Optimal Drug Policy in Low-Income Neighborhoods

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Abstract

The control of drug activity currently favors supply-side policies: drug suppliers in the U.S. face a higher arrest rate and longer sentences than demanders. We construct a simple model of drug activity with search and entry frictions in labor and drug markets. Our calibration analysis suggests a strong "dealer replacement effect." As a result, given a variety of community objectives, it is beneficial to lower supplier arrests and raise the demand arrest rate from current values. A 10% shift from supply-side to demand-side arrests can reduce the population of potential drug dealers by 22-25,000 and raise aggregate local income by $380-400 million, at 2002 prices. (JEL Classification: D60, J60, K42, H70)

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1. Introduction

The prevalence of drug trafficking and use continue to be of significant and increasing policy concern in the U.S. Evidence of this comes from the fact that spending on all forms of domestic drug control by the U.S. government has increased over the period 1996-2007 by almost 66% in real terms.[1] Those who are arrested and prosecuted can be segmented into two broad categories: those arrested for the sale and/or manufacture of drugs, and those arrested for possession. We will, for convenience, characterize these two types of arrests as supply-side and demand-side arrests, and efforts to concentrate on one type of arrest or another as supply- or demand-side policies[2].

The mix of supply-side and demand-side policy has shifted over the years. Figure 1 displays the ratio of possession arrests in the US to arrests for sale and manufacture for the past two and a half decades. Through the 1980s a shift toward supply side policy was undertaken as the ratio fell from nearly 4:1 down to 2:1; since 1991 however there has been a consistent shift toward demand side arrests, and to the point where in 2007 the ratio stands at almost 4.7:1.[3] The sentencing patterns are quite different for demanders and suppliers. In 2002, drug suppliers in the U.S. face an average arrest rate of 3% and an average sentence of 3.6 years, while drug demanders' arrest rate is only one sixth (0.5%) with a sentence that is about half of drug suppliers (1.83 years).

Demand-side policies generally have their critics – indeed the whole notion of a "war on drugs" is broadly criticized – but some scholars have advocated policies more oriented toward the demand-side in place of supply-side oriented policies. Among these is Meares (1998) who recommends the so-called "reverse sting" operation, where law enforcement officials pose as drug sellers in order to gather evidence on buyers, rather than the usual method of posing as buyers to arrest dealers. While not denying that inner city neighborhoods can be the site of active markets in illegal drugs, perhaps as many as 80% of drug buyers come from outside the market-neighborhoods.[4] The emphasis on supply-side policy therefore has a disproportionate effect on those low-income areas of a community that are often the site of drug markets, which can have an aggravating impact on its law-abiding residents.

We formally examine the effects of supply and demand side policy using an occupational choice framework, emphasizing that these policies have different impacts on the price of drugs and therefore on the incentives of those on the margin between the drug and legitimate labor markets.[5] The basic idea is simple. A supply-side policy that reduces (at least temporarily) the number of sellers may drive up the price of the drug and so provide incentives for those previously employed in the legitimate labor market to take up drug-selling.[6] A demand-side policy, conversely, drives down the number of demanders and the price, which provides an incentive for dealers to enter the legitimate market. Thus, supply-side policy drains the local neighborhood of its resources without necessarily reducing drug traffic, while the demand-side policy reduces drug traffic without the negative side

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[1] http://www.whitehousedrugpolicy.gov/publications/policy/budgetsum04/drug_control.pdf (Office of National Drug Control Policy, *National Drug Control Strategy*).

[2] The analysis in this paper can be applied to many illicit goods. Our focus on drugs is due to the policy relevance and the ability to undertake a quantitative simulation.

[3] The data also suggest a stronger focus on selling and distributing more harmful drugs. While cocaine accounted for about half of the total retail sales of illegal drugs, it accounted for more than two-thirds of the supply-side incarcerations.

[4] Rosen's (1997) discussion of drug markets in Chicago indicates that almost 80% of the drug buyers come from outside the inner-city neighborhood s where the exchanges took place.

[5] Despite the absence of direct empirical evidence, the finding by Gould, Mustard and Weinberg (2002) that changes in the wage can account for up to 50% of the trend in violent crimes and in property crimes suggests there is a negative relationship between incentives in drug and legitimate labor markets.

[6] Despite the absence of any formal analysis, the sentiment that this "replacement effect" exists is widespread. See for example an aforementioned opponent of the war on drugs: "[T]the imprisonment of one drug dealer (or even an entire network) only temporarily disrupts the flow of illegal drugs. As soon as one supplier is gone, another quickly moves in to take his place. Basic economic laws of supply and demand say that as long as there is a demand for a product, a market will make that product available" (Krause 2009).

effect. This side effect is magnified when the low-income community must pay for at least a portion of its own law enforcement activities.

These characteristics of the drug market have been discussed in the literature. Eatherly (1974) was perhaps the first to discuss supply vs. demand policies in an economic framework. He discusses the effects of the two types of policies on the price of drugs and their participants (but without considering the occupational choice that is crucial to our analysis). Yet in the absence of a formal framework he cannot analyze the relative consequences of policy for low income communities. Lee (1993) focuses on the distinction between demand-side policies that focus on transactions and those that focus on possession. We do not concentrate on this aspect in our desire to distinguish between the effects of supply and demand side policies. In more recent work, Galenianos, Pacula and Persico (2012) construct a search-theoretic model for illegal drugs to study the possibility of long-term relationships between drug sellers and buyers when the quality of drugs cannot be observed by buyers before a trade is made – the presence of such a long-term relationship may make drug enforcement policy less effective[7].

We propose, to our knowledge for the first time, an analytical model capable of analyzing the consequences of both demand-side and supply-side drug policies and comparing the effectiveness of these policies based on various local government's objectives by calibration and simulation analysis in a way similar to the general-equilibrium tax incidence framework. We follow the standard set by Becker (1968) in assuming optimizing behavior on the part of (potential and active) participants in illegal activities. Residents of a neighborhood decide whether to participate in the legitimate labor market or engage in the drug trade within an occupational choice framework.[8] We introduce market frictions in both labor employment and drug transactions using a search-theoretic framework that not only captures naturally informational uncertainty in drug trade but also provides an elegant method for modeling arrest probabilities and incarceration durations. The structure of the legitimate labor market is much simplified under an exogenous wage rule with endogenous search and matching.[9] The drug trade is, however, modeled in some detail. The drug market is cleared in the usual supply-and-demand fashion, while the entry of sellers continues until reaching *ex ante* zero profit.[10] The extent to which community members opt for a career in the drug market determines the supply of drugs by the community. We assume in the benchmark setup that demand for drugs is exogenous to the community and that drug demand is downward-sloping.[11] The community government, by incurring law enforcement spending, can determine the optimal arrest/release rates of not only drug suppliers but drug demanders. To a large degree, the arrest and release rates, respectively, can be regarded as a tax on and a subsidy to participants in illegal activities. Something like the conventional tax incidence framework can thus be applied to evaluation of demand-side versus supply-side drug policies.

