Prescription Drug Use and Abuse: Theory and Policy Implications

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Abstract

Prescription drug abuse is studied in a model where individuals with imperfectly observable health conditions seek prescription drugs for either recreational purposes or medical reasons. The equilibrium numbers of drug abusers and legitimate users are endogenous and depend on economic and non-economic barriers to drugs consumption, such as pricing, healthcare costs, refill policies, monitoring programs, and the medical community’s prescription standards. The model calibrated to U.S. data reveals that policies centered around raising economic barriers reduce prescription drug abuse but inhibit legitimate demand. Improving drug monitoring programs, such as instituting a national drug registry, effectively prevents drug abuse.

Keywords: Health, Doctors, Drugs, Search

JEL: D83, I1, I11, I18
1 Introduction

Prescriptions for drugs based on controlled substances have increased at a staggering pace in the U.S., 150% over the years 1992-2003 (Manchikanti, 2007, p.400). This trend has been especially dramatic for opioids such as Hydrocodone and oxycodone. To get a sense of the magnitude of this phenomenon, by 2004 about 80 percent of the global supply of opioids and virtually the entire world supply of Hydrocodone was consumed in the U.S. Hydrocodone with acetaminophen, a highly addictive prescription, has been the most prescribed medication of any category for at least the 5 years preceding 2007, with more than 100 million prescriptions in 2005 (Manchikanti, 2007, p.400-401).

To understand this phenomenon, one must realize that chronic pain affects 1/3 of the U.S. population at some point in life, while acute pain affects nearly everyone and is the main complaint in one out of three primary care visits; see (Monthly Prescribing Reference, 2008, p. 4). In the last two decades, U.S. doctors have increasingly treated and managed pain by relying on drug prescriptions for controlled substances.

The increase in legitimate use of controlled substances has been associated to an equally staggering increase in the number of patients seeking drugs simply for recreational purposes (drug-seekers). This has led to substantial abuse of and addiction to controlled prescription drugs. The Substance Abuse and Mental Health Services Administration reports in its 2003 survey that the number of U.S. adults abusing controlled substances increased 81 percent from 1992 to 2003, vis a vis a 14 percent population increase. The 2005 survey found that about 6 percent of the population above 12 years used a psychotherapeutic drug non-medically in the past year, a rate that has doubled since 1995 and is three times higher than cocaine use. Overall, substance abuse and addiction is thought to have generated health care costs of a quarter of a trillion dollars, roughly 2 percent of U.S. GDP in 2005, (see (Manchikanti, 2007, p.400,402)) and the annual amount of expenditures on substance abuse treatment is 20.7 billion per year (National Center for Health Statistics, 2005, Table 127). This social and economic burden has recently led president Obama’s administration to devise a plan to fight prescription drug abuse. Part of this plan revolves around improving prescription drug monitoring, and enforcement.

In this paper we develop an economic model of primary care to accomplish two objectives. First, to identify factors, economic and non-economic, that are primarily responsible for drug-seeking behavior and the high incidence of prescription-drug overuse and abuse. Second, to quantify the effect that policies have on drug abuse, including policies that have been recently proposed, such as increasing prescription drug monitoring programs. To accomplish these objectives, we develop a model where individuals with heterogeneous and imperfectly observable health profiles choose whether to search for a primary care physician. They search for a physician in order to obtain a prescription pain medication (prescription drugs). This search process is assumed random. After the patient meets a doctor, the

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1 Examples of brand names are Vicodin (hydrocodone/acetaminophen) and OxyContin (oxycodone). The second and third most prescribed medications were the cholesterol-lowering atorvastatin with about 63 million prescriptions, and the antibiotic amoxicillin, with about 52 million prescriptions.

2 Modeling patient-doctor matches as being random is reasonable because primary care physicians are generally prevented from engaging in price
doctor evaluates the patient and chooses whether to prescribe the drug. It is assumed that there is some uncertainty regarding whether the doctor prescribes the drug, either because doctors do not always make an accurate diagnosis or because they may have heterogeneous dispositions towards prescribing drugs. However, it is assumed that on average doctors are more likely to write a prescription for someone who does have a legitimate medical need for drugs, than for someone who does not: a drug seeker. That is, on average drug seekers are less likely to secure drugs from doctors than patients with a legitimate reason.

In equilibrium, the demand for drugs is endogenous and it is generated by two types of patients; those who have a legitimate need for prescription drugs and those who do not, i.e., they are purely drug seekers. In equilibrium illegitimate drug use, or loosely speaking drug abuse, occurs when a drug seeker obtains a prescription for drugs. The analysis reveals that the equilibrium incidence of drug abuse depends upon a variety of factors that can be partitioned into two categories. The first category includes economic barriers to the demand for drugs, such as healthcare costs and the price of prescription drugs. These economic factors affect drug abuse indirectly because they impact an individual’s incentive to seek drugs from doctors. The second category encompasses various non-economic barriers to acquiring drugs from doctors. Examples include doctors’ disposition to prescribing drugs, refill policies, and doctors’ monitoring of their patients’ medical history. These non-economic factors affect the incentives to seek drugs and prevent drug abuse.

The analysis reveals that, on the one hand, interventions focused on reducing demand by manipulating economic factors, such as taxing prescription drugs, are problematic. Interventions of this kind are not well-suited to prevent drug abuse and, in addition, discourage all drug demand without differentiating between legitimate and purely recreational demand. On the other hand, we find that interventions centered around a manipulation of non-economic barriers, such as improving drug monitoring programs or education of the medical community, are much more effective. Raising barriers to securing drugs from doctors not only prevents drug abuse but in addition differentially affects incentives to seek drugs, mainly or solely discouraging demand associated to the recreational use of drugs.

The model is calibrated to recent U.S. healthcare data in order to quantify the likely impact of several possible modes of economic and non-economic intervention to stem drug abuse. The calibrated model suggests that barriers to securing prescription drugs from doctors, which are already built into the health-care system, discourage to some extent drug seeking behavior. Yet, they are insufficient to eradicate drug-abuse. In the benchmark scenario only a small fraction of those who would like to consume drugs simply for a recreational purpose end up seeking drugs from doctors. As a result at any point in time about 25% of the population consumes drugs for a legitimate medical reason while 2.6% of the population can be classified as drug abusers. These numbers are in line with U.S. healthcare data. We find that interventions of a purely economic nature can have a problematic impact. For instance, an increase in advertising. In addition, studies such as Grant (2005), which focuses on the patient-physician relationship, show that the search process uses very little information and can be considered effectively random.
the drug price that reduces drug abuse by 65% also reduces legitimate use by about 40%. Alternatively, considerable reductions in drug abuse can only be obtained by tremendous increases in the out-of-pocket cost to patients from a doctor’s visit; for example one would need a 50% increase in out-of-pocket costs to reduce drug abuse by slightly more than half.

We also consider some non-economic interventions that have been recently suggested. These include improving a professional’s assessment of a patient’s need for prescription drugs, controlling the drug supply by requiring stricter refill policies, and improving prescription drug monitoring (e.g., see Manchikanti (2007)). We find that mandating stricter refill policies, such as decreasing by 50% the drug supply that can be obtained by patients before requiring a new doctor’s visit, can reduce drug abuse by almost 90% and reduces legitimate use by only 5%. Education of the medical community about the safe use of prescription drugs is also very effective; an education program that would cut in half the chance that a prescription is written for a healthy patient would reduce drug abuse by almost 90% and does not impact legitimate users. Neither of these policies, however, are extremely effective at preventing drug abuse due to their increased cost on physicians or patients. They reduce the incentives to seek drugs, sometimes differentially for potential abusers, sometimes not, but they also increase the effort required to screen patients or increase the frequency of doctor visits required to maintain a prescription. As a result, they either directly or indirectly inhibit legitimate use.

Most importantly, we find that improving drug monitoring programs, such as implementing a national drug registry, is very effective in preventing drug abuse as well as reducing the incentives to seek drugs purely for recreational purposes. We report that a national system that maintains records of recognized drug abusers for only six months can reduce drug abuse by almost 90% if doctors can make a positive identification at least 50% of the time. Moreover, adding a small fine, such as $50, for patients reported to be drug abusers can virtually eliminate drug abuse. This last result is complementary to a small literature on illicit behavior in search markets such as the study of use of illegal drugs in Galenianos, Pacula, and Persico (2009), the study of the use of money for illicit transactions in Camera (2001), and the study of crime in Engelhardt, Rocheteau, and Rupert (2008).

