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Nonmedical Prescription Drug Use: Theory and Policy Implications

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Abstract

The illicit nonmedical use of prescription drugs is studied in a model where individuals with imperfectly observable health conditions seek prescription drugs for either medical or nonmedical reasons. The equilibrium number of medical and nonmedical users is endogenous and depends on economic and non-economic barriers to drugs consumption, such as pricing, health care costs, refill policies, monitoring programs, and the medical community's prescription standards. The results show policies centered around raising economic barriers reduces nonmedical use but inhibits medical use due to imperfect screening. Alternatively, the results suggest a national drug registry may be more effective at preventing nonmedical use.

JEL Classification Codes: D83, I1, I11, I18

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1 Introduction

Prescriptions for drugs in general, and retail sales of opioids in particular, increased 150% between 1992-2003 (Manchikanti, 2007, p.400-401). To understand the phenomenon as it relates to opioids, 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). From this, U.S. doctors have increasingly prescribed opioids over the past two decades to treat and manage pain.

The increase in prescriptions has been associated with an even larger increase in the number of patients seeking drugs for nonmedical purposes, which we call (*drug-seekers*). The number of individuals 12 or older who have taken a prescription-type pain reliever for nonmedical use in the past twelve months has risen from 2.4% in 1992 to 4.9% in 2003 (SAMHSA, 2008, Table C.8). The nonmedical use of other prescription drugs have seen a similar increase.

In this paper we develop an economic model of prescription drug use to accomplish two objectives. First, we identify key factors in the prescription drug market including legitimate and illegitimate use and explore how these factors interact. Second, we use the model to consider the effects different policies can have on the market's players. We characterize the model and policies both analytically and explore the analytic results with a quantitative exercise.

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. The search process is assumed to be random.¹ After the patient meets a doctor, the 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.

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, nonmedical drug use occurs when a drug seeker obtains a prescription for drugs. The model demonstrates how the incidence of nonmedical drug use 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 factors affect drug use 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 as well as provide physical barriers, or time delays, to nonmedical drug use.

¹Modeling patient-doctor matches as being random is reasonable because primary care physicians are generally prevented from engaging in price 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 analysis reveals that, on the one hand, interventions focused on reducing illegitimate demand by manipulating economic factors, such as taxing prescription drugs, are problematic. Interventions of this kind are not well-suited to prevent nonmedical drug use because they do not differentiate between legitimate and illegitimate demand. Thus, they discourage illegitimate demand, but simultaneously reduce legitimate use. On the other hand, we find that interventions centered around non-economic barriers, such as reducing the number of refills, are more effective both analytically and within our empirical exercise. Raising barriers obviously inhibits acquiring the drug, however the barriers are tilted against the nonmedical user because of the screening. Also, the barriers make it necessary for illegitimate users to go through the screening process more, which is costly. Therefore, the barriers also decrease the economic incentives to obtain the drugs for nonmedical uses. The inclusion of addiction does not affect the overall results. However, the variation of utility from recreational use across the population is critical to the relative effects of these policies and how the policies affect legitimate versus illegitimate demand.

Beyond the analytic results, the model is calibrated to recent U.S. healthcare data in order to quantify the impacts of the economic and non-economic policies. The numerical exercise suggests that barriers to securing prescription drugs from doctors, which are already built into the health-care system, can limit illicit use effectively. However, they would do not eradicate nonmedical consumption. Also, our results do not imply the use of these tools are efficient as we do not quantify the costs. However, the numerical results put many of the issues in perspective.

To summarize our numerical results, an increase in the price that reduces 65% of the illicit consumption reduces roughly 40% of its use for legitimate medical purposes. Alternatively, out-of-pocket cost to patients from a doctor's visit can more directly focus costs towards drug-seekers as long as they are likely to be rejected for prescriptions and pay the cost of the visit without receiving the benefit of the prescription. Specifically, our numerical results suggest one would need a 50% increase in out-of-pocket costs to reduce nonmedical use by slightly more than half while legitimate use would only fall by roughly 5%.