Therefore, the central features of our paper are to consider (i) endogenous demand/supply of

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[7] See also Burdett, Lagos, and Wright (2004), Huang, Laing and Wang (2004), Engelhardt, Rocheteau and Ruppert (2008) and Chang, Lu and Wang (2009) for other search-theoretic models of crime, and Becker, Murphy and Grossman (2004) on the consequences of inelastic drug demand.

[8] Banerjee and Newman (1993) are among the first developing a general equilibrium model of occupational choice. In the 1989 NBER Inner City Youth Survey, more than 50% of subjects in Boston reported having several chances a day to make illegal income and over 60% reported earning significantly

more from criminal than legal activities. Even though many criminals do participate in the legal labor market, most full time workers earn little or no income from criminal activities. In this paper, for simplicity, we consider that most agents tend to specialize in either criminal or legal activities and hence model occupational choice as being binary. We will return to this issue when we construct the model in Section 2.

[9] Despite this simplification, our wage rule is consistent with the Nash bargain outcome obtained in labor market search literature (e.g., see those cited in Laing, Palivos and Wang 1995 and Coulson, Laing and Wang 2001); adding labor-market search would not alter any of the main findings concerning the effectiveness of drug policies.

[10] This search and endogenous entry setup is, broadly speaking, in the style of the labor-matching framework developed by Laing, Palivos and Wang (1995) and Coulson, Laing and Wang (2001).

[11] See, for example, the empirical documentation by Chaloupka, Grossman and Tauras (1999).

2

drugs and active trading prices, (ii) individually optimizing occupational choice between legitimate and illegitimate activities, and (iii) the community government's exercises in incarcerating drug suppliers and demanders. Specifically, the participants in the drug market may be active or incarcerated, depending on the arrest and release rate chosen by the local community government, whose point of view we choose. By restricting our attention to the low-income community in which the sellers live and transactions take place, we do not consider the effect that drug policies might have on the global economy.

We derive value functions for each occupation, based on legitimate labor market payoffs as well as expected returns on drug sales. Endogenous occupational choice and drug market equilibrium together determine the price and the actively traded quantity of drugs. Since the release rates within our analytical framework are simply mirror images of the arrest rates, we focus on examining the effects of the rates at which drug demanders and suppliers are incarcerated. In assessing these drug policies, we consider an array of plausible community objectives with regard to reducing drug activity and improving the standard of living, and explicitly account for the law enforcement spending that is partly financed by a tax on legitimate labor income earned in the low-income community.

We then calibrate the model economy using the U.S. data and conduct quantitatively comparative-static analysis and drug policy simulation. Our primary conclusion is that *supply side policy is dominated by demand side in nearly every environment we consider and under a multitude of community objectives*. A tax-revenue neutral shift in arrest rate from supply-side to demand-side by 10% can reduce the number of potential drug dealers by 0.36-0.42% (equivalent to reductions in the populations of potential drug dealers by 22-25 thousand) and raise aggregate local income by 0.15-0.17% (equivalent to increases of 380-400 million dollars at 2002 prices). This primary conclusion remain valid even with an array of extensions to the benchmark model, including endogenous drug demand, neighborhood externalities from drug selling, multi-unit drug dealing, utility costs of incarceration and the social costs of drugs.

2. The Economic Environment of the Community

This section describes the basic economic environment for a local community. We utilize a continuous-time search and matching framework, in which the community is populated by a continuum of identical agents, each possessing the instantaneous discount rate over consumption of $r > 0$. The agents in this community are engaged in one of two economic activities. One is the **legitimate labor market** in which community members and unfilled vacancies are brought together via a stochastic matching technology in the background. The other is the **drug market** in which dealers living in this community provide illegal drugs for outside demanders. All agents are endowed with one unit of labor that they can either supply to firms or devote to drug selling (without disutility from effort). Due to law enforcement, participants in the drug activity (suppliers and demanders) may be active or incarcerated.

The search and matching framework captures the presence of informational incompleteness regarding the identification of drug demanders and suppliers. Moreover, it provides a parsimonious structure for our policy analysis because both arrest and release rates can be modeled as Poisson arrival parameters, which greatly simplifies the specification of the value functions (Bellman equations). In the benchmark setup, we abstract from any externality arising from drug dealing and ignore the utility cost of incarceration and the social cost of drugs. Additionally, we assume that each dealer at a point in time possesses only one unit of drug for sale. These assumptions will all be relaxed in Section 5.

Population

Denote the population of workers as N and the population of drug dealers as Q_s,[12] where

$$N + Q_s = 1.$$

(1)

Within the labor market workers may be either employed or unemployed and, similarly, drug dealers may be either active or incarcerated. Denote the population of employed and unemployed workers, and active and incarcerated drug dealers as L, U, A_s and I_s, respectively. The two sub-group

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[12] Throughout, the subscript s represents suppliers and d, demanders.

population identities are $N = L + U$ and $Q_s = A_s + I_s$.[13]

Labor Market

In the labor market, firms provide job vacancies for workers. Once residents have made their occupational choices to become workers, they enter the labor market as unemployed and search for employment. Searching workers and unfilled vacancies are brought together via a stochastic matching technology. Once employed, each worker produces Y unit of output, of which some fraction θ accrues to the worker. Thus, θY is the pre-tax wage of the worker. Since the formal labor market is not the focus of the paper, the Nash bargaining process that determines this share is neglected for brevity.[14] Obviously, a higher output enlarges the entire surplus from a match and so the wage increases.

In the labor market, there are turnovers in existing jobs. Firms lay off workers at a constant rate, δ. In the steady state the inflows and outflows into and out of employment must be the same:

$$\mu U = \delta L.$$

(2)

where μ is the rate at which an unemployed worker is able to locate a vacant job.

Drug Market

As noted, in the benchmark model we regard the community as a "small open" economy in the sense that all drug demanders come from outside the community, which simplifies greatly the welfare analysis as consumer surpluses can now be completely ignored (see Section 5 for a generalization). That is, the total population of drug demanders, denoted by Q_d, is predetermined in our model. However, some are incarcerated and some are active. Let A_d and I_d, respectively, denote the population of active and incarcerated drug demanders respectively[15]. The population identity requires: $A_d + I_d = Q_d$.