The paper proceeds as follows. Section 2 presents the model. Section 3 characterizes equilibrium. Section 4 reports details on the calibration. Section 5 collects the results and Section 6 concludes.

2 The model

Consider a continuous time economy populated by a fixed mass of individuals normalized to one. There is a single indivisible object, called a prescription pain medication, drug for short, which is prescribed by primary care physicians and can be purchased with an out-of-pocket expenditure \( p > 0 \) per dose (in utility terms), only with a doctor’s prescription. The implicit assumption here is that direct prescriptions are the key source of drugs while other channels, such as resale by legitimate users and black market sales, are not important. This reflects empirical evidence indicating

\[ \text{The price is taken as given because insurance companies and the government play a large role in drug pricing.} \]
that drug dealers or other strangers are a minimal source of prescription pain relievers, and Internet sales are basically irrelevant (see (Monthly Prescribing Reference, 2008, p.6)).

Individuals are ex-ante heterogeneous in their medical need for pain medications and in their preferences for the recreational use of pain medications. An individual may have a legitimate medical need for the drug or may simply be interested in its recreational uses. It is convenient to characterize preferences over the value of being sick and the value from the use of prescription medications as \( i = \{0, y\} \) and \( U \), respectively. Both values are private information. The variable \( i \) defines the value from being sick as a flow disutility from being without the drug; an individual of type \( i \) has flow utility \(-i\) if she is not consuming the drug, and zero otherwise. The variable \( U \), instead, defines any additional flow utility that an individual derives from consuming a dose of the drug for reasons other than the specific medical condition the drug is intended for. To be specific, a positive \( U \) implies the drug has a recreational value for the individual. Otherwise, the drug has negative side effects or is simply disliked for reasons other than medical reasons. We let \( i = 0 \) for a fraction \( x \in (0,1] \) of the population, whom we denote healthy individuals, and \( i = y \) for the remaining fraction, called sick individuals who have a medical need for the drug because they suffer from pain. Hence, \( x \) individuals are potential (prescription) drug abusers and the value from being healthy is normalized to zero.

Let \( u \) denote the utility to an individual who is currently consuming the drug, where \( u := U - p \) because one dose of the drug costs \( p \). It is assumed that individuals are heterogeneous in their preferences for a recreational use of prescription drugs. More specifically, \( U \) is i.i.d. on \([U, \bar{U}]\) with smooth and time-invariant c.d.f. \( G \), and \( U < p < y < \bar{U} \). This set up implies that drug consumption eliminates the disutility \( y \) from being sick, and may also have a recreational value, since it may generate \( u > 0 \) (net) utility to some patients. The assumptions on \( U \) imply that the price of the drug is low enough that at least some individuals exist who have an incentive to buy the drug and consume it simply for recreational purposes. Indeed, \( u \) can be considered as including utility from illegally sharing or reselling the drug; hence the setup can be considered a reduced-form approach to accounting for secondary markets for prescription drugs.

**The patient-doctor matching process.** Individuals who wish to obtain prescription drugs must see a doctor, and each visit costs \( c > 0 \) in utility terms. For instance, this includes the opportunity cost of taking time off for a doctor’s visit and any out-of-pocket expenses. Doctor-patient encounters are regulated by a random matching process.\(^4\) Considering a stationary environment, denote \( \Pi \) as the mass of individuals who seek medical care, for any reason, at any point in time; we call these individuals patients and note that they include not only individuals that are seeking to obtain prescription drug medications but also individuals who are visiting doctors for any reason other than prescription drugs. At each point in time let \( D \) be the mass of primary care doctors available to see patients and let the total

\(^4\)If individuals directed their search across homogeneous physicians who cannot differentiate them by means of public histories or price schedules, then the process would be random in a symmetric equilibrium. Here patients could choose among doctors but in equilibrium are indifferent between meeting any specific doctor. In this case, the arrival rate of matches can be interpreted as the endogenous queue length.
number of doctor-patient matches be $\zeta(D, \Pi)$, where $\zeta : \mathbb{R}^2_+ \to \mathbb{R}_+$ is a matching function. Assume the function $\zeta$ is homogeneous of degree 1 (i.e., there are constant returns to scale from the matching process), strictly increasing and concave in each argument, $\zeta(0, \cdot) = \zeta(\cdot, 0) = 0$ and $\zeta(\cdot, \infty) = \zeta(\infty, \cdot) = \infty$.

Define the queue length as patients per doctor or $\frac{1}{\theta} = \frac{\Pi}{D}$. Let the instantaneous matching rates for doctor and patient be $q(\theta)$ and $\theta q(\theta)$, i.e., on average patients wait $\frac{1}{\theta q(\theta)}$ periods to be seen by a doctor, while doctors experience an interval of time $\frac{1}{q(\theta)}$ between patients’ visits. When the number of matches between doctors and patients equals the number of matches between patients and doctors, we have

$$Dq(\theta) = \zeta(D, \Pi) = \Pi \theta q(\theta).$$

Constant returns to scale from matching imply $q(\theta) = \zeta \left( \frac{1}{\theta} \right)$. We have $q'(\theta) < 0$ and $\frac{d\theta q(\theta)}{d\theta} > 0$ from concavity of $\zeta$ in both arguments. $\lim_{\theta \to 0} q(\theta) = \infty$, and $\lim_{\theta \to \infty} q(\theta) = 0$.

Once matched, the doctor conducts a physical examination of the patient. Consider a match with a patient who is complaining of pain and asking for prescription drugs. Due to private information on $i$ and $u$, we assume doctors are not able to determine with certainty the type $i$ of the patient. Let $\gamma_i$ denote the probability that a doctor prescribes the pain medication after physically examining a patient of type $i$. We assume $0 < \gamma_0 < \gamma_i \leq 1$, i.e., sick patients are more likely to be prescribed the drug. Finally, when a doctor writes a prescription for pain medication, let the drug supply be identified by the rate $\delta > 0$ at which the prescribed amount of drug runs out, i.e., the typical drug prescription lasts $\frac{1}{\delta}$ periods. The prescription length is defined as the amount of the drug a patient can receive before undergoing another examination. Therefore, by definition, a new prescription cannot be granted without the patient undergoing an additional physical examination.

3 The equilibrium demand for prescription drugs

Here we study the optimal individual decisions under the conjecture of stationarity, and derive the endogenous demand for prescription drugs in a stationary outcome.

3.1 Optimal search strategy for an individual

An individual characterized by $i$ and $u$ chooses whether to see a physician in order to get prescription drugs. This choice is made while taking as given the matching rate $\theta q(\theta)$, and the probability $\gamma_i$ of a favorable outcome (the doctor writes a prescription).

At each point in time the individual can be in one of three states: idle, seeking medical care, or holding a prescription and consuming the drug. In a stationary outcome, define expected payoffs over each state as follows. Being idle generates the payoff $-\frac{1}{r}$, i.e., the present discounted value of the constant disutility flow $i$. Considering patients, let $V_i$ and $V_{i,u}$ denote the expected lifetime utility to a patient of type $i$ who is seeking medical care, and who has a
prescription, respectively. Standard recursive methods allow us to calculate patients’ payoffs using the flow payoffs associated to each state.

The flow payoff from choosing to seek medical care is

\[ r_V = -i + \theta q(\theta) \left[ -c + \gamma (V_{i,u} - V_{i}) \right]. \tag{2} \]

Being without medication generates instantaneous disutility \( i \), where \( i = 0 \) is the value from being healthy and \( i = y \) is the value from having pain. The patient is seen by a doctor at rate \( \theta q(\theta) \) and the visit costs \( c \) in utility terms, independently of whether a drug is obtained or not. With probability \( \gamma \) the doctor determines (correctly or incorrectly) that the patient should be prescribed the controlled medication. With the complementary probability, the patient must see another doctor to obtain the drug; hence, the net payoff is zero.

The flow payoff to a patient holding a prescription is

\[ r_{V_{i,u}} = u + \delta (\tilde{V}_i - V_{i,u}), \tag{3} \]

where \( u \) is the instantaneous net utility from buying and consuming the drug. Note that \( i \) does not appear in (3) because if \( i = 0 \), then the drug has no medical significance; and if \( i = y \), then the drug eliminates entirely the pain and the patient enjoys the value from being healthy, which is normalized to zero. The supply of medications runs out at rate \( \delta \), which is when the patient gets net payoff \( \tilde{V}_i - V_{i,u} \), where \( \tilde{V}_i < \infty \) is a generic continuation payoff. Later, we provide more structure for \( \tilde{V}_i \), considering situations in which it depends only on individual-specific medical factors or also on the possibility of addiction to drugs.