We also consider some non-economic interventions. These include improving a doctor's assessment of a patient's need for the prescription and controlling the drug supply by requiring stricter refill policies. In our numerical results, we find that mandating stricter refill policies, such as decreasing them by 50%, can reduce nonmedical use by almost 90% and reduces legitimate use by only 5%. Increasing the medical community's ability to recognize nonmedical drug use in patients could be challenging. Conditional on its feasibility, an education program that would cut in half the chance that a prescription is written for a healthy patient would reduce nonmedical drug use by almost 90% and does not impact legitimate users. To reiterate, these policies are extremely effective at preventing nonmedical use but can greatly increase costs to physicians or patients.

As an additional policy tool, we explore the effect of a drug monitoring program, such as a national drug registry, where drug-seekers caught using drugs for nonmedical purposes are collected in a database and blocked from future use. The policies clearly discourage nonmedical use even when type 1 and 2 errors are made. In our numerical

simulation, we find such a policy that keeps illegitimate users in a system for six months can reduce nonmedical use by almost 90% when doctors can make a positive identification of drug seekers at least 50% of the time. Moreover, adding a small fine, such as \$50, for patients reported to be nonmedical users can virtually eliminate illicit use. These results are based upon the choice of parameters. However, they suggest a possible avenue for further study.

Our results relate to a number of studies. Due to the legitimate and illegitimate demand of prescription drugs and doctors screening for legitimate users, our work relates to a large literature on asymmetric information. Both types of demand choose to seek, or signal, their need for the prescription by paying an upfront payment to doctors. Thus, our work follows the signaling literature as pioneered in [Spence \(1973\)](#) among others. Also, the doctors screen by placing limits on the likelihood of granting, and length of, the prescription. However, our work takes the screening as a policy and fixed although it can be easily made conditional on market conditions. As a result, our work also relates to the large literature on screening as pioneered by [Rothschild and Stiglitz \(1976\)](#) and [Wilson \(1977\)](#) among others. Besides asymmetric information, our model of nonmedical prescription drug use is extended to include addiction as pioneered by [Becker and Murphy \(1988\)](#) or more recently analyzed in [Bernheim and Rangel \(2004\)](#). Our model more closely follows the former where agents' past consumption plays a critical role in determining their addictive state today and they maximize utility overtime. The model goes beyond the addiction, or demand side, literature and ties into the broader literature on drug markets such as [Rydell and Everingham \(1994\)](#). We find both the demand and addiction as well as supply side policies are important factors in determining consumption. Our analysis is most closely tied to the research on the interaction of illicit behavior and search markets as analyzed in [Camera \(2001\)](#), [Burdett, Lagos, and Wright \(2003\)](#), [Engelhardt, Rocheteau, and Rupert \(2008\)](#), and [Galenianos, Pacula, and Persico \(2012\)](#) among others. To our knowledge, the economics literature does not contain a theoretical study of nonmedical prescription drug use.

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.² 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 significantly less important. However, we will consider the model under varying elasticities in demand when considering the model's empirical results. Our focus on prescriptions reflects empirical evidence indicating that drug dealers or other strangers are a minimal source of prescription pain

²The price is taken as given because insurance companies and the government play a large role in drug pricing.

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, or nonmedical, 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 a specific medical condition. 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 nonmedical prescription drug users 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 $[\underline{U}, \bar{U}]$ with smooth and time-invariant c.d.f. G , and $\underline{U} < p < y < \bar{U}$. 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 for recreational purposes only. 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.³ Considering a stationary environment, denote Π 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 number of doctor-patient matches be $\zeta(D, \Pi)$, where $\zeta : \mathbb{R}_+^2 \rightarrow \mathbb{R}_+$ is a matching function. Assume the function ζ is homogeneous of degree 1 (i.e., there are constant returns to scale from the matching process), strictly increasing and

³If 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.

concave in each argument, $\zeta(0, \cdot) = \zeta(\cdot, 0) = 0$ and $\zeta(\infty, \cdot) = \zeta(\cdot, \infty) = \infty$.