The demand for drugs is a function of its price and the number of active drug demanders. The drug demand schedule is downward-sloping (see Chaloupka and Grossman, 1998, Chaloupka, Grossman and Tauras, 1999, and Saffer and Chaloupka,1999) and satisfies the usual regularity conditions:

Assumption 1. (Drug Demand) *The aggregate drug demand function*, $D: \mathbf{R}_+^2 \rightarrow \mathbf{R}_+$, *is strictly decreasing, convex and twice continuously differentiable in p, and strictly increasing in A_d, i.e., $\partial D/\partial p < 0$, $\partial^2 D/\partial p^2 \geq 0$ and $\partial D/\partial A_d > 0$.*[16]

Each agent who chooses to become a full-time dealer is endowed with a single unit of drugs.[17] As long as we consider linear drug pricing, this simplifying assumption is innocuous with regard to price determination. In this case, the total supply of drugs depends only on the number of active

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[13] Since total population in this category is normalized to unity, these population measures can be interpreted as "percentages".

[14] We have formally examined such a framework, which does not change any of the main findings concerning the effectiveness of drug policies.

[15] Thus both employed and unemployed are (potential) drug demanders.

[16] The aggregate drug demand function is more general: without interdependence in demands or interactive responses to policy, one may simply write $D = A_d\, d(p)$ where $d(p)$ is individual drug demand. In this case, drug policy only affect the extensive margin of drug demand via A_d rather than the intensive margin via $d(p)$.

[17] We ignore part-time drug-dealing for the sake of simplicity. One may view a part-time drug-dealer as a cluster of two agents, with one in illegal markets and another in formal labor markets where the fraction of time devoted to each activity is modeled by the measure of each type of agent within this cluster. By assuming that dealers are endowed with their supply, we are eschewing analysis of policies, such as increased monitoring by customs officials, directed at affecting the dealer's price of drugs. The case of multi-unit drug dealing will be discussed in Section 5 below.

dealers, A_s, where all dealers are identical *ex ante*. (*Ex post* some may be active and others incarcerated.) In equilibrium, it is required that supply equals demand:

$$A_s = S = D(p, A_d)$$

(3)

The drug price, p, satisfies a no-arbitrage condition for the occupational choice between drug dealing and working in the legitimate labor market (to be determined below) and the equilibrium condition in the drug market described in (3).

We do not consider organized crime nor international drug markets, but rather competitive drug-dealing by many domestic sellers with matching frictions in which search theory is an appropriate framework. We assume drug dealers are arrested and released at constant rates, τ_s and ρ_s. In the steady state, the outflow from the pool of active drug dealers (i.e., those arrested) must be equal to the inflow (i.e., those released from jail):

$$\tau_s A_s = \rho_s I_s.$$

(4)

Similarly, with drug demander arrest and release rates, τ_d and ρ_d, the steady state requires:

$$\tau_d A_d = \rho_d I_d.$$

(5)

This completes the description of the structure of the local economy.

Local Government

To close the model, we need to specify the cost structure of drug policies facing the local government and the budget constraint. We use the simplest possible specification for the costs of drug enforcement, assuming an identical unit cost $\varphi > 0$ of incarcerating a drug supplier and a drug demander. Additionally, such law enforcement costs are assumed to be partly financed by lump-sum taxes, T, on low income workers. Denoting this fraction of spending financed by taxes on low income workers as σ, we can write the government budget constraint as: $T = \sigma\varphi(\tau_d Q_d + \tau_s Q_s)$.[18] Since we are free to choose the unit of account, we will do so in a convenient way by setting $\sigma\varphi = 1$.[19] Thus, the government budget constraint can be simplified as:

$$T = \tau_d Q_d + \tau_s Q_s.$$

(6)

Accordingly, each worker's after-tax wage is given by,

$$w = \theta Y - T/L,$$

(7)

whereas the community's aggregate income is,

$$\Omega = wL - T.$$

(8)

Throughout the paper, we focus only on the case where the legitimate sector is nondegenerate in the sense that the after-tax wage is positive (i.e., $\theta Y > T/L$).

Value Functions and Drug Price Offer Function

Now we are able to describe the expected returns of workers and drug dealers by applying

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[18] The purpose of the simple form of T here is to close the model so as to assess the effectiveness of different drug policies. In the interest of low income neighborhoods, much of the financing of the war on drugs and the provision of some incarceration costs come from higher levels of government, and as such we could posit an exogenous net transfer as an additive term on the left hand side of the constraint. This would not affect the marginal conditions we discuss below. In any case our analysis concentrates on the enforcement strategies that are available to local communities—that is, incarceration of drug market participants.

[19] A uniform unit cost of demand and supply arrests may potentially bias our analysis in favor of supply policy, because it may be argued in reality that supply arrests are more costly. Since our calibrated results suggest demand policy is more effective, the assumption of uniform unit cost can be viewed as a conservative benchmark against our finding. Also, our normalization would not affect the analysis. In the calibration analysis below, we can compute the "nominal value" of $\sigma\varphi$ and then recover the nominal value of drug price, wage and output by multiplying p, w and Y, respectively, by the nominal value of $\sigma\varphi$.

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standard dynamic programming techniques.[20] We first define the flow values for each agent. Define J_i ($i = L, U, A_s, I_s$) as the (lifetime) **value functions** for each of the types of residents. Then the Bellman equations specifying these asset values are given by,[21]

$$rJ_L = w + \delta(J_U - J_L)$$
(9a)

$$rJ_U = \mu(J_L - J_U)$$
(9b)

$$rJ_{As} = p + \tau_s(J_{Is} - J_{As})$$
(9c)

$$rJ_{Is} = \rho_s(J_{As} - J_{Is})$$
(9d)

These equations have standard interpretations. For example, (9c) indicates that the flow value of an active drug dealer is the sum of the flow revenue from selling one unit of drug and the flow value from changing the state (from active to incarcerated). From equations (9a-d), the asset values related to workers and criminals can be written as functions of the wage rate or drug price:

$$J_L = \frac{r + \mu}{r + \delta + \mu} \frac{w}{r}$$
(10a)

$$J_U = \frac{\mu}{r + \delta + \mu} \frac{w}{r}$$
(10b)

$$J_{As} = \frac{r + \rho_s}{r + \rho_s + \tau_s} \frac{p}{r}$$
(10c)

$$J_{Is} = \frac{\rho_s}{r + \rho_s + \tau_s} \frac{p}{r}$$
(10d)

We now turn to the determination of the drug supply function. We assume that all occupational choice decisions are made instantaneously according to an **occupational choice rule**, so that the two careers provide equal expected values in equilibrium. That is,

$$J_U = J_{As} > 0.$$
(11)

When residents face their occupational choices, they treat the wage as given as in (1). Using (9) and (11), we can derive the drug supply function, which turns out to be a linear function of wage and is perfectly elastic[22]:

$$p(w, \mu, \delta, r, \tau_s, \rho_s) = \frac{\mu}{r + \mu + \delta} \frac{r + \rho_s + \tau_s}{r + \rho_s} w.$$
(12)

The perfectly elastic drug supply suggests drug dealers are price takers. Once the wage has been given, the occupational choice rule and the equilibrium condition suggest the drug price will be set so that both Eqs. (12) and (3) hold. The drug market is cleared through the adjustment of distribution of population (in the community) only.