From expression (2) it should be clear that if \( -c + \gamma (V_{i,u} - V_{i}) \geq 0 \), then the individual of type \( i \) optimally chooses to seek drugs from a doctor. This immediately implies \( V_{i,u} - V_{i} > 0 \) is necessary, i.e., in equilibrium a patient who intends to be physically examined by a doctor strictly prefers to consume prescription drugs than not. In particular, this means that the individual’s medical condition, summarized by \( i \), is not the only determinant of whether the patient wishes to seek to obtain the medicinal drug. The Lemma that follows defines a condition for an individual to seek to consume the medicinal drug in a benchmark case when drug consumption does not affect the underlying patient’s type, i.e., \( \tilde{V}_i = V_{i} \). This is equivalent to assuming that the medical condition of sick patients is chronic, while healthy patients remain healthy. We study variations in later sections.

**Lemma 1** Consider an agent characterized by \((i,u)\). Let \( \tilde{V}_i = V_{i} \). If \( u \geq u_i \) with

\[ u_i := \frac{c(r + \delta)}{\gamma i} - i \]

then the individuals seeks to obtain the medicinal drug.
Proof of Lemma 1. Using (2)-(3), we obtain

\[ V_{i,u} - V_i = \frac{i + u + \theta q(\theta)c}{r + \theta q(\theta)\gamma_i} + \frac{\delta (\bar{V}_i - V_{i,u})}{r + \theta q(\theta)\gamma_i}. \]

This implies

\[ V_i = \frac{1}{r + \theta q(\theta)\gamma_i} \left\{ -i[r + \delta + \theta q(\theta)\gamma_i] + \theta q(\theta) \left[ -c(r + \delta) + \gamma_i(i + u + \delta \bar{V}_i) \right] \right\}. \]

For the case \( \bar{V}_i = V_i \), we have

\[ V_{i,u} - V_i = \frac{i + u + \theta q(\theta)c}{r + \delta + \theta q(\theta)\gamma_i}. \]

A type \( i \) chooses to search for a doctor if \( -c + \gamma_i(V_{i,u} - V_i) \geq 0 \) which implies

\[ \frac{c}{\gamma_i} \leq \frac{u + i}{r + \delta} \]

that is, as long as the present discounted value of the expected net utility from drug consumption is greater than the cost. Notice that in this case both sick and healthy patients will attempt to obtain the drug. When the above inequality holds with equality it defines the unique threshold value

\[ u_i := \frac{c(r + \delta)}{\gamma_i} - i. \]

The value \( u_i \) increases in \( c, r \) and \( \delta \) and falls in \( \gamma_i \). When \( \bar{V}_i = V_i \) then

\[ rV_i = -i + \frac{\theta q(\theta)}{r + \delta + \theta q(\theta)\gamma_i} \left[ -c(r + \delta) + \gamma_i(u + i) \right], \]

so that \( rV_i \geq -i \) whenever \( \frac{c}{\gamma_i} \leq \frac{u + i}{r + \delta} \) holds.

The Lemma has three immediate implications. First, the recreational value derived from consuming drugs is the only element that matters in a healthy individual’s choice to seek drugs from doctors. Second, all else equal, sick individuals are more likely to seek drugs because the drug eliminates their disutility from pain, i.e., \( u_0 < u_y \) for \( \gamma_y = \gamma_0 \). In particular, the disutility from being sick may be a sufficient incentive to induce someone sick to obtain prescription drugs, i.e., \( u_y < 0 \) is possible. Third, the recreational value derived from consuming drugs can also be an element in a sick individual’s choice to obtain drugs from doctors. These three considerations will be instrumental in assessing the strengths and weaknesses of different policies proposed to combat drug abuse. We will refer to \( u_i \) as the minimum recreational value that an individual of type \( i \) must derive in order to seek prescription drugs.

In terms of costs and benefits, an individual characterized by \( (i, u) \) chooses to see a doctor when the expected cost of obtaining prescription medications is lower than the benefit derived from consuming them, i.e.,

\[ \frac{c}{\gamma_i} \leq \frac{u + i}{r + \delta}. \]
The left hand side of (4) is the expected cost from the doctor’s visit, which accounts for the possibility of being refused prescription drugs. In the model, a patient of type $i$ must try $\frac{1}{\gamma}$ different doctors on average before succeeding in obtaining a prescription. This is important to study policy interventions because a way to deter recreational drug use is to simply decrease the probability of prescribing drugs.\(^5\)

The right hand side of (4) collects net discounted benefit from consuming prescription drugs; it is net of the disutility from the out-of-pocket expenditure for drugs. Use of medications gives net utility $u$ for an average of $\frac{1}{\delta}$ periods because prescription drugs run out at rate $\delta$. So the net stream of benefits is $\frac{u_i + r_i}{r + \delta}$. Note that the size of the prescription, captured by the rate $\delta$ at which the prescription runs out, affects discounting and the benefits from searching for prescription drugs.

Given Lemma 1, we define the hazard function

$$F(u_i) := \begin{cases} 
    x[1 - G(u_i)] & \text{if } i = 0, \\
    (1-x)[1 - G(u_i)] & \text{if } i = y.
\end{cases}$$

(5)

The value $F(u_i)$ gives us the demand for prescription drugs coming from patients of type $i = \{y, 0\}$. It is the mass of patients of type $i$ who have chosen to meet a doctor with the goal to obtain prescription drugs. We will call patients of type $i = 0$ drug seekers, i.e., individuals who visit a doctor to obtain prescription drugs that will be simply used recreationally. In contrast, patients of type $i = y$ demand prescription drugs for legitimate medical reasons.

Three considerations follow from this initial analysis. First, a way to combat drug abuse is to discourage drug-seeking behavior, i.e., the seeking of drugs for purely recreational purposes. Second, drug seeking behavior can be discouraged by raising the reserve value $u_i$ derived from consuming prescription drugs for recreational purposes. Third, the model suggests three types of interventions increase the reserve recreational value of prescription drugs:

- raising the cost from consuming prescription drugs ($p, c$);
- reducing the average drug amount prescribed ($\delta$);
- improving the screening of patients by the medical community ($\gamma$).

In general, only the last type of intervention can differentially impact demand from potential abusers and from legitimate users. In particular, if sick patients also attach some recreational value to consuming prescription drugs, $u_y > 0$, then the first two types of interventions will discourage healthy as well as sick patients from seeking drugs.\(^6\)

To analyze how these policies impact drug abuse, we must calculate equilibrium drug consumption, which is done in the following section.

\(^5\)Each doctor’s visit is an independent draw for a patient. So, the expected number of trials is $\sum_{n=0}^{\infty} (1 - \gamma)^{n-1} \gamma n = \frac{1}{\gamma}$. If, for example, there is a 50-50 chance to get refused a prescription for controlled drugs, then the patient on average must seek two different doctors to obtain a prescription.

\(^6\)Notice that since $\gamma_y > \gamma_0$, for any $u_i \in [u, \bar{u}]$ we have that if $F(u_0) > 0$ then $F(u_y) > 0$, i.e., we do not have to worry about the situation in which only healthy patients seek medical care. In addition, we have $F'(u_i) < 0$ for $i = y, 0$ because $G$ is a c.d.f.
3.2 Equilibrium consumption of prescription drugs

Divide patients of type $i = \{0, y\}$ into two groups, the mass of patients who are trying to obtain drugs from a doctor and those who have secured a drug prescription, or $\pi_i$ and $\pi_{i,d}$, respectively. The quantity of drugs consumed at any point in time corresponds to the mass of patients, sick or healthy, who have a prescription, i.e.,

$$Q = \pi_{0,d} + \pi_{y,d}.$$  

In general, the amount of drugs consumed in society will be a function of doctors’ professional choices reflected in the probability $\gamma_i$, the length of a prescription $1/\delta$, the time it takes to see a doctor $\frac{1}{\theta q(\theta)}$, the need for pain medication summarized by $x$ and $i$, and the distribution of preferences over a recreational use of prescription medications, summarized by the net utility thresholds $u_i$.  

To complete the analysis we define an equilibrium.

**Definition 1** A stationary equilibrium is a list $\{\theta, \pi_0, \pi_y\}$ that is consistent with optimality and stationarity conditions, i.e., (4) and (7)-(8) must hold.

We can now discuss existence of a stationary equilibrium.