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

$$Dq(\theta) = \zeta(D, \Pi) = \Pi\theta q(\theta). \quad (1)$$

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

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 γ_i denote the probability that a doctor prescribes the pain medication after physically examining a patient of type i . We assume $0 < \gamma_0 < \gamma_y \leq 1$, 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 γ_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 $-\frac{i}{r}$, 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

$$rV_i = -i + \theta q(\theta) [-c + \gamma_i(V_{i,u} - V_i)]. \quad (2)$$

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 γ_i 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

$$rV_{i,u} = u + \delta (\tilde{V}_i - V_{i,u}), \quad (3)$$

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 δ , 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 $-c + \gamma_i(V_{i,u} - V_i) \geq 0$, 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

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

This implies

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

For the case $\tilde{V}_i = V_i$, 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 δ and falls in γ_i . When $\tilde{V}_i = V_i$ then

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

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 nonmedical drug use. 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.,

$$\frac{c}{\gamma_i} \leq \frac{u + i}{r + \delta}. \quad (4)$$

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 $\frac{1}{\gamma_i}$ 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.⁴

The right hand side of (4) represents the 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 δ . So the net stream of benefits is $\frac{u+i}{r+\delta}$. Note that the size of the prescription, captured by the rate δ at which the prescription runs out, affects discounting and the benefits from searching from prescription drugs.

Given Lemma 1, we define the demand for prescription drugs as

$$\mathcal{F}(u_i) := \begin{cases} x[1 - G(u_i)] & \text{if } i = 0, \\ (1-x)[1 - G(u_i)] & \text{if } i = y. \end{cases} \quad (5)$$

The value $\mathcal{F}(u_i)$ 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. To reiterate, we 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, i.e., for nonmedical reasons. In contrast, patients of type $i = y$ demand prescription drugs for legitimate medical reasons.

Three considerations follow from the description of demand. First, a way to combat illegitimate drug use 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 (u_i):

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

In general, only the last type of intervention can differentially impact demand from potential recreational users 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

⁴Each doctor's visit is an independent draw for a patient. So, the expected number of trials is $\sum_{n=1}^{\infty} (1-\gamma)^{n-1} \gamma n = \frac{1}{\gamma}$. 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.

drugs.⁵ To analyze how these policies impact illicit drug use, we must calculate equilibrium drug consumption, which is done in the following section.

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 π_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 will be a function of doctors' professional choices reflected in the probability γ_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 $\{\theta, \pi_i, \pi_{i,d}\}$ 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*

$$\pi_i = \kappa_i \pi_{i,d} \text{ and } \pi_{i,d} = \frac{\mathcal{F}(u_i)}{1 + \kappa_i}$$

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

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

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

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

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

⁵Notice if $\gamma_y > \gamma_0$, for any $u_i \in [\underline{u}, \bar{u}]$, and $\mathcal{F}(u_0) > 0$, then $\mathcal{F}(u_y) > 0$, i.e., the market contains illegitimate users.

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 γ_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 illegitimate 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, $\pi_{0,d}$ *nonmedical drug users* and $\pi_{y,d}$ *medical users*. These portions are also a function of the model's parameters.

The equilibrium results in not everyone in the population consuming drugs at each point in time, i.e., $Q < 1$. Not everyone seeks drugs, due to heterogeneous medical needs and preferences over the recreational utility 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 (γ_i), and the average drug supply lasts $\frac{1}{\delta}$ periods. These non-economic barriers, which prevent patients from accessing drugs at their leisure, are captured by the term κ_i . A greater κ_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 γ_i or $\theta q(\theta)$ falls, and if δ or c rise.*

Proof of Lemma 3 u_i and κ_i increase if γ_i or $\theta q(\theta)$ falls, or δ or c rise. Then notice that Q falls in κ_i and in u_i . ■

We are now in a position to make two additional considerations on how to combat nonmedical prescription drug use. We have already shown recreation use 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 recreation use 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 illegitimate use 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 illegitimate drug use 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 set the parameters of the model to match multiple empirical aspects of the U.S. market for prescription drugs. Using the parameters, we report the patterns of demand. Finally, 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. We consider the effect of the policies using varying elasticities of demand and likelihood of being screened.

4 Choice of parameters

In this section we choose parameters to match 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. Although we are technically calibrating the model, we are not fully estimating it. Choosing different “moments” to calibrate to, adding additional moments, or using different sources can change the chosen parameters. Therefore, the empirical results are primarily to highlight the theoretical results and suggest possible outcomes for further research.

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 ζ 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 θ , we have $\theta = D/\Pi$. Inserting the calibrated values for θ 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

$$\Pi = \frac{.3}{0.0151} = 19.88 \text{ million}.$$

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 $X \leq 1 - \pi_0 - \pi_y$.