For any given value of r, let $p(w, \mu, \delta, \tau_s, \rho_s)$ denote the **drug price offer function**. We then have,

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[20] The welfare of firms is not essential to our analysis and, from the community's point of view, the welfare of the outside drug demanders is not the concern.

[21] The instantaneous utility for employed workers is the wage w, and for dealers it is the price of drugs, p. Both unemployed workers and prisoners have utility of zero, but see below.

[22] A positively sloped drug supply function would obtain if the drug price function is determined by both the occupational choice rule and the equilibrium condition. Therefore, the drug demand plays a role in determining drug price (see Section 4).

6

Proposition 1. (Drug Price Offer Function) *The drug price offer function, $p(w, \mu, \delta, \tau_s, \rho_s)$, determined by the occupational choice rule* (11) *and by the drug market equilibrium condition* (3), *is given by* (12), *which satisfies*: $\partial p/\partial w > 0$, $\partial p/\partial \mu > 0$, $\partial p/\partial \delta < 0$, $\partial p/\partial \tau_s > 0$, *and* $\partial p/\partial \rho_s < 0$.

The properties of $p(w, \mu, \delta, \tau_s, \rho_s)$ have intuitive interpretations. Since the drug price is a linear function of the (after-tax) wage rate, an increase in the wage (through increases in productivity or the share of output accruing to labor or decrease in per capita taxes) will increase the (expected) asset values of workers, and consequently will raise the drug price (proportionately) to keep the two career values the same. A more frequent matching rate of workers with vacancies, μ, makes alternative options more accessible to workers, thereby raising the asset values of workers and the drug price. A high layoff rate, δ, lowers the asset values of workers and therefore the drug price.

Two properties related to the drug market parameters are worthy of special attention. Given the occupational choice rule, an increase in the supply-side arrest rate, τ_s, lowers the expected value of being a drug dealer and consequently raises the drug price. In contrast to the arrest rate, an increase in the supply-side release rate, ρ_s, raises the expected value of being a drug dealer and lowers the drug price. Importantly, it should be noticed that neither the arrest nor the release rates for drug demanders affect the drug price offer function.

3. Steady-State Equilibrium

To begin, consider the following:

Definition 1. *A **steady-state equilibrium** is an after-tax wage w, a drug price function $p(w, \mu, \delta, \tau_s, \rho_s)$, and a list of populations $(A_d, I_d, A_s, I_s, Q_s, N, L, U)$ satisfying the following conditions*:
(i)   *(Occupational choice)*: (11);
(ii)   *(After-tax Wage)*: (7);
(iii)   *(Local government budget balance)* (6);
(iv)   *(Drug market equilibrium)*: (3);
(v)   *(Steady state)*: (2), (4) and (5);
(vi)   *(Population identities)*:

$$N + Q_s = 1$$
(13a)

$$L + U = N$$
(13b)

$$A_s + I_s = Q_s$$
(13c)

$$A_d + I_d = Q_d.$$
(13d)

Condition (i) pins down the drug price function as in (12). While Condition (ii) requires the local government to balance budget, Condition (ii) requires the drug market to clear. Condition (iii), as noted, is the government's budget constraint while (iv) equates the supply and demand for drugs. Conditions (v) provide necessary and sufficient conditions for constant populations of workers and drug market participants. Conditions (vi) summarize the four population identities described in Section 2.

The model possesses a convenient recursive structure, which can be exploited to prove the existence of equilibrium and analyze its properties. Under the benchmark setup with exogenous potential drug demanders (Q_d), we can combine (5) and (13d) to obtain the equilibrium values of A_d and I_d:

$$A_d = [\rho_d/(\rho_d + \tau_d)]Q_d$$
(14a)

$$I_d = [\tau_d/(\rho_d + \tau_d)]Q_d.$$
(14b)

Then (4) and (13c) together enable us to express the equilibrium populations of incarcerated and potential drug dealers, I_s and Q_s, in terms of the endogenous population of active drug dealers alone (A_s). From (2), (13a) and (13b), in conjunction with the expression for Q_s, the equilibrium populations of employment and unemployment, L and U, can also be written as functions of A_s.

These arguments imply:

$$I_s = (\tau_s/\rho_s)A_s,$$

(15a)

$$Q_s = [(\rho_s + \tau_s)/\rho_s]A_s,$$

(15b)

$$L = [\mu/(\delta + \mu)]\{1 - [(\rho_s + \tau_s)/\rho_s]A_s\},$$

(15c)

$$U = [\delta/(\delta + \mu)]\{1 - [(\rho_s + \tau_s)/\rho_s]A_s\}.$$

(15d)

Next, using (15b) and (15c), we write the tax per worker as a function of A_s:

$$\frac{T}{L} = t(A_s) = \frac{\tau_d Q_d + \tau_s[(\rho_s + \tau_s)/\rho_s]A_s}{[\mu/(\mu + \delta)]\{1 - [(\rho_s + \tau_s)/\rho_s]A_s\}},$$

(16)

which is rising in A_s. This expression can be substituted into the occupational choice rule, (12), to derive the drug price as a decreasing function of A_s:

$$p = \Pi(A_s) = \frac{\mu}{r + \delta + \mu} \frac{r + \rho_s + \tau_s}{r + \rho_s}[\theta Y - t(A_s)],$$

(17)

This function is displayed in the southeast quadrant of Figure 2. The price/after-tax wage combination that equalizes the values for the two careers creates a downward sloping *occupational choice (CC) locus*. For any given arrest rate, a greater number of active dealers requires a higher tax per worker, which lowers the return from lawful employment and the price necessary to equilibrate the two career values.

It is convenient to define a choke price for drugs, $p^{\max}$, as one corresponding to zero demand. Depending on the drug demand specification $D(p, A_d)$, one may have a finite value of the choke price (e.g., when D is linear in p) or an infinite value (e.g., when D takes the constant-elasticity form). Therefore, given the link between the wage and the price specified in (12), one may define a maximum wage at or above which all residents will choose the legitimate labor market because the corresponding drug price drives demand to zero: $w^{\max} = \frac{r + \delta + \mu}{\mu} \frac{r + \rho_s}{r + \rho_s + \tau_s} p^{\max}$. Define the "relative wage" as: $R(A_s) = \frac{\theta Y - t(A_s)}{w^{\max}}$. Then if $R \geq 1$, it implies the expected returns of workers always exceed or equal to that of drug dealers even without drug policy. In this case, the wage offers in the labor market are high enough to prevent people from being drug dealers, which is not interesting. For this reason we need only consider *low-income neighborhoods* such that,

Assumption 2. $R(A_s) < 1$.