**Lemma 2** A unique equilibrium exists in which $\pi_0 + \pi_y \leq 1$ individuals search for and consume prescription drugs with

$$\pi_0 = \kappa_0 \pi_{0,d} \text{ and } \pi_{y,d} = \frac{\mathcal{F}(u_y)}{1 + \kappa_y}$$

where $\mathcal{F}(u_i)$ is defined in (5) and

$$\kappa_i := \frac{\delta}{\theta q(\theta) \gamma_i}.$$  

In equilibrium, a portion $Q < 1$ of the population consumes drugs, where

$$Q = \frac{\mathcal{F}(u_0)}{1 + \kappa_0} + \frac{\mathcal{F}(u_y)}{1 + \kappa_y}. \tag{6}$$

**Proof of Lemma 2.** The derivation centers around finding the stationary $\pi_{i,d}$ for $i = y, 0$. In a stationary outcome, for each $i = y, 0$ we must have

$$\pi_{i,d} \delta - \pi_i \theta q(\theta) \gamma_i = 0, \tag{7}$$

$$\pi_i + \pi_{i,d} = \mathcal{F}(u_i). \tag{8}$$

Equation (7) is the requisite that inflows and outflows of patients of type $i$ must be equal; it ensures that at each point in time the mass of patients given a new prescription must equal the number of patients for whom a prescription has just run out, who return to their original state of health $i$. The probability $\gamma_i$ accounts for doctors’ probability to write prescriptions. Equation (8) is an adding-up constraint.

From (7)-(8) we have

$$\pi_i = \frac{\delta \pi_{i,d}}{\theta q(\theta) \gamma_i}.$$
\[ \pi_{i,d} = \mathcal{F}(u_i) \frac{\theta q(\theta) \gamma_i}{\delta + \theta q(\theta) \gamma_i}. \]

We get \( Q = \pi_{y,d} + \pi_{0,d} \) as in (6). Since \( \sum_{i=y,0} \mathcal{F}(u_i) \leq 1 \) from (5), we have \( Q < 1. \)

To summarize, the model determines the percentage of drug demand that comes from potential abusers and legitimate users, as a function of the parameters defining the healthcare system, the costs from obtaining the drugs, the costs from pain, and the preferences for recreational uses of drugs. Lemma 2 shows that the equilibrium level of consumption can be divided into two components, \( \pi_{0,d} \) drug abusers and \( \pi_{y,d} \) legitimate users. These portions are also a function of the model’s parameters.

The Lemma establishes that not everyone in the population consumes drugs at each point in time, i.e., \( Q < 1. \) Not everyone seeks drugs, due to heterogeneous medical needs and preferences over recreational uses of drugs. Second, non-economic barriers exist that prevent drug consumption: it takes time to see a doctor (\( \frac{1}{\theta q(\theta)} \) periods on average), doctors write prescriptions only after screening patients (\( \gamma_i \)), and the average drug supply is lasts \( \frac{1}{\delta} \) periods. These non-economic barriers, which prevent patients from accessing drugs at their leisure, are captured by the term \( \kappa_i \). A greater \( \kappa_i \) corresponds to more restricted access to drugs because \( \frac{1}{1+\kappa_i} \) is the equilibrium proportion of type \( i \) patients who consume drugs at any point in time. The term falls if it takes longer to be seen by a doctor, if doctors prescribe a smaller quantity of drugs or if they less frequently prescribe drugs.

**Lemma 3** Equilibrium drug consumption \( Q \) falls if \( \gamma_i \) or \( \theta q(\theta) \) falls, and if \( \delta \) or \( c \) rise.

**Proof of Lemma 3** Notice that \( u_i \) increases and \( \kappa_i \) rises if \( \gamma_i \) or \( \theta q(\theta) \) falls, and if \( \delta \) or \( c \) rise. Then notice that \( Q \) falls in \( \kappa_i \) and in \( u_i \).

We are now in a position to make two additional considerations on how to combat drug abuse. We have earlier seen that drug abuse can be reduced by removing incentives to seek drugs in the first place, i.e., by focusing on economic factors capable of reducing the demand for drugs. In this section we have demonstrated that drug abuse can also be reduced through interventions that limit patients’ access to drugs once patients enter the healthcare system. These interventions are based on non-economic barriers that include strict refill policies, limiting the amounts of drugs prescribed per visit, improved prescription drug monitoring, and doctors’ disposition towards prescribing drugs. Non-economic barriers have a complementary effect on drug abuse because they also reduce the incentive to seek drugs in the first place. In sum, the analysis shows that raising barriers to accessing drugs from doctors is a policy that not only can prevent drug abuse but can also discourage drug-seeking behavior in the first place.

To quantitatively assess these two types of policies, based on economic barriers and non-economic barriers, we proceed as follows. First, we calibrate the healthcare factors in the model using recent U.S. data. Second, we report the patterns of demand, as well as use and abuse for prescription drugs predicted by the calibrated model. Third, we
run some policy experiments in which we vary some of the baseline parameters to determine how changes in economic and non-economic factors impact demand and the patterns of use for prescription drugs in the U.S. This is done in the sections that follow.

4 Calibration

In this section we calibrate the model to U.S. Data primary taken from the years 2004 and 2005. In calibrating the parameters, we will work under the conjecture that the U.S.’s use of prescription drugs is in a stationary state. The calibration considers a daily time period. So, we set

\[ r = 1.34 \times 10^{-4}, \]

which means the annual rate of time preference is 0.05, a standard value.

**The doctor-patients matching function.** Recall that \( \theta = \frac{D}{\Pi} \), so \( \frac{1}{\theta} \) is the “queue” or the average number of patients, of any kind, per doctor. To pin down the rate \( \theta q(\theta) \) at which a patient who seeks health care is physically examined by a doctor, we proceed as follows. From Section 2 we know that \( \theta q(\theta) = \frac{\zeta(D, \Pi)}{\Pi} \), where \( \zeta \) is the matching function. Assuming a Cobb-Douglas function, which is standard, we let \( \zeta(D, \pi) = AD^{1-\eta} \Pi^{\eta} \) with \( \eta = 0.5 \) and \( A \) to be pinned down. Homogeneity of degree one implies \( \frac{\zeta(D, \Pi)}{\Pi} = \zeta(\theta, 1) \), so

\[ \theta q(\theta) = A \theta^{1-\eta}. \]

We use several data sources to calibrate the matching function. The average patient waits 4.7 days to see a doctor (Commonwealth Fund International, 2005, p. 5). So, the daily rate at which a patient is seen by a doctor is \( \frac{1}{4.7} \), or

\[ \theta q(\theta) = 0.213. \]

To find the queue \( 1/\theta \) at the average doctor, we use two surveys. First, in 2005 there were approximately 0.3 million general primary care specialists which includes general practice, internal medicine, obstetrics and pediatric specialists (National Center for Health Statistics, 2005, Table 108). Second, the average physicians saw 99.1 patients per week in the year 2001 (Kane and Loeblich, 2003, p. 5). Therefore, the aggregate number of patient-physician matches (patients seen by physicians) is the product of the average number of patients seen by a physician per week, multiplied by the number of physicians, divided by the number of days in a week or \( \zeta(D, \Pi) = 0.3 \times 99.1/7 = 4.25 \) million per day.

From (1) we have \( Dq(\theta) = \zeta(D, \Pi) \). Using \( D = 0.3 \) million, and \( \zeta(D, \Pi) = 4.25 \) million, we obtain the daily rate at which a doctor meets a patient

\[ q(\theta) = 14.16. \]
Now we can determine
\[ \theta = \frac{.213}{14.16} = 0.0151. \]

Finally, we pin down \( A \) using \( \theta_q(\theta) = A\theta^{1-\eta} \) with \( \eta = 0.5 \), which gives
\[ A = 1.732. \]

From the calibration of \( \theta \), we have \( \theta = D/\Pi \). Inserting the calibrated values for \( \theta \) and \( D \), we get the number of patients, of any kind (not only those who seek prescription drugs) who are seeking health care at each point in time is
\[ \Pi = \frac{0.0151}{0.0151} = 19.88 \text{ million}. \]

Normalizing by the total population, at each point in time a fraction \( \frac{19.88}{296.4} = 0.067 \) of the population is waiting to see a doctor. In terms of our notation, \( \pi_0 + \pi_y + X = 0.067 \) where \( X \) is the portion of individuals who seek a physician for reasons other than pain medication and \( X \leq 1 - \pi_0 - \pi_y \). This is used to complete the calibration.