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, δ captures prescription size and number of refills possible without a new visit. To identify δ , 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 Stanford 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 δ 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 δ accounts for refills that are granted without re-visiting his or her physician.

Doctors' disposition to writing a prescription. We determine γ_y from a survey which asks individuals who went to see a doctor about whether they were provided relief (ABC News, USA Today, and Stanford Medical Center Poll, 2005, Question 13). 95% of the interviewed report they were given some relief; as a result, we calibrate $\gamma_y = 0.95$. Given our calibrated values of δ , $\theta q(\theta)$, γ_y , and an estimate of $\pi_{y,d}$, we determine $\pi_y = 0.0038$. To determine γ_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 $\gamma_0 = 0.0387$. We consider in the results section what happens when this parameter is larger, i.e., doctors are less effective at screening.

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 Π 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 Stanford 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 $\mathcal{F}(u_0)$ and $\mathcal{F}(u_y)$, to calibrate μ and σ .

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., $u_i := \frac{c(r+\delta)}{\gamma_i} - i$. Plugging in the known parameters results in $u_0 = 1.68$ and $u_y = -1.00$. The negative costs on the side of licit users could arise due to the normalizing of $p = 0$ and the fact consuming the medication can be a nuisance. However, we vary related parameters when exploring the results.

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

$$G(u) := \frac{1}{2} \left[1 + \operatorname{erf} \left(\frac{u - \mu}{\sqrt{2}\sigma} \right) \right]$$

where erf is the error function. Using the calibrated values $\mathcal{F}(u_0) = (1 + \kappa_0)\pi_{0,d} = 0.0331$ and $\mathcal{F}(u_y) = (1 + \kappa_y)\pi_{y,d} = 0.253$, along with several other key parameters, we have two equations with two unknowns, μ and σ ,

$$\begin{aligned} \mathcal{F}(u_0) &= x \frac{1}{2} \left[1 - \operatorname{erf} \left(\frac{u_0 - \mu}{\sqrt{2}\sigma} \right) \right] \\ \mathcal{F}(u_y) &= (1 - x) \frac{1}{2} \left[1 - \operatorname{erf} \left(\frac{u_y - \mu}{\sqrt{2}\sigma} \right) \right] \end{aligned}$$

which imply

$$\begin{aligned} \mu &= \frac{Bu_y - Cu_0}{B - C} \\ \sigma &= \frac{1}{\sqrt{2}} \frac{u_0 - u_y}{B - C} \end{aligned}$$

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

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

Table 1 provides a summary of the calibrated parameters. To reiterate, the selected parameters are not as a result of a complete estimation method as well as assumptions about the curvature of the matching function and utility from recreation use. Therefore, the following numerical results are for illustrative purposes and suggest possible effects.

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%. This suggests the markets screening mechanism and waiting times are not cumbersome. 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, including nonmedical ones, are heterogeneous and, for some individuals, are too small or negative.

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. Roughly 73% of drug seekers consume drugs on any one day, hence the model predicts that nonmedical drug users make up 2.6% of the U.S. population. These numbers are sensitive to the screening by doctors, or γ_0 . A less effective screening would result in a larger number of individuals seeking prescriptions for nonmedical purposes, or in terms of the calibration, a smaller number who receive benefits from non-recreational use.

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 nonmedical reasons. This could change

depending upon the calibration. However, the model suggests that these barriers are not very effective at preventing nonmedical drug use because a very large fraction of drug seekers are securing a prescription from a doctor at any one point. This is due to a variety of factors, but not least of all the length of the prescription. For these reasons we will consider two types of policies that are capable of reducing nonmedical use 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 nonmedical drug use. In other words, 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 illicit use.

5.1 Combating nonmedical drug use by raising economic barriers

A basic economic mechanism to deter consumption of a specific commodity is to increase its 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 with 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 nonmedical use while it can significantly reduce legitimate 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 and illegitimate users. 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 illicit use also significantly reduces legitimate use of drugs. For instance consider Table 2, columns 1-2. Using our chosen parameters, we find 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 nonmedical drug use and a 21% reduction in legitimate use. More importantly, we find that price increases cannot prevent nonmedical drug use because they do not reduce access to drugs for recreational users. To reiterate from above, our estimates are dependent upon the chosen parameters and can change significantly as a result. To consider a variety of possible empirical results, Table 3 provides estimates of the elasticity between the price and illicit and licit use. The variety of results point predominantly to the importance of the elasticity of illicit utility. If σ is lower, or the underlying utility from recreational use is more elastic, then the price can have a significantly more

important effect. If the elasticity of legitimate use is low, or y is the dominant factor in obtaining a prescription, then the price is less of an issue. The high elasticity of illicit utility represents a situation where outside options, such as other types of drugs including marijuana or competitive “street” markets for recreational prescription drugs, are readily available.