As $p^{\max}$ goes to infinity, $w^{\max}$ does too and hence $R(A_s)$ approaches zero, implying that Assumption 2 is always met.

We can substitute the price in (17) into the linear demand function to produce an *equilibrium drug (ED) correspondence* as a function of the population of active dealers,

$$D = D(\Pi(A_s), A_d) = \Delta(A_s).$$

(18)

That the ED locus is upward sloping is clear from the fact that D is decreasing in p and Π is negatively related to A_s. Under Assumption 2, $\Delta(0) > 0$. We can then plot the ED locus in the northeast quadrant of Figure 2, which traces out the locus of points in (A_s, D) space that are congruent with both the occupational choice rule (i.e., the CC locus in the southeast quadrant) and the demand function (i.e., the $D(p, A_d)$ schedule in the northwest quadrant). Should there be a downward shift in the demand curve or an upward shift in the CC locus, the ED locus will shift downward. The equilibrium amount of drug activity is pinned down where the ED locus crosses the 45° line, which equates supply $(S = A_s)$ and demand (D specified as in (18) above):

8

$$A_s = \Delta(A_s),$$

(19)

Thus, Δ can be regarded as a fixed point mapping, determining the equilibrium amount of drug trade, A_s. Without a fully specified drug demand schedule, we can only be assured that Δ is an increasing function with $\Delta(0) > 0$. A unique interior fixed point A_s is guaranteed, however, if we impose:

Assumption 3. $\Delta(\Pi^{-1}(0)) < \Pi^{-1}(0)$ and $d\Delta(A_s)/dA_s < 1$.

Technically, the boundary condition on the maximal value (possibly infinite) of A_s, $\Pi^{-1}(0)$, together with $\Delta(0) > 0$, implies the existence of a fixed point. When the slope of this fixed point mapping evaluated at a fixed point is flatter than the $45°$ line, Δ cannot cross the $45°$ line more than once and hence the fixed point must be unique. This unique equilibrium value of A_s obtained from (19) can then be substituted into (7), (15), (16) and (17) to derive equilibrium wage, equilibrium drug price, as well as equilibrium populations of potential and incarcerated drug dealers.

The comparative static properties are obtained through examination of the population equations (14) and (15), the drug demand schedule, the occupational choice locus (17), and the community aggregate income equation (8). All factors in the labor market (including θ, μ and δ) and the supply-side drug policy parameters (τ_s and ρ_s) influence the steady-state equilibrium populations of active drug demanders/suppliers, potential drug dealers, formal sector employment and aggregate community income only through their effect on the equilibrium drug price via the occupational choice locus.

An increase in workers' wage share (θ) or productivity (Y) raises the incentive for agents to participate in the formal job market. In equilibrium, the reward to drug dealing must rise in order to maintain the equality of value in the two careers – that is, the CC locus shifts up whereas the ED curve shifts down. This leads to a higher drug price, but lower populations of potential and active drug dealers, and greater employment and community income. An increase in workers' matching rate (μ) or a reduction in their job separation rate (δ) generates similar effects to an increase in the wage share. Additionally, the per worker tax (T/L) is lower as indicated by (16) – this ***tax effect*** reinforces the incentive for agents to move away from drug dealing.

Increasing the arrest rate of drug demanders (τ_d) or decreasing the corresponding release rate (ρ_d) reduces the number of active drug demanders (14a) so that the demand function in the northwest quadrant of Figure 2 shifts to the left. At a given level of per worker taxes, demand-side arrests have no effect on the drug price and as a result, the number of (potential and active) drug sellers must fall to maintain drug market equilibrium – that is, the ED locus shifts down. This tends to raise employment in the formal job sector and community income. However, the increase in τ_d directly causes an increase in enforcement costs (T) and, as a consequence of the downward shift in the number of drug dealers stated above, the population of legitimate labor-market participants (L) over whom the cost can be spread is also higher. The net effect of these actions can cause either a rise or fall in the per worker tax, T/L. In the worst-case scenario where the direct effect dominates, T/L rises and the fall in the after-tax wage lowers the price necessary to equalize the two career values. In the diagram this causes a shift toward the origin of the CC locus and hence an upward shift of the ED locus. The respective shifts in the demand curve and the CC locus move the ED locus in opposite directions and so have a generally ambiguous effect on the amount of drug market activity (measured by D = S = A_s). More plausibly, the per worker tax effect is likely secondary; so the demand shift is likely to dominate the supply shift caused purely by the tax effect, leading to a net reduction in active drug trade.

An increase in the supply-side arrest rate (τ_s) or a reduction in the corresponding release rate (ρ_s) is a bit more complicated in its effects. In addition to the complication from changes in the per worker tax as the demand-side drug policy, there are two offsetting effects. There is, first, a ***direct incarceration effect***. A higher arrest rate puts more drug dealers in jail, given the population of active dealers, as evidenced in (15a). The drug price that equates the two occupational choices must rise, and given the downward sloping demand, the number of active dealers (A_s) must fall, but the extent to

which it falls depends on the form of the demand curve. We call this the ***dealer replacement effect***. Some of newly incarcerated dealers are replaced by new entrants into the drug market, depending on the level of demand at the higher price. Thus, even ignoring the tax effect, the impact on potential drug dealers (Q_s), which is the sum of active and incarcerated dealers, is ambiguous, as is the effect on its complement, the number of people in the legitimate labor market ($N = L + U$). The key is the elasticity of drug demand: in the limiting case of inelastic demand, a supply-side policy is completely self-defeating.[23] The putative reduction in the drug trade caused by arresting dealers is exactly counterbalanced by a price rise sufficient to attract an equal number of new dealers out of the legitimate labor market. However, if demand is very elastic, the price rise needed to draw new dealers into the market in the face of greater incarceration risk is high enough to turn away most of the demand – in this case, the steady state population of workers may actually increase. The offsetting nature of the direct incarceration and dealer replacement effects associated with the supply-side policy is in sharp contrast with the direct deterrence effect associated with the demand-side policy. In summary, we have:

Proposition 2. (Comparative Statics) *Under Assumptions 1-3, the unique steady-state equilibrium possesses the following properties:*
(i)   an increase in the workers' wage share, productivity or matching rate, or a reduction in the job separation rate, raises the drug price, legitimate employment and community income and lowers both active and potential drug dealers;
(ii)   when the tax effect is small, an increase in the arrest rate of drug demanders or a decrease in the corresponding release rate raises legitimate employment and community income and lowers active drug demanders as well as active and potential drug dealers without affecting the equilibrium price of drugs;
(iii)   when the tax effect is small, an increase in the supply-side arrest rate or a reduction in the corresponding release rate raises the drug price, lowers active drug dealers, and, as a result of the opposing direct incarceration and dealer replacement effects, generates ambiguous effects on potential drug dealers, legitimate employment and community income.