**The amount of drug prescribed and prescription refills.** Recall that \( 1/\delta \) is the average time that a patient consumes prescription drugs, after having been prescribed the drugs. Hence, \( \delta \) captures prescription size and number of refills possible without a new visit. To identify \( \delta \), we introduce several new pieces of data. First, we know 25% of the U.S. population is currently taking a prescription drug for pain (ABC News, USA Today, and Standford Medical Center Poll, 2005, Question 16) while Manchikanti (2007) reports that 2.6% of the population has used a drug recreationally over the past month. Therefore, we fix \( \pi_{y,d} = 0.25 \) and \( \pi_{0,d} = 0.026 \). In combining these pieces of data with the model, we realize \( \pi_0 = \kappa_0\pi_{0,d} = \frac{\delta}{\theta_q(\theta)\gamma_0}0.026 \) and \( \pi_y = \kappa_y\pi_{y,d} = \frac{\delta}{\theta_q(\theta)\gamma_y}0.25 \). This is important because Olsen, Daumit, and Ford (2006) reports that 5.9% of primary care physicians’ visits resulted in a prescription for an opioid or
\[ 0.059 = \frac{\pi_0\gamma_0 + \pi_y\gamma_y}{\pi_0 + \pi_y + X}, \]
and if we substitute for \( \theta_q(\theta) = 0.213, \pi_y = \frac{\delta}{\theta_q(\theta)\gamma_y}0.25, \pi_0 = \frac{\delta}{\theta_q(\theta)\gamma_0}0.026, \) and \( \pi_0 + \pi_y + X = 0.067 \) from above, we can simplify the equation to
\[ 0.059 = \frac{\frac{\delta}{0.213}0.026 + \frac{\delta}{0.213}0.25}{0.067}. \]

As a result, we infer \( \delta = 3.07 \times 10^{-3} \), which means a patient who has been prescribed drugs consumes these drugs for a year on average. This may seem excessive. However, note that \( \delta \) is small because many individuals are on pain medication yet so few such medications are prescribed per doctor’s visit. In addition, each prescription in our model is considered to be a prescription that follows a physician’s visit. Since many individuals in the data have recurrent pain, then \( \delta \) accounts for refills that are granted without re-visiting his or her physician.
Doctors’ disposition to writing a prescription. We determine $\gamma$ from a survey which asks individuals who went to see a doctor about whether they were provided relief (ABC News, USA Today, and Standford Medical Center Poll, 2005, Question 13). 95% of the interviewed report they were given some relief; as a result, we calibrate $\gamma = 0.95$. Given our calibrated values of $\delta$, $\theta_q(\theta)$, $\gamma$, and an estimate of $\pi_{y,d}$, we determine $\pi_y = 0.0038$. To determine $\gamma_0$, we know 20% of primary care patients report persistent pain when visiting a primary care physician (Manchikanti, 2007, p. 408). Within the model, this implies

$$0.2 = \frac{\pi_0 + \pi_y}{\pi_0 + \pi_y + X},$$

and using the fact $\pi_0 + \pi_y + X = 0.067$ and $\pi_y = 0.0038$ we find $\pi_0 = 0.0097$. As a result, we substitute in $\theta_q(\theta) = 0.213$ and $\delta = 3.07 \times 10^{-3}$ into $\pi_0 = 0.0097 = \frac{\delta}{\theta_q(\theta)\gamma_0} - 0.026$ to find $\gamma_0 = 0.0387$.

Non-pain related medical visits. We have determined $\pi_0 = 0.0097$ and $\pi_y = 0.0038$ while the total proportion of the population waiting to see a doctor is $\pi_0 + \pi_y + X = 0.067$. The remaining fraction who are waiting to see a physician is

$$X = 0.054.$$

Summing up the matching function, $\theta_q(\theta) = A\theta^{1-\eta}$ with $\theta = D/\Pi$. Given the definition of $\Pi$ above

$$\theta_q(\theta) = A \left( \frac{D/P}{X + \pi_0 + \pi_y} \right)^{1-\eta},$$

where $A = 1.732$, $\eta = 0.5$, $X = 0.054$, and $D/P = .3/296.4 = 0.001$ or the proportion of physicians per individual in the population.

The cost of chronic pain. Many estimates exist on the cost of pain. We consider Stewart, Ricci, Chee, Morganstein, and Lipton (2003) who estimates the cost to be $61.2 billion per year. The estimate is a lower bound as the results only include lost production time from work. We see that 53% of the U.S. population has chronic or recurrent pain (ABC News, USA Today, and Standford Medical Center Poll, 2005, Question 4). Therefore, $1 - x = 0.53$. Equivalently,

$$x = 0.47.$$

Because 53% of the total population experiences pain, we estimate the daily cost of pain per person to be $y = \frac{61.2}{296.4 \times 0.53/365} = 1.067$.

The distribution of recreational utility from drugs. The distribution of $u$ for individuals who have preferences defined over drugs is unobservable. So, we will assume a normal distribution, $u \sim N(\mu, \sigma)$. We use information from the stationary distribution of patients seeking care, or $F(u_0)$ and $F(u_y)$, to calibrate $\mu$ and $\sigma$. 
In using the stationary distributions, we must calibrate the threshold values $u_0$ and $u_y$. We find the average out of pocket costs to see a physician is $20.3$ (Machlin and Carper, 2004, p. 6). Therefore, considering risk neutrality we have $c = 20.3$ and we can pin down $u_0$ and $u_y$ using the results in Lemma 1, i.e., $u_i := \frac{e^{(r+\delta)}}{B} - i$. Plugging in the known parameters results in $u_0 = 1.68$ and $u_y = -1.00$. The negative costs on the side of legitimate users could arise due to the normalizing of $p = 0$ and the fact consuming the medication can be a nuisance.

Assuming a normal distribution for the utility derived from the use of prescription drugs is identical to saying

$$G(u) := \frac{1}{2} \left[ 1 + e^{\text{rf}} \left( \frac{u - \mu}{\sqrt{2}\sigma^2} \right) \right]$$

where $erf$ is the error function. Using the calibrated values $\mathcal{F}(u_0) = (1 + \kappa_0)\pi_0 = 0.0331$ and $\mathcal{F}(u_y) = (1 + \kappa_y)\pi_y = 0.253$, along with several other key parameters, we have two equations with two unknowns, $\mu$ and $\sigma$,

$$\mathcal{F}(u_0) \quad = \quad \frac{1}{2} \left[ 1 - erf \left( \frac{u_0 - \mu}{\sqrt{2}\sigma^2} \right) \right]$$

$$\mathcal{F}(u_y) \quad = \quad (1 - x) \frac{1}{2} \left[ 1 - erf \left( \frac{u_y - \mu}{\sqrt{2}\sigma^2} \right) \right]$$

which imply

$$\mu \quad = \quad \frac{Bu_y - Cu_0}{B - C}$$

$$\sigma \quad = \quad \frac{1}{\sqrt{2}} \frac{u_0 - u_y}{B - C}$$

where $B = erf((1 - 2\mathcal{F}(u_0)/x))^{-1}$ and $C = erf((1 - 2\mathcal{F}(u_y)/(1 - x)))^{-1}$. The parameters $\mu$ and $\sigma$ are unique because the error function is monotonic and the alternative root to the quadratic function results in a negative $\sigma$. Therefore, the remaining parameters are

$$\mu = -1.102, \quad \text{and} \quad \sigma = 1.943.$$

Table 1 provides a summary of the calibrated parameters.

5 Results

We start by reporting the level of demand and access to prescription drugs predicted by the calibrated model in the benchmark scenario (Table 2, column 1). Specifically, consider the legitimate medical uses of prescription drugs. From the data, we find 53% of the population suffers from some form of pain at any point in time. Of those who suffer, we find about half of them visit doctors to obtain prescription drugs, i.e., 25.4% of the population demands prescription drugs at any point in time for a legitimate reason. Almost all of these patients consume drugs at each point in time; their access to drugs in the calibrated model is very high, 98.5%. Some who want drugs do not consume them currently either because their doctor denied them a prescription, or because their prescription ran out and they
are waiting to obtain a new one. Finally, not everyone who has a medical reason to use prescription drugs seek drugs because the overall health benefits of drugs are heterogeneous and, for some individuals, are too small.