Note within the model, if pharmaceuticals can decrease the recreational value of the prescription (lowering μ), while holding its medical benefit constant (y), then it will have the same effects as raising p . They are equivalent because the threshold utility u_i is additive in p while μ is additive to u_i in $\mathcal{F}$ due to its normality. As a result, the policy of making μ smaller decreases illicit use, but it implies the negative nonmedical costs modeled by $\mathcal{F}$ also pushes out legitimate use because the medicine is less easy to take for everyone. The identical results between raising p and lowering μ holds because of the functional form of $\mathcal{F}$. If it were a different function, then the results could vary although the direction of the effect would be the same.

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 ($1/\gamma_0 = 25.83$). 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 nonmedical drug use relative to the taxation of prescription drugs. If γ_0 were chosen differently, then the results would change. For instance, in the benchmark case, we estimate that if c were to increase by 50% relative to current values, then illicit demand and use would both fall approximately 58% while legitimate demand and use of prescription drugs would barely fall (Table 2, column 4). Alternatively, if γ_0 were higher as demonstrated in Table 3, then the elasticity would plummet although it would still be more effective than p .

5.2 Combating nonmedical drug use by raising non-economic barriers

A second mechanism that can be used to deter nonmedical use is to enact physical barriers or queues. 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 illicit use, 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. 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 δ as a stricter refill policy.

A stricter refill policy reduces the overall use of drugs for two reasons. First, it prevents illicit use 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, nonmedical use 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 illicit use. We find that halving the drug supply reduces access to drugs for recreational users by nearly 20%. In terms of the results under alternative parameters, they follow the changes coming from c as well. A loss in the screening mechanism γ_0 reduces the effectiveness while the elasticity of recreational utility has a large impact.

Patients' screening. An alternative non-economic barrier to nonmedical use relies on doctors' screening of patients. Ongoing policy discussions about 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 γ_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 γ_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. Actually, the physician's problem is arguable to minimize illicit use. Therefore, the current level of γ_0 is likely set near or at its efficient level. As before, the empirical results are dependent upon the choice of parameters. The effectiveness of screening under different parameters as seen in Table 3 follows the refill policy results closely.

Introducing a drug registry. The non-economic barriers considered above take an indirect approach to combating nonmedical drug use 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. 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 β_0 , they are put onto a nationwide drug registry and fined the amount $\phi \geq 0$ to recoup the cost from maintaining the registry. Therefore, nonmedical drug users enter the drug registry with probability $(1 - \gamma_0)\beta_0$ each time he or she visits a physician. In other words, type 2 errors occur with probability $1 - (1 - \gamma_0)\beta_0$. The registry can suffer a type 1 errors too. An individual in need of the drug can fail to be prescribed the drug with probability $(1 - \gamma_y)$ and with probability β_y are incorrectly placed on the registry. Therefore, type 1 errors occur with probability $(1 - \gamma_y)\beta_y$. Let λ 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 $\pi_{i,r}$ for $i = \{0, y\}$ denote the portion of the population included in the drug registry. The stationarity conditions $\dot{\pi}_y = \dot{\pi}_0 = \dot{\pi}_{0,r} = \dot{\pi}_{y,r} = 0$ respectively imply four laws of motion

$$\begin{aligned}\pi_{y,d}\delta + \pi_{y,r}\lambda - \pi_y\theta q(\theta)[\gamma_y + (1 - \gamma_y)\beta_y] &= 0, \\ \pi_{0,d}\delta + \pi_{0,r}\lambda - \pi_0\theta q(\theta)[\gamma_0 + (1 - \gamma_0)\beta_0] &= 0, \\ \pi_y\theta q(\theta)(1 - \gamma_y)\beta_y - \pi_{y,r}\lambda &= 0, \text{ and} \\ \pi_0\theta q(\theta)(1 - \gamma_0)\beta_0 - \pi_{0,r}\lambda &= 0.\end{aligned}$$

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

$$\begin{aligned}\pi_y + \pi_{y,d} + \pi_{y,r} &= \mathcal{F}(u_y) \\ \pi_0 + \pi_{0,d} + \pi_{0,r} &= \mathcal{F}(u_0).\end{aligned}$$

The identities account for the fact that agents seeking drugs hold a prescription, are trying to obtain one, or are on the drug registry where u_y and u_0 take into account the costs and barriers associated with the registry.

