adjusted Life Years — a different method from the above two studies, which both used health care utilisation. Crime estimates were taken from Mayhew (2003) — again, a different estimate from the above two studies. The estimate of social costs per heroin user per annum was $105 342. Given the large variance from the other two figures and the use of substantially different methodology, we leave Moore’s figure aside and focus on the other two figures.

As has been noted in many economic analyses (see Belenko et al., 2005), most costs associated with untreated heroin use are associated with criminal activity. We cannot, however, assume that every heroin user committed crime prior to treatment, and that for the duration of treatment, no crimes were committed. We know from ATOS data (Teesson, Ross, Darke et al., 2006) that a large minority (45%) reported that they committed no crime prior to treatment entry. Likewise we know that some patients in treatment continue to commit crime. Therefore, the crime estimates above need to be adjusted to reflect a more realistic figure of the potential crime savings associated with treatment. We do this through combining the self-reported crime rates from the ATOS study, with the cost of crime figure provided by the study by Clark et al. (We use the Clark estimate rather than the Harris estimate because the Clark estimate is based on a number of clinical trials of heroin treatment.)

Thus, $13 620 was the average cost for all heroin users prior to treatment for the year preceding treatment. If 55 per cent of the people committed those crimes, the cost for crime by those who committed them is $24 763 (13 620/0.55). ATOS data indicate that 24 per cent stopped committing crime in the subsequent year of treatment. Therefore, there was a cost of $5943 associated with cost savings for less crime during treatment (24 x 24 763/100).

So the net saving from crime reduction associated with treatment is $13 620 minus $5943, a saving of $7677 per annum, per person in treatment.

Another data source can be used to provide a second estimate of the crime cost reductions associated with treatment. Lind, Chen, Weatherburn and Mattick (2004) estimate the amount of crime reduction for people in methadone maintenance treatment for one year. They reported that, for every 100 persons in methadone maintenance for one year, there were 12 fewer robberies, 57 fewer break and enters, and 56 fewer motor vehicle thefts. They did not provide a cost estimate for these crimes. Therefore, we applied the Mayhew figures (Mayhew, 2003) to estimate the net savings from crime reduction associated with treatment. Mayhew reports $3600 per robbery, $2400 per burglary, and $6000 per motor vehicle accident (societal

\textsuperscript{28} The Clark et al. study included the Buprenorphine Implementation Trial as one of its studies so the two estimates are not independent of each other.
perspective, total costs). Using these figures for our calculations, we estimate that the net crime savings are $5160 per annum per person in treatment.

Thus, we have two figures in reasonably close proximity: $5160 per annum per person and $7677 per annum per person for crime. Given the imprecision in the various estimates, we round these out to be a low figure of $5000 crime cost savings and a high figure of $8000 crime cost savings.

We now turn to the health care utilisation figures. We needed to calculate a similar figure for the health care utilisation as that for crime: that is, some health care utilisation (over and above treatment costs) will continue, and indeed increase during treatment; other health care costs will remain the same; and some may reduce. Unfortunately, however, it was not possible to obtain details on the relative health care utilisation changes not associated with treatment.

Therefore, we include health care estimates as a crude approximation. The two figures available are $3506 (Harris et al., 2003) and $1848 (Clark et al., 2003) in health care utilisation prior to treatment (i.e. while using heroin). We round this out to be a low figure of $1000 and a high figure of $4000 per annum in health care costs.

Therefore, we apply the following figures to the analyses reported in the body of this report:

<table>
<thead>
<tr>
<th></th>
<th>High estimate (p.a.)</th>
<th>Low estimate (p.a.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crime costs associated</td>
<td>$8000</td>
<td>$5000</td>
</tr>
<tr>
<td>with being out of drug</td>
<td></td>
<td></td>
</tr>
<tr>
<td>treatment (i.e. using</td>
<td></td>
<td></td>
</tr>
<tr>
<td>heroin) per person</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Health care costs</td>
<td>$4000</td>
<td>$1000</td>
</tr>
<tr>
<td>associated with being</td>
<td></td>
<td></td>
</tr>
<tr>
<td>out of treatment (i.e.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>using heroin) per person</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TOTAL</td>
<td>$12 000 per annum</td>
<td>$6000 per annum</td>
</tr>
<tr>
<td></td>
<td>$1000 per month</td>
<td>$500 per month</td>
</tr>
</tbody>
</table>
8.6 Appendix F: Further estimates of dispensing fee costs

The base-case dispensing fees analysis (without the putative behavioural changes) involved the following assumptions/parameters:

- daily dispensing
- 100 per cent compliance
- no patient co-payments
- $5 per day.

It was applied to those not dispensed in public clinics, and resulted in an estimate of $3.9 million per month.

In the table below, we provide some alternate calculations, based on varying the above assumptions. In the first rows, we examine varying the cost that the government would pay: in the original work, we assumed a cost of $5 per day, per patient. Below we provide the total per month cost of dispensing fees to the federal government if that figure was $2.50 instead of $5 (and $7.50).

In the next set of rows, we vary the assumption about daily dispensing, assuming that less than daily dispensing incurs a lower cost to pharmacies. If patients are dosed three times per week (instead of seven times per week), we calculate the average daily dispensing cost to be $2.15. We apply this to 30 per cent of the population; and to 50 per cent of the population.

In the final set of rows, we provide a calculation that assumes that 20 per cent (and 40 per cent) of patients would not fall under the safety net and would continue paying dispensing fees.
<table>
<thead>
<tr>
<th>Scenario</th>
<th>Modelled cost per month (at end of simulation)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Varying the cost the federal government would pay to pharmacies</td>
<td></td>
</tr>
<tr>
<td>Base case $5</td>
<td>$3.9m</td>
</tr>
<tr>
<td>$2.50</td>
<td>$2.0m</td>
</tr>
<tr>
<td>$7.50</td>
<td>$5.9m</td>
</tr>
<tr>
<td>Varying daily dispensing, assuming that less than daily dispensing incurs a lower cost to pharmacies, and that this lowers cost per patient per week</td>
<td></td>
</tr>
<tr>
<td>Base case: 100%</td>
<td>$3.9m</td>
</tr>
<tr>
<td>30% of patients dispensed three times per week = $15 per week</td>
<td></td>
</tr>
<tr>
<td>= $2.15 per dose</td>
<td>$3.2m</td>
</tr>
<tr>
<td>50% of patients dispensed three times per week = $15 per week</td>
<td></td>
</tr>
<tr>
<td>= $2.15 per dose</td>
<td>$2.8m</td>
</tr>
<tr>
<td>Varying the proportion of patients under the safety net</td>
<td></td>
</tr>
<tr>
<td>Base case: 100%</td>
<td>$3.9m</td>
</tr>
<tr>
<td>80%</td>
<td>$3.1m</td>
</tr>
<tr>
<td>60%</td>
<td>$2.3m</td>
</tr>
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</table>