Now consider the fraction of the population who does not have a medical need for drugs. In the model 34% of the population has a positive recreational value from using drugs, i.e., $u_0 > 0$ for $xF(0) = 0.34$ people; this amounts to about 71% of all healthy individuals. Only about 10% of these individuals seek prescription drugs from a doctor; these are the individuals who attach a very high recreational value to drugs. The remaining 90% have no incentive to seek drugs either due to the costs involved or barriers in accessing drugs. Consequently, the model finds that only 3.5% of the population demands prescription drugs from doctors purely for recreational purposes. Many of these individuals are drug abusers; about 73% of drug seekers consume drugs on any day, hence the model predicts that drug abusers make up 2.6% of the U.S. population.

In sum, the calibrated model suggests that barriers to accessing drugs built into the health-care system already discourage a large segment of the population from demanding drugs for non-medical reasons. However, the model suggests that these barriers are not very effective at preventing drug abuse because a very large fraction of drug seekers ends up securing a prescription from a doctor. For these reasons we will consider two types of policies that are capable of reducing drug abuse and examine how they change demand and consumption patterns. We divide the policies into two subsets according to whether they are primarily designed to discourage demand for prescription drugs or if they are primarily designed to prevent drug abuse from patients. In particular, first we study interventions that target economic elements capable of reducing prescription drug demand. Then, we study ways to manipulate non-economic barriers to prevent drug-abuse.

### 5.1 Combating drug abuse by raising economic barriers

A basic economic mechanism to deter consumption of a specific commodity is to increase its relative price. Two primary ways to do so within our model is either to raise the price of the drug or to raise the costs associated to a doctor’s visit. Neither of these strategies can effectively differentiate between legitimate and illegitimate users. Hence, the main finding for this subsection can be summarized as follows.

**Result 1:** *Raising the cost of use of prescription drugs can reduce but cannot eliminate drug abuse while it can significantly reduce legitimate drug demand.*

One can think of a variety of ways to increase the market price of a drug, such as reducing subsidies, increasing taxation on the controlled substances, implement tougher FDA standards on production and distribution, or reduce competition through patent laws. These different policies all should result in an increase in $p$. Raising $p$ increases the minimum utility $u_i$ an individual must have in order to optimally demand the drug from doctors. This means that raising $p$ deters demand for the drug from legitimate users and potential abusers. The relative impact on these two segments of the demand for prescription drugs depends on the relative price elasticities. We find that an increase in
the price of prescription drugs $p$ that significantly reduces abuse also significantly reduces legitimate use of drugs. For instance consider Table 2, columns 1-2. An increase in the drug price that reduces recreational demand for prescription drugs by about 41% also reduces legitimate demand by about 21% (price $= 0.5$). The effect on drug consumption is similarly distributed. The reduction in drug demand brings about a 38% reduction in drug abuse and a 21% reduction in legitimate use. More importantly, we find that price increases cannot prevent drug abuse because they do not reduce access to drugs for potential abusers.

Another economic barrier to prescription drug consumption is represented by out-of-pocket expenses for doctors’ visits, summarized by $c$. One can think of a variety of ways to increase $c$ such as increasing co-payments, increasing the costs to physicians such as educational related expenses, etc. Raising $c$ also raises the reservation value $u_i$. Hence, it deters overall demand. The impact is stronger on the recreational segment of demand thanks to the screening process provided by doctors’ assessment of patients. In the calibrated model patients with a legitimate medical reason to use drugs are rarely refused a prescription ($\gamma = 0.95$), while purely recreational users must, on average, undertake 25 doctor visits before obtaining a prescription ($1/\gamma = 25.83$). As a result, if the cost for a physician visit increases by $10$, then the average medical costs for a drug-seeker would increase by $250$, but only by about $10$ for a legitimate patient. This suggests that increasing patients’ out of pocket expenses is a more effective policy in reducing drug abuse relative to the taxation of prescription drugs. For instance, we estimate that if $c$ were to increase by 50% relative to current values, then recreational demand and drug abuse would both fall approximately by 58% while legitimate demand and use of prescription drugs would barely fall (Table 2, column 4). An obvious shortcoming, which is not captured by the model, is that an increase in healthcare costs would affect costs for every patient.

5.2 Combatting drug abuse by raising non-economic barriers

A second mechanism that can be used to deter drug abuse is to increase its opportunity cost. This can be done by non-economic means, in particular by interventions designed to raise the difficulty in obtaining prescription drugs from doctors by increasing prescription drug monitoring.

We summarize the main result from this subsection as follows

**Result 2:** Restricting access to prescription drugs reduces drug abuse, and can discourage recreational demand without affecting legitimate demand.

**Refill policy and drug supply.** A primary non-economic barrier is represented by the refill procedures in place, captured by $1/\delta$ in the model. The calibrated model reveals that once a prescription is obtained, then the average patient is guaranteed about a year supply of the drug. In our setup $1/\delta$ captures not only the quantity of drugs initially prescribed but also the number of refills that are possible without undergoing a new physical examination. Therefore, we can broadly interpret an increase in the parameter $\delta$ as a stricter refill policy.
A stricter refill policy reduces the overall use of drugs for two reasons. First, it prevents drug abuse by raising the frequency of medical check-ups, thus allowing physicians to better screen out drug seekers. This raises the opportunity cost of using prescription drugs mostly for recreational users and barely for legitimate users. Second, a stricter refill policy discourages demand because more frequent doctor’s visits imply a greater cost from consuming drugs. We report that cutting the average drug supply by half is very effective at deterring recreational demand, as it falls by 83% vis a vis a minimal decline in legitimate demand. As a consequence, drug abuse would fall by 87.5% and legitimate use by a mere 4% (Table 2, column 7). These numbers are nearly identical to a doubling of the out-of-pocket cost from doctor’s visits. Yet, raising this barrier does not imply the adverse economic effects associated to raising $c$ and can also prevent drug abuse. We find that halving the drug supply reduces access to drugs for recreational users by nearly 20%.

**Patients’ screening.** An alternative non-economic barrier to drug abuse relies on doctors’ screening of patients. Part of the plan announced by President Obama’s administration involves requiring drug makers to educate the medical community about the safe use of prescription drugs. Training physicians to more accurately identify drug seekers or mandating more extensive physical examinations for patients who seek drugs is also another way to do this. This type of physician-based focus is equivalent, in our model, to reducing $\gamma_0$. Presuming that this intervention involves no additional cost to patients or doctors, this policy would clearly discourage recreational demand without affecting legitimate demand. We report that cutting by half the probability $\gamma_0$ that a prescription is written for someone who has no medical reason to use prescription drugs has almost the same effect as reducing the drug supply $1/\delta$ (Table 2, columns 8-9). This policy largely discourages recreational demand because it differentially raises barriers for drug seekers, without affecting those who have a legitimate demand for drugs. A potential drawback comes from its possible costs; more thorough screening processes amount to asking physicians to allocate more time to patients’ visits.

**Introducing a drug registry.** The non-economic barriers considered above take an indirect approach to combating drug abuse and do not exploit the wealth of data that doctors have on a patient’s history. Hence, we explore a policy that directly targets drug seekers by improving prescription drug monitoring programs.

Specifically, we consider a “drug registry” available at a national level. The registry includes names of patients known to be potential recreational drug users or drug abusers. To do so, the model is augmented as follows. Retain the assumption that drug seekers can incorrectly be prescribed drugs. However, if they are found to be healthy, then they are denied prescription drugs and, with probability $\beta$, they are put onto a nationwide drug registry and fined the amount $\phi \geq 0$ to recoup the cost from maintaining the registry. For a patient included in the drug registry, let $\gamma_K \in [0, \gamma_0)$ be the probability with which a doctor prescribes drugs to an individual on the registry, possibly due to inefficient functioning of the system, and let $1 - \gamma_K$ be the probability with which an individual on the registry is recognized as being a drug user.
seeker and denied the pain medication.