Following the flows and identities, agents in each state are

$$\pi_i = \frac{\delta}{\theta q(\theta)\gamma_i}\pi_{i,d}, \quad \pi_{i,r} = \pi_i \frac{\theta q(\theta)(1 - \gamma_i)\beta_i}{\lambda}, \quad \text{and} \quad \pi_{i,d} = \frac{\mathcal{F}(u_i)}{1 + \bar{\kappa}_i}, \quad \text{for } i = 0, y,$$

where

$$\bar{\kappa}_i = \frac{\delta}{\theta q(\theta) \gamma_0} \left(1 + \frac{\theta q(\theta)(1 - \gamma_i) \beta_i}{\lambda} \right).$$

In determining u_i with the registry in the case $\tilde{V}_i = V_i$ for $i = \{0, y\}$, we have

$$V_{i,r} = \frac{-i + \lambda V_i}{r + \lambda}, \text{ and } V_{i,u} = \frac{u + \delta V_i}{r + \delta}$$

for the asset values of those on the registry and holding prescriptions, respectively.

We can no longer use (2). Instead, we have

$$\begin{aligned} rV_i &= -i + \theta q(\theta) [-c + \gamma_i(V_{i,u} - V_i) + (1 - \gamma_i)\beta_i(-\phi + V_{i,r} - V_i)], \text{ or} \\ &= -i + \frac{\theta q(\theta)}{\Phi_i} \left[-c - (1 - \gamma_i)\beta_i\phi + \gamma_i \frac{u + i}{r + \delta} \right], \end{aligned}$$

where $\Phi_i := 1 + \theta q(\theta) \frac{\gamma_i(r + \lambda) + (1 - \gamma_i)\beta_i(r + \delta)}{(r + \delta)(r + \lambda)}$. Individuals search as long as $rV_i \geq -i$; if $\phi = 0$, this is still satisfied by $u \geq u_i$ for $i = \{0, y\}$. The intuition is simple. If there is no penalty and it simply takes longer to obtain drugs, then nothing changes. If $\phi > 0$, then individuals seek drugs if $u \geq u_i$ where

$$u_i := \frac{[c + (1 - \gamma_i)\beta_i\phi](r + \delta)}{\gamma_i} - i, \text{ for } i = \{0, y\}.$$

To quantify the impact of a drug registry consider $\phi = 0$, $\beta_0 = 1$, and $\beta_y = 0$. This is a transparent place to start a quantitative analysis because in this case the drug registry is costless to operate and does not contain type 1 or 2 errors if a prescription is not given. We find that if drug-seekers are flagged by a physician and put on the registry for a year, then nonmedical drug use falls by 95% (Table 4, column 3). If one year seems long, then a six months permanence on the drug registry still reduces nonmedical drug use 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 nonmedical drug use to zero because it virtually eliminates all recreational demand without affecting legitimate demand (Table 4, column 5).

The quantitative results do not vary much when considering less efficient drug registries with type 1 and 2 errors. Suppose that 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 $\beta_0 < 1$ while those who are sick are at times added to the registry, or $0 < \beta_y$. Even in this case a registry provides an effective means of reducing nonmedical drug use. For instance, if there is a one-in-eight chance of being added to the drug-registry and no financial penalty, then nonmedical drug use drops by half while legitimate use only drops by roughly 1%.

In short, a national drug registry reduces nonmedical drug use by preventing access to drugs to those who desire

drugs for recreational purposes, hence it discourages drug-seeking behavior while having a minimal effect on legitimate use if type 1 errors occur. This mechanism is analogous to mechanisms proposed in the economics literature to reduce crime. Specifically, the parameter λ can be thought of as the length of imprisonment, ϕ as the economic cost generated by being caught such as a fine, and β 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 α . 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.