The comparative static properties presented in parts (ii) and (iii) of this proposition can be used to formulate and characterize the optimal drug policy to which we now turn.

4. Optimal Drug Policy with a Balanced Local Government Budget

The major concern of this paper lies in the effectiveness of supply- and demand-side drug policies, as represented by the two enforcement policy instruments – that is, the two arrest rates, τ_s and τ_d. While the two release rates, ρ_s and ρ_d, are two other parameters of interest, their effects are essentially the mirror image of the arrest rates, and will not be emphasized.

To compare the effectiveness of these two policies, it is necessary to further specify the objective function of the local government. Among several possibilities, we consider three potential objectives that local governments may have. The first one is the reduction of illegal drug activity, A_s, in their communities. The second is the reduction of the total population of criminals, Q_s. The third objective is to increase the legitimate income flow in the community, Ω.[24]

Note that the general form of drug demand described in Assumption 1 can not provide closed-form solutions for the optimal drug policy. We therefore consider two special cases of drug demand, linear and constant elasticity forms, to gauge the optimal arrest rates under the three objectives mentioned above. The implications for the design of optimal drug policy derived from these two

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[23] One of the interesting facets of the war on drugs is that despite the intense efforts to thwart supply, the price of drugs has not risen at all, largely due to the kinds of supply replacement effects discussed here. See e.g. Porter (2012).

[24] Alternatively, we may define the income flow as the total local income. That is, $\Omega' = wL + (Y-w)F - T/L$. If we assume that each job can have one at most one worker, then $F = L$. That is, the number of matched firms is same as the number of employed workers. As a result, $\Omega' = YL - T$, which differs from Ω only by a factor θ. Thus, the results of analysis on the arrest policies would not change under this alternative definition.

10

special cases may provide some insights for the general case. The benchmark case features a linear drug demand schedule: $D(p, A_d) = B_0 A_d - b\,p$, where $B_0 > 0$ and $b > 0$ are constant parameters. The alternative is to consider a drug demand function with constant price elasticity: $D(p) = D_0 A_d p^{-\eta}$, where $D_0 > 0$ and $\eta > 0$ is the price elasticity of drug demand (an exogenous constant). Under the linear and constant-elasticity specifications, respectively, we can solve for equilibrium active drug dealers from (19) as:

$$A_s = [1 - R(A_s)]\frac{\rho_d}{\rho_d + \tau_d}Q_d$$

(20a)

$$A_s = \left[\left(\frac{r + \mu + \delta}{\mu}\right)\left(\frac{1}{\theta Y - t(A_s)}\right)\left(\frac{r + \rho_s}{r + \rho_s + \tau_s}\right)\right]^{\eta}\frac{\rho_d}{\rho_d + \tau_d}Q_d$$

(20b)

It is clear that Assumption 2 is needed for $A_s > 0$ only in the case of linear demand, whereas Assumption 3 is always met in either case.

We can now examine the government's policy in the face of the various objectives it might have. Given the first objective, a local government attempts to lower A_s given in (19). From Proposition 2 and the discussion in the previous section, the superiority of one policy or the other can never be guaranteed for all parameter values, so there cannot be a definitive statement that demand-side policy is best at reducing drug activity. One of the key parameters is the slope of the drug demand function. It is important to note that in the absence of a first-order demand deterrence effect, the supply-side arrest policy only works through its influence on occupational choice. Should the demand schedule be rather inelastic (i.e., $D(p, A_d)$ is flat in (p, D) space as plotted in the northwest quadrant of Figure 2), the resulting shift in the CC locus is negligible, thereby making the supply-side policy less effective. Indeed, for inelastic demand curves, not only is the direct incarceration effect of arresting demanders stronger, but the dealer replacement effect is as well, under supply-side policy. These reinforce previous arguments: the less sensitive drug demand is to price, the more appropriate will demand policy be.[25] More generally, we can compare these two drug policies in the context of "tax incidence" under constant law enforcement spending, T. While demand arrests have a direct demand deterrence effect, and supply arrests reduce the drug trade via their impact on occupational choice (through the increase in p), the demand-side policy increases legitimate employment while the supply-side policy reduces it, due to the replacement effect. These labor-market effects make demand-side policy under many scenarios superior to supply-side policy. Thus, we can summarize the main results as follows:

Proposition 3. (Optimal Drug Policy) *Under Assumptions 1-3 and a community government's objective to minimize the active drug trade, the effectiveness of drug policies is characterized as follows:*
(i) *demander arrests have a direct effect on drug trade via deterrence of demand, whereas and supplier arrests reduce drug trade via the choice of careers;*
(ii) *demand-side policy increases legitimate employment whereas the supply-side policy reduces it, making demand policy more effective under constant law enforcement spending;*
(iii) *the less sensitive drug demand is to price, the more appropriate will demand policy be.*

We turn next to the other two objectives facing the local government. It is now useful, for illustrative purposes, to consider the two specific functional forms for drug demand. Since all cases examined here use the same approach and economic reasoning, we focus our discussion on the case of linear drug demand, while referring to another case to the extent that it is of separate interest. Under a linear drug demand schedule, we can derive the second objective where a local government minimizes potential drug activity, as measured by the population of potential dealers:

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[25] It is not our intention to draw any formal conclusion with respect to the price elasticity of drug demand, as its values vary along the linear demand schedule. We will return to this issue later under the consideration of a constant elasticity demand function.

$$Q_s = \frac{\rho_s + \tau_s}{\rho_s}[1 - R(A_s)]\frac{\rho_d}{\rho_d + \tau_d}Q_d .$$

(21)

With this objective, the case for demand-side policy becomes stronger. This is because the previous discussion of the dealer replacement effect suggests that there is an unambiguously positive impact on Q_s from increasing the supplier arrest rate, while the tax per worker increases in the same manner as before (which can be seen by comparing (21) with (20a)).

With regard to the third objective, a community government maximizes its aggregate income,

$$\Omega = \frac{w\mu}{\mu + \delta}\left\{1 - \frac{\rho_s + \tau_s}{\rho_s}[1 - R(A_s)]\frac{\rho_d}{\rho_d + \tau_d}Q_d\right\} - T(A_s; \tau_d, \tau_s) .$$

(22)

Comparing (22) with (21), we note that minimization of potential drug activity and maximization of aggregate community income only differs because of the negative law enforcement spending effect.

It remains to examine the optimal drug policy under the alternative, constant-elasticity drug demand schedule. By comparing (20b) and (20a), one can see that the qualitative effects of policy can be carried over to the constant-elasticity case, although the quantitative effects are naturally different. More specifically, if η <1, the threat from demand arrests is more effective and hence demand-side policy is preferred under the first local government objective of minimizing drug traffic. That is, if the community suffers a severe drug problem in the sense that drug demand is price-inelastic, demand policy is more advantageous – this corresponds to a well-known property of the optimal taxation literature in a very different context. The analyses regarding to the other two objectives are parallel to those discussed above and hence omitted without further elaboration in the interest of space.