Now we have three possible types of patients: drug-seekers who are not in the drug registry, drug seekers who are in the drug registry, and sick patients. A drug-seeker who is included in the drug registry has value from searching for drugs:

$$rV_R = \theta q(\theta) [-c + \gamma R(V_{R,u} - V_R)]$$

and for the case $\tilde{V}_R = V_R$ we have

$$V_{R,u} - V_R = \frac{u + \theta q(\theta)c}{r + \delta + \theta q(\theta)\gamma_R}.$$

Someone in the drug registry seeks drugs from a physician if $\frac{c}{\gamma_R} \leq \frac{u}{r + \delta}$. Hence, as long as $\gamma_R < \gamma_0$, the incentive to seek drugs from doctors falls for those placed on the drug registry. Clearly, there is no incentive when $\gamma_R = 0$. We assume that once included in the drug registry detection is certain, i.e., $\gamma_R = 0$, though inclusion in the drug registry is temporary. Let $\lambda$ denote the probability that someone included in the drug registry is granted a “fresh start.” We interpret $1/\lambda$ as the number of periods a drug-seekers remains on the list after being caught. Let $\pi_R$ denote the portion of the population included in the drug registry. The stationarity conditions $\dot{\pi}_y = \pi_0 = \pi_R = 0$ respectively imply three laws of motion

$$\pi_{y,d} \delta - \pi_y \theta q(\theta)\gamma_y = 0,$$

$$\pi_{0,d} \delta + \pi_R \lambda - \pi_0 \theta q(\theta) |\gamma_0 + (1 - \gamma_0)\beta| = 0$$

$$\pi_0 \theta q(\theta)(1 - \gamma_0)\beta - \pi_R \lambda = 0.$$

The second line follows from the fact that a patient of type $i = 0$ who meets a doctor either receives a prescription or is denied a prescription and then is included in the drug registry with probability $\beta$. The third line follows from the fact that someone in the drug registry is removed from the registry at rate $\lambda$. We also must have

$$\pi_y + \pi_{y,d} = \mathcal{F}(u_y)$$

$$\pi_0 + \pi_{0,d} + \pi_R = \mathcal{F}(u_0).$$

The last line accounts for the fact that all drug-seekers either have prescription drugs, are trying to obtain them, or are on the drug registry.

We now have

$$\pi_i = \frac{\delta}{\theta q(\theta)\gamma_i} \pi_{i,d} \text{ and } \pi_R = \pi_0 = \frac{\theta q(\theta)(1 - \gamma_0)\beta}{\lambda} \text{ and } \pi_{i,d} = \mathcal{F}(u_i) \text{ for } i = 0, y,$$

where

$$\tilde{\kappa}_y = \kappa_y \text{ and } \tilde{\kappa}_0 = \frac{\delta}{\theta q(\theta)\gamma_0} \left(1 + \frac{\theta q(\theta)(1 - \gamma_0)\beta}{\lambda}\right).$$
For the case $V_0 = V_0$ we have

$$V_R = \frac{\lambda}{r + \lambda} V_0, \text{ and } V_{0,u} = \frac{u + \delta V_0}{r + \delta}.$$ 

We can no longer use (2) for $i = 0$. Instead, we have

$$r V_0 = \theta q(\theta) \left[ -c + \gamma_0 (V_{0,u} - V_0) + (1 - \gamma_0) \beta (-\phi + V_R - V_0) \right]$$

$$= \frac{\theta q(\theta)}{\Phi} \left[ -c - (1 - \gamma_0) \beta \phi + \gamma_0 \frac{u}{r + \delta} - r V_0 \frac{\gamma_0 (r + \lambda) + (1 - \gamma_0) \beta (r + \delta)}{(r + \delta)(r + \lambda)} \right]$$

$$= \frac{\theta q(\theta)}{\Phi} \left[ -c - (1 - \gamma_0) \beta \phi + \gamma_0 \frac{u}{r + \delta} \right]$$

where $\Phi := 1 + \theta q(\theta) \frac{\gamma_0 (r + \lambda) + (1 - \gamma_0) \beta (r + \delta)}{(r + \delta)(r + \lambda)}$. Healthy individuals search as long as $r V_0 \geq 0$; if $\phi = 0$, this is still satisfied by $u \geq u_0$. The intuition is simple. Sick individuals are not affected by the existence of a drug-registry, while drug-seekers have no penalty and it simply takes them longer to obtain drugs if they are caught. If $\phi > 0$, then a healthy patient seeks drugs if $u \geq u_\phi$ where

$$u_\phi := \frac{[c + (1 - \gamma_0) \beta \phi](r + \delta)}{\gamma_0}.$$ 

To quantify the impact of a drug registry consider $\phi = 0$ and $\beta = 1$. This is a transparent place to start a quantitative analysis because in this case the drug registry is costless to operate and is extremely efficient. We find that if drug-seekers are flagged by a physician and put on the registry for a year, then drug-abuse falls by 95% (Table 3, column 3). If one year seems long, then a six months permanence on the drug registry still reduces drug abuse by 90%. The effectiveness of a drug registry hinges on its ability to restrict access to drugs for drug-seekers, without affecting legitimate users. This simple mechanism can be augmented by introducing elements that act as a deterrent against undesirable behavior, as is well known from the economic literature on crime. Consider, for instance, a one-time fine $\phi > 0$ that is paid by those patients positively identified to be pure drug seekers. We report that a penalty of only $50 reduces drug abuse to zero because it virtually eliminates all recreational demand without affecting legitimate demand (Table 3, column 5).

The quantitative results do not vary much when considering less efficient drug registries. Suppose that a someone who is healthy and is denied a prescription by a doctor is not always added to the drug registry; let the probability of inclusion in the registry be $\beta \leq 1$. Even in this case a registry provides an effective means of reducing drug abuse. For instance, if there is a one-in-eight chance of being added to the drug-registry and no financial penalty, then abuse drops by half. With a $50 penalty, then the registry reduces drug abuse by 80% (Table 3, column 6).

In short, a national drug registry reduces drug abuse by preventing access to drugs to those who desire drugs for recreational purposes, hence it discourages drug-seeking behavior without affecting legitimate demand. This mechanism is analogous to mechanisms proposed in the economics literature to reduce crime. Specifically, the parameter $\lambda$ can be thought of as the length of imprisonment, $\phi$ as the economic cost generated by being caught such as a fine,
and $\beta$ as the likelihood of being caught. An increase in any of these measures reduces the illegal use of prescription drugs because it raises the costs, directly or indirectly, from engaging in undesirable behavior without affecting other individuals; see for example Becker (1968) or more recently Polinsky and Shavell (2000).

### 5.3 Addiction

As a final step, we study the case when drugs may generate addiction. The main result is that the quantitative impact of the different types of interventions changes some, but not very much.

To see how this result is obtained, suppose that an individual who has consumed prescription drugs can develop addiction with probability $\alpha$. Addiction amounts to disutility suffered from being without prescription drugs for someone who is otherwise healthy. Hence, for simplicity we make disutility of the addicted identical to $y$. We also assume that only healthy individuals can become addicted, i.e., sick patients do not experience additional disutility from being without the drug.

Let $V_a$ denote the payoff from seeking medical care for someone who is addicted.

$$rv_a = \gamma y + \theta q(\theta) [c + \gamma_0 (V_{a,n} - V_a)].$$

The key difference between $V_y$ and $V_a$ is that $\gamma_0$ appears in the second expression, since an addicted patient is intrinsically healthy. The flow payoff to an addicted patient holding a prescription is

$$rv_{a,n} = u + \delta (V_a - V_{a,n}),$$

where the continuation payoff satisfies

$$V_a = V_a + \psi (V_0 - V_a),$$

capturing the fact that a addicted patient overcomes addiction with probability $\psi$ after stopping consumption of the drug. It follows that

$$V_{a,n} - V_a = \frac{y + u + \theta q(\theta) c}{r + \theta q(\theta) \gamma_0} + \frac{\delta \psi (V_0 - V_a)}{r + \theta q(\theta) \gamma_0}.$$ 

The last expression implies that an individual who has become addicted to prescription drugs will try to obtain prescription drugs if

$$u \geq u_a := \frac{c(r + \delta)}{\gamma_0} - y - \delta \psi (V_0 - V_a).$$

We have $V_0 \geq V_a$ because $i = 0$. Therefore, addiction simply increases the probability that a patient who has consumed prescription drugs in the past will seek to obtain these same medications again. This is so because the addicted patient suffers disutility from being without the drug. Notice also that $u_a > u_y$ because the probability of obtaining a prescription after a doctor’s visit is $\gamma_0$ for addicted individuals.