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

The key difference between V_y and V_a is that γ_0 appears in the second expression, since an addicted patient is intrinsically healthy. The flow payoff to an addicted patient holding a prescription is

$$rV_{a,u} = u + \delta (\tilde{V}_a - V_{a,u}),$$

where the continuation payoff satisfies

$$\tilde{V}_a = V_a + \psi(V_0 - V_a),$$

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

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

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 γ_0 for addicted individuals.

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

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

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 nonmedical drug use by 17% (Table 5, 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 γ_0 by half lower nonmedical drug use by 92% as opposed to 88% with no addiction (Table 5). 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, using our choice of parameters, 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 given the benchmark choice of parameters.

6 Conclusion

Non-medical prescription drug use is considered to have a large economic and social burden. 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 legitimate and illegitimate 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 nonmedical prescription drug use 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 nonmedical use by discouraging mostly the recreational segment of the drug demand. However, the costs to implementing these policies could be substantial.

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 \(1972\)](#), the effects of requiring insurance, or increasing costs on the length of the prescription. Other policies could be considered as well such as increasing copays or future prescriptions conditional on an individual's history. These later extensions can be handled by additional states for the agents coupled with corresponding threshold utility levels for whether an agent would seek a prescription given the past information (or state variables). Also, the model could introduce value based purchasing. This would require incorporating the doctors problem by allowing D and γ_i for $i = \{0, y\}$ to be set endogenously and penalties placed on the choice of screening. These model can incorporate these and other extensions and provide a good source for future research.

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Table 1: Calibrated parameters for a daily model

Variable	Value	Description
r	0.000137	real interest rate (daily)
$1/\delta$	326	average supply of medication in days
A	1.732	efficiency of matching technology
η	0.5	elasticity of matching technology
X	0.054	fraction seeking a doctor for reasons other than pain
D	0.001	physicians per capita
c	20.3	patient out-of-pocket cost for a doctor's visit in \$
$1 - x$	0.53	population proportion with pain-related health conditions
γ_0	0.0387	probability healthy patient obtains prescription drugs
γ_y	0.95	probability sick patient obtains prescription drugs
μ	-1.102	mean utility from recreational use of pain medications in \$
σ	1.943	variance of recreational utility from drugs in \$
y	1.067	disutility from pain (daily) in \$

Table 2: The impact of medical costs and the accuracy and frequency of physician visits

	Benchmark	Drug price		Cost of visit		Drug supply		γ	
		0.5	1	+50%	+100%	+50%	+100%	-25%	-50%
Drug Demand:									
Illicit	3.6	2.1	1.2	1.5	0.5	1.5	0.6	2	0.5
Licit	25.4	20	15.1	25	24.6	25	24.7	25.4	25.4
Access to drugs:									
Illicit	72.6	73.4	73.9	73.6	74	64.4	57.8	67.1	58.6
Licit	98.5	98.5	98.6	98.6	98.6	97.8	97.1	98.5	98.6
Drug consumption:									
Total	27.6	21.3	15.8	25.7	24.7	25.4	24.3	26.3	25.3
Illicit	2.6	1.6	0.9	1.1	0.4	1	0.3	1.3	0.3
Licit	25	19.7	14.9	24.6	24.3	24.5	23.9	25	25

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 recreational users $\mathcal{F}(u_0)$ and legitimate users $\mathcal{F}(u_y)$. *Access to drugs* reports the percentage of patients of each type who consume prescription drugs at any point in time, i.e., $1/(1 + \kappa_i)$. *Drug consumption* reports the population percentage using prescription pain medications, divided by type of use, i.e., *Abuse*, $\pi_{0,d}$, and *Legitimate*, $\pi_{y,d}$. *Drug price* p was implicitly normalized to zero in the benchmark; its inclusion would only affect the scale factor μ if it were included. The variables *Drug supply* $1/\delta$, *Cost of visit* c and the screening parameter γ_0 are varied relative to the benchmark case by the percentages indicated.