These arguments can be carried over to more general drug demand schedules, as long as Assumptions 1-3 are met.

Proposition 4. (Optimal Drug Policy) *Under Assumptions 1-3, the effectiveness of drug policies is characterized as follows:*
(i)   when the community government's objective is to minimize the potential drug tradedemand-side policy is more effective than supply-side policy because of the dealer replacement effect inherent in the supply side policy.
(ii)   when a community government's objective is to maximize community income, the relative effectiveness of demand and supply-side policies is the same as when a community government's objective is to minimize the potential drug trade, as long as the law enforcement effect remains constant;
(iii)   the less responsive drug demand is to the price, the more advantageous will the demand policy be.

5. Calibration and Policy Simulation

Propositions 3 and 4 have provided us useful general guidelines about evaluating the effectiveness of drug policies. However, it remains ambiguous whether demand-side policy or supply-side policy is more effective. In this section, we will calibrate the U.S. economy and then quantify our comparative statics and policy evaluations around the calibrated equilibrium.
Calibration

We use primarily data from the 2001-02 fiscal year. The *National Household Survey on Drug Abuse*[26] indicates that about 15.9 million people are current (active) illicit drug users. This survey also reports that virtually all sellers are users. From a survey of clients undergoing drug rehabilitation, the *Services Research Outcomes Study*,[27] 34.7% of users in the survey admitted to selling; thus, we estimate that the number of active illicit drug sellers is 5.517 million (0.347·15.9 million). According to the Department of Justice's 2002 survey *Felony Sentences in State Courts*,[28]

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[26] http://www.whitehousedrugpolicy.gov/drugfact/nhsda01.html
[27] http://oas.samhsa.gov/Sros/sros8020.htm#E28E19
[28] http://www.ojp.usdoj.gov/bjs/pub/pdf/fssc02.pdf

12

about 127,500 persons were convicted for drug possession, and of those, 62% were imprisoned. Since convictions in federal courts on drug offenses have been almost entirely for sale and manufacture (rather than possession), we can simply use the state courts figures to compute the annual flow of incarcerated illicit drug users as 79,000 (0.62·127,500). Also according to *Felony Sentences in State Courts* there were 212,800 convictions in state courts for sale and manufacture, of which 68% were imprisoned, along with 24,200 convictions in federal courts of which 91% were imprisoned. These can be used to compute the annual flow of incarcerated illicit drug sellers as 166,700. Thus, we can calibrate the drug demander arrest rate and the drug supplier arrest rate: τ_d = 79000/15900000 = 0.5% and τ_s = 166,700/5517000 = 3.02%.

According to *Felony Sentences*, the average sentence for possession for those imprisoned in state courts was 22 months (1.83 years). The average sentence for distribution was 38 months in state and 76 months in federal prisons, implying an average sentence for distribution of 0.68·212800·38 + 0.91·24200·76 = 43.43 months (3.6 years). These are used to calibrate the respective release rates: ρ_d = 1/1.83 = 54.64% and ρ_s = 1/3.6 = 27.78%. Now utilizing the annual flows, we can obtain the stock of incarcerated drug demands and the stock of incarcerated drug suppliers, respectively, as: 76000/ρ_d = 144,570 and 166700/ρ_s = 600,120. We can then compute the total populations of drug demanders and drug dealers, respectively, as: 15900000 + 144570 = 16,044,570 and 5517000 + 600,120 = 6,117,120.

We turn now to the legitimate low-income labor market. *Bureau of Labor Statistics* reports that there were 135 million civilian employment in 2002, of which about 10% received less than a high school diploma. We regard this 13.5 million figure as the population of low-income employment. According to *Current Population Survey*, the unemployment rate of those receiving less than a high school diploma is 7.36% and their average spell of unemployment is 14.5 weeks. We can therefore compute the population of unemployed in the low-income legitimate sector as: [0.0736/(1-0.0736)]·13,500,000 = 1,072,500. So the total population in the low-income legitimate sector is 13,500,000 + 1,072,500 = 14,572,500 and the total population in the low-income legitimate and illicit sectors is POP = 14,572,570 + 6,117,120 = 20,689,690. This latter number is the total population of the low-income economy, which is normalized to one in the model. Thus, we need to divide all population figures by this number to obtain: Q_d = 16044570/POP = 0.7755, Q_s = 6117120/POP = 0.2957, A_d = 15900000/POP = 0.7685, A_s = 5517000/POP = 0.2667, I_d = 144570 /POP = 0.0070, I_s = 166700/POP = 0.0290, L = 13500000/POP = 0.6525, U = 1072500/POP = 0.0518, and N = 14572500/POP = 0.7043[29]. From the average unemployment spell, we can compute the job finding rate (converting from weekly to annually): $\mu = 1 - [1 - (1/14.5)]^{52} = 0.9757$. This, together with (2), enables us to obtain the job separation rate δ = μ·U/L = 0.0775. Using these figures, one may easily verify all the population relationships given in equations (13)-(15).

Reuter, MacCoun and Murphy (1990) estimate that in 1988 a cocaine seller earned a median of $7 per hour when working in the licit labor market. Adjusting this figure by the cost of living (150%) and the average hours (1,768), we obtain the average annual wage earned by low-income workers of $18,564. According to estimates, Department of Justice spending on drug enforcement is about $1.6 billion.[30] We cannot find comparable figures for state and local law enforcement agencies but according the US Department of Justice's *Law Enforcement Management and Administrative Statistics*, *2000*,[31] the operating costs of a state or local drug enforcement officer is about $100,000 per officer, and there were 13,664 officers assigned to drug enforcement, giving state and local spending on drug enforcement at 1.37 billion. Thus, we estimate a total drug enforcement spending as 3 billion. In 2002, GDP per civilian worker is $77,681. Then, using (6), we can compute T = 0.0128 and hence the unit of account of the calibrated model is $3000000000/(T·POP) = $11,340. Thus, the wage defined in the model is θY = 18564/11340 = 1.6370. To calibrate Y, we must select a value for the wage share of low-income workers, θ. Mankiw, Romer and Weil (1992) estimate a Cobb-Douglas

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[29] The population figures are, as noted, those of the low income population and so inflate the number of drug users and in the calibrated economy. Nonetheless, such a level change in populations would not affect our tax incidence exercise on which our policy analysis is based.

[30] http://www.usdoj.gov/opa/pr/2002/February/02_ag_056.htm

[31] http://www.ojp.usdoj.gov/bjs/pub/pdf/lemas00.pdf

form of the aggregate production and find the income share of raw labor approximately 1/3. This is used to set $\theta = 1/3$, which implies $Y = 4.9110$ and, by multiplying the unit of account, the output per low-income worker is \$55,692. This is about 72% of the average output per worker in the U.S., which is reasonable for the legitimate low-income sector. Moreover, these figures imply the effective tax rate for the war on drugs on low-income workers is about 1.2%, which is also sensible.

Furthermore, Warner and Pleeter (2001) provide a consistent estimate of the subjective discount rate of low-skilled workers about 35%, which is taken as our benchmark value of r. We then utilize (7) and (12) to compute: $w = 1.6174$ and $p = 1.1788$. We can also use (8) to obtain: $\Omega = 1.0554$. We are now only left to calibrate drug demand parameters. Saffer and Chaloupka (1999) estimate both the price and the participation price elasticities of the demand for illicit drugs. The participation price elasticities are more relevant to our model. Their results suggest such elasticities to fall in (-0.55, -0.36) for cocaine and in (-0.90, -0.80) for heroin. We therefore choose our benchmark value as: $\eta = 0.65$ (the absolute value of the elasticity). Under the linear drug demand schedule, we can recover the slope parameter: $b = 0.65 \cdot A_s/p = 0.1470$. We can also compute the scaling parameter under each drug demand specification: $B_0 = (1+0.65) \cdot (A_s/A_d) = 0.5725$ and $D_0 = p^{0.65} \cdot (A_s/A_d) = 0.3861$.

Comparative Statics

We can now use the fully calibrated model to perform comparative static analysis quantitatively. The results are reported in Table 1. One can see that the effects of legitimate labor market parameters (δ, θ, Y) reconfirm Proposition 2: favorable legitimate labor market conditions raise drug price, reduce (active and potential) drug activity, and increase legitimate-sector employment and aggregate income. Quantitatively, drug and legitimate activities are more responsive to changes in pre-tax wage than shifts in the job separation rate.

The findings concerning drug policy instruments are quite intriguing. In calibrated equilibrium, we find that, not surprisingly, the tax effects associated with drug policy changes are quantitatively inessential. As a consequence, a tightened demand-side drug policy (either an increase in τ_d or a decrease in ρ_d) reduces drug price and (active and potential) drug activity, and increase legitimate-sector employment and aggregate income. We also find that the effects of a tightened supply-side drug policy (either an increase in τ_s or a decrease in ρ_s) are to raise drug price, suppress active drug trade, but induce greater potential drug activity and reduce legitimate-sector employment and aggregate income. This implies, in the benchmark economy, the dealer replacement effect outweighs the direct incarceration effect, making the supply-side policy less effective.

We can also go beyond the analytic results to examine the effects of drug demand parameters. While increases in the slope/elasticity parameters (b, η) have a positive effect on the drug price, the scaling parameters (B_0, D_0) have a negative effect. More interestingly, when drug demand is more responsive to prices (a higher value of b or η), there is a sizable shift from drug to legitimate activity.

Policy Evaluation

We are now ready for the main numerical task to quantitatively assess the effectiveness of drug arrest policies. We accomplish this by performing a tax incidence exercise commonly used in the public finance literature. Specifically, under each of the three local government objectives and each of the two drug demand schedules, we compare the effectiveness of the two arrest instruments (τ_s, τ_d) and quantify the effects of shifting from one instrument to another while maintaining drug enforcement spending at the benchmark value T. It turns out that, out of the six cases, the supply-side arrest policy is more effective only when the local government objective is to minimize active drug-dealing and the drug demand schedule takes the constant-elasticity form. For all the other five cases, the demand-side arrest policy is more effective.

Thus, a general conclusion is that when the local government objective is to minimize potential drug-dealing or to maximize aggregate income, it should focus more on the demand-side policy. If one raises τ_d by 10% while lowering τ_s to maintain T at the benchmark value, then the number of potential drug dealers will fall by 0.42% under linear demand and by 0.36% under constant-elasticity demand – these percentages can be converted to reductions in the populations of potential drug dealers by 25,498 and 22,139, respectively. By a similar tax incidence exercise, we find that aggregate income rises by 0.17% and 0.15% under the two respective demand specifications, or by \$439 million and \$381 million at 2002 prices. For either objective, the gains from such policy

14

shifts are substantial.

The policy recommendation becomes inconclusive when the local government objective is to minimize active drug-dealing. Under linear demand, shifting from supply-side to the demand-side is still a beneficial policy – under a similar tax incidence exercise, increasing τ_d by 10% reduces active drug dealing by 0.033%, a reduction of only 1,828. Under constant-elasticity demand, it is beneficial to shift from the demand-side to the supply-side; in this case, a tax incidence exercise that decreases τ_d by 10% lowers active drug dealing by 0.026% or 1,441, which is again very slight.

One may also stretch the local analysis to compute an optimal policy mix, assuming the responses around the calibrated equilibrium hold for global shifts in the two policy instruments (τ_s, τ_d). Then, we can derive optimal policy mix (τ_s^{*}, τ_d^{*}) in each of the six cases:

1) active dealing minimization with linear demand: (τ_s^{*}, τ_d^{*}) = (0, 1), which reduces active drug dealing by 69% from the benchmark;

2) potential dealing minimization with linear demand: (τ_s^{*}, τ_d^{*}) = (0, 1), which reduces potential drug dealing by 72% from the benchmark;

3) aggregate income maximization with linear demand: (τ_s^{*}, τ_d^{*}) = (0, 0.081), which raises aggregate income by 4.9% from the benchmark;

4) active dealing minimization with constant-elasticity demand: (τ_s^{*}, τ_d^{*}) = (0.14, 0.64), which reduces active drug dealing by 37% from the benchmark;

5) potential dealing minimization with constant-elasticity demand: (τ_s^{*}, τ_d^{*}) = (0, 0.76), which reduces potential drug dealing by 41% from the benchmark;

6) aggregate income maximization with constant-elasticity demand: (τ_d^{*}, τ_s^{*}) = (0, 0), which raises aggregate income by 4.1% from the benchmark.

Summarizing, in all but one case (active dealing minimization with constant-elasticity demand), it is beneficial to the local government to lower the supply arrest rate as low as possible from its benchmark of 0.0302; in all but one case (aggregate income maximization with constant-elasticity demand), raising the demand arrest rate far above its benchmark of 0.005 is beneficial. Our results are robust to reasonable variations in parametrization (as displayed in an unpublished appendix).

6. Extensions

In this section, we extend the basic model in six interesting directions – (i) to consider endogenous drug demand, (ii) to let the drug policy to affect *intensive* drug demand, (iii) to allow for a neighborhood externality from drug transactions, (iv) to permit multi-unit drug dealing, (v) to incorporate utility costs of incarceration, and (vi) to consider social costs of drugs on workers. For brevity, all mathematical details are relegated to the Appendix.

Endogenous Drug Demand

In the benchmark model, drug demand is assumed exogenous in the sense that all demanders reside outside of the