Let $a$ denote the portion of healthy individuals who are addicted to drugs. Because addiction occurs after consum-
ing the drug with probability $\alpha$, an additional law of motion allows us to pin down the fraction of addicted patients of type $i$:

$$\pi_{0,d}(1-a)\delta a - \pi_{0,d} a \delta \psi = 0 \Rightarrow a = \frac{\alpha}{\alpha + \psi}.$$  

When the model is calibrated by setting $\psi = \alpha = 0.25$ we obtain the following. First, if the prescription drug is addicting, then including its addictive nature in the model reduces drug abuse by 17% (Table 4, column 1). The reason is that addiction generates disutility in healthy patients, a cost that is taken into account by rational agents in deciding whether to seek drugs for purely recreational purposes. Hence, the danger of addiction in itself acts as a deterrent for a healthy (and rational) patient. Second, policies in the model with addiction generate quantitatively similar results to the same policy in the model without addiction, even if the impact on the incentives for drug-seeking behavior differ. For instance, stricter medical examinations that reduce $\gamma_0$ by half lower drug abuse by 92% as opposed to 88% with no addiction (Table 4). In the model without addiction this is so because the reserve recreational value of pain medication doubles; in the model with addiction, instead, $u_0$ does not change as much. Therefore, addiction is an important component of the overall level of use; we find that it should act as a deterrent on recreational use among rational healthy individuals. However, it does not change the results of our policy experiments in any meaningful way.

### 6 Conclusion

Prescription drug abuse is the source of a large economic and social burden in the U.S.. Recently, president Obama’s administration announced a plan to fight what was called an “epidemic” of drug abuse. We have developed a search-theoretic model to study this phenomenon and to assess the effectiveness of various policy interventions. In the model, individuals with imperfectly observable health conditions may seek prescription drugs from doctors either for recreational purposes or medical reasons. The equilibrium numbers of drug abusers and legitimate users are endogenous and depend on economic as well as non-economic barriers to prescription drugs consumption, such as pricing, healthcare costs, refill policies, drug monitoring programs, and prescription standards in the medical community. The model calibrated to U.S. data reveals that policies centered around raising economic barriers inhibit legitimate drugs demand and reduce prescription drug abuse without eliminating it. Instead, tightening prescription standards by educating the medical community about a safer use of prescription drugs, or improving drug monitoring programs, such as instituting a national drug registry, are much more effective interventions because they prevent drug abuse by discouraging mostly the recreational segment of the drug demand. The model could be extended to include other health-care market factors such as investment of drug companies into new drugs as discussed in Acemoglu and Linn (2004), health insurance, health investment similar to Grossman (1972) and the effects of requiring insurance.
References


Table 1: Calibrated parameters for a daily model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r$</td>
<td>0.000137</td>
<td>real interest rate (daily)</td>
</tr>
<tr>
<td>$1/\delta$</td>
<td>326</td>
<td>average supply of medication in days</td>
</tr>
<tr>
<td>$A$</td>
<td>1.732</td>
<td>efficiency of matching technology</td>
</tr>
<tr>
<td>$\eta$</td>
<td>0.5</td>
<td>elasticity of matching technology</td>
</tr>
<tr>
<td>$X$</td>
<td>0.054</td>
<td>fraction seeking a doctor for reasons other than pain</td>
</tr>
<tr>
<td>$D$</td>
<td>0.001</td>
<td>physicians per capita</td>
</tr>
<tr>
<td>$c$</td>
<td>20.3</td>
<td>patient out-of-pocket cost for a doctor's visit in $</td>
</tr>
<tr>
<td>$1 - x$</td>
<td>0.53</td>
<td>population proportion with pain-related health conditions</td>
</tr>
<tr>
<td>$\gamma_0$</td>
<td>0.0387</td>
<td>probability healthy patient obtains prescription drugs</td>
</tr>
<tr>
<td>$\gamma_1$</td>
<td>0.95</td>
<td>probability sick patient obtains prescription drugs</td>
</tr>
<tr>
<td>$\mu$</td>
<td>-1.102</td>
<td>mean utility from recreational use of pain medications in $</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>1.943</td>
<td>variance of recreational utility from drugs in $</td>
</tr>
<tr>
<td>$y$</td>
<td>1.067</td>
<td>disutility from pain (daily) in $</td>
</tr>
</tbody>
</table>
Table 2: The impact of medical costs and the accuracy and frequency of physician visits

<table>
<thead>
<tr>
<th>Drug demand:</th>
<th>Drug price</th>
<th>Cost of visit</th>
<th>Drug supply</th>
<th>γ₀</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Benchmark</td>
<td>0.5</td>
<td>1</td>
<td>+50%</td>
</tr>
<tr>
<td>Recreational</td>
<td>3.6</td>
<td>2.1</td>
<td>1.2</td>
<td>1.5</td>
</tr>
<tr>
<td>Medical</td>
<td>25.4</td>
<td>20</td>
<td>15.1</td>
<td>25</td>
</tr>
<tr>
<td>Access to drugs:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recreational</td>
<td>72.6</td>
<td>73.4</td>
<td>73.9</td>
<td>73.6</td>
</tr>
<tr>
<td>Medical</td>
<td>98.5</td>
<td>98.5</td>
<td>98.6</td>
<td>98.6</td>
</tr>
<tr>
<td>Drug consumption:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>27.6</td>
<td>21.3</td>
<td>15.8</td>
<td>25.7</td>
</tr>
<tr>
<td>Abuse</td>
<td>2.6</td>
<td>1.6</td>
<td>0.9</td>
<td>1.1</td>
</tr>
<tr>
<td>Legitimate</td>
<td>25</td>
<td>19.7</td>
<td>14.9</td>
<td>24.6</td>
</tr>
</tbody>
</table>

Note to Tables: The first column is the benchmark calibrated model. Drug demand reports the percentage of the population seeking prescription drugs; it is divided into two types according to the two possible types of patients: potential abusers $F(u_0)$ and legitimate users $F(u_i)$. Access to drugs reports the percentage of patients of each type who consume prescription drugs at any point in time, i.e., $1/(1 + \kappa)$. Drug consumption reports the population percentage using prescription pain medications, divided by type of use, i.e., Abuse, $\pi_{0,d}$, and Legitimate, $\pi_{i,d}$. Drug price $p$ was implicitly normalized to zero in the benchmark; its inclusion would only affect the scale factor $\mu$ if it were included. The variables Drug supply $1/\delta$, Cost of visit $c$ and the screening parameter $\gamma_0$ are varied relative to the benchmark case by the percentages indicated.
Table 3: The impact of a national drug registry

<table>
<thead>
<tr>
<th></th>
<th>Benchmark</th>
<th>$1/\lambda$</th>
<th>$\phi$</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>180</td>
<td>360</td>
<td>25</td>
</tr>
<tr>
<td><strong>Drug demand:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recreational</td>
<td></td>
<td>3.6</td>
<td>3.6</td>
<td>3.6</td>
</tr>
<tr>
<td>Medical</td>
<td></td>
<td>25.4</td>
<td>25.4</td>
<td>25.4</td>
</tr>
<tr>
<td><strong>Access to drugs:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recreational</td>
<td></td>
<td>72.6</td>
<td>6.6</td>
<td>3.5</td>
</tr>
<tr>
<td>Medical</td>
<td></td>
<td>98.5</td>
<td>98.6</td>
<td>98.6</td>
</tr>
<tr>
<td><strong>Drug consumption:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>27.6</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td>Abuse</td>
<td></td>
<td>2.6</td>
<td>0.2</td>
<td>0.1</td>
</tr>
<tr>
<td>Legitimate</td>
<td></td>
<td>25</td>
<td>25</td>
<td>25</td>
</tr>
</tbody>
</table>

Note to Table 3: The benchmark, or calibrated environment with no drug registry, is equivalent to setting $\beta = 0$ or $\lambda = \infty$. The average number of days that a drug abuser is kept on the registry is $1/\lambda$. For $0 < \phi$ and $\beta < 1$ we set the registry to six months. For $\beta < 1$ we set $\phi = 0$.

Table 4: The model with addiction: patients’ screening and drug registry

<table>
<thead>
<tr>
<th></th>
<th>Benchmark</th>
<th>$\gamma_0$</th>
<th>$1/\lambda$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>-25%</td>
<td>-50%</td>
</tr>
<tr>
<td><strong>Drug demand:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recreational</td>
<td></td>
<td>2.97</td>
<td>1.53</td>
</tr>
<tr>
<td>Medical</td>
<td></td>
<td>25.37</td>
<td>25.37</td>
</tr>
<tr>
<td><strong>Access to drugs:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recreational</td>
<td></td>
<td>72.9</td>
<td>67.4</td>
</tr>
<tr>
<td>Medical</td>
<td></td>
<td>98.5</td>
<td>98.5</td>
</tr>
<tr>
<td><strong>Drug consumption:</strong></td>
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</tr>
<tr>
<td>Total</td>
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<td>27.2</td>
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</tr>
<tr>
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<td>2.2</td>
<td>1</td>
</tr>
<tr>
<td>Legitimate</td>
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<td>25</td>
<td>25</td>
</tr>
</tbody>
</table>