Table 3: The impact of medical costs and the accuracy and frequency of physician visits

Elasticity of recreational use (σ)	Benchmark				Higher			
	Benchmark		Lower		Benchmark		Higher	
	Benchmark	Higher	Benchmark	Higher	Benchmark	Higher	Benchmark	Higher
Elasticity of illness (y)								
Illicit screening (γ_0)								
Drug supply elasticities (δ)								
Elasticity of illicit use ($\frac{\Delta\pi_{0,d}/\pi_{0,d}}{\Delta\delta/\delta}$)	-1.961	-0.076	-1.972	-0.077	-5.505	-0.168	-5.52	-0.17
Elasticity of licit use ($\frac{\Delta\pi_{y,d}/\pi_{y,d}}{\Delta\delta/\delta}$)	-0.045	-0.046	-0.027	-0.028	-0.076	-0.076	-0.022	-0.022
Illicit screening elasticities (γ_0)								
Elasticity of illicit use ($\frac{\Delta\pi_{0,d}/\pi_{0,d}}{\Delta\gamma_0/\gamma_0}$)	1.961	0.075	1.966	0.076	5.647	0.169	5.654	0.17
Elasticity of licit use ($\frac{\Delta\pi_{y,d}/\pi_{y,d}}{\Delta\gamma_0/\gamma_0}$)	-0.001	0	-0.001	0	0	0	0	0
Cost of visit elasticities (c)								
Elasticity of illicit use ($\frac{\Delta\pi_{0,d}/\pi_{0,d}}{\Delta c/c}$)	-1.733	-0.058	-1.732	-0.058	-5.479	-0.155	-5.479	-0.155
Elasticity of licit use ($\frac{\Delta\pi_{y,d}/\pi_{y,d}}{\Delta c/c}$)	-0.016	-0.017	-0.005	-0.006	-0.033	-0.033	-0.003	-0.003
Drug price elasticities (p)								
Elasticity of illicit use ($\frac{\Delta\pi_{0,d}/\pi_{0,d}}{\Delta p/p}$)	-0.06	-0.04	-0.06	-0.04	-0.193	-0.108	-0.194	-0.108
Elasticity of licit use ($\frac{\Delta\pi_{y,d}/\pi_{y,d}}{\Delta p/p}$)	-0.027	-0.027	-0.01	-0.01	-0.057	-0.057	-0.005	-0.005

Note to Table 3: A higher elasticity of recreational use is defined as $\sigma = 1.0$ compared to the benchmark $\sigma = 1.943$, a lower elasticity of illness is defined as $y = 3$ compared to the benchmark $y = 1.067$, and a higher illicit screening level is defined as $\gamma_0 = 0.75$.

Table 4: The impact of a national drug registry

		$1/\lambda$		ϕ		β_0 (=1 - β_y)	
	Benchmark	180	360	25	50	0.125	0.5
Drug Demand:							
Illicit	3.6	3.6	3.6	0.3	0	3.6	3.6
Licit	25.4	25.4	25.4	25.4	25.4	25.4	25.4
Access to drugs:							
Illicit	72.6	6.6	3.5	6.6	6.6	32.3	12.1
Licit	98.5	98.6	98.6	98.6	98.6	96.1	97.2
Drug consumption:							
Total	27.6	25.3	25.1	25	25	25.5	25.1
Illicit	2.6	0.2	0.1	0	0	1.2	0.4
Licit	25	25	25	25	25	24.4	24.7

Note to Table 4: The benchmark, or calibrated environment with no drug registry, is equivalent to setting $\beta_i = 0$ or $\lambda = \infty$. The average number of days that a nonmedical drug users is kept on the registry is $1/\lambda$. For $0 < \phi$ and $\beta_0 < 1$ and $\beta_y > 0$ we set the registry to six months. For $\beta_0 < 1$ and $\beta_y > 0$ we set $\phi = 0$.

Table 5: The model with addiction: patients' screening and drug registry

		γ_0		$1/\lambda$	
	Benchmark	-25%	-50%	180	360
Drug Demand:					
Illicit	72.9	67.4	58.7	6.6	3.5
Licit	98.5	98.5	98.6	98.6	98.6
Access to drugs:					
Illicit	2.97	1.53	0.31	3.29	3.38
Licit	25.37	25.37	25.37	25.37	25.37
Drug consumption:					
Total	27.2	26	25.2	25.2	25.1
Illicit	2.2	1	0.2	0.2	0.1
Licit	25	25	25	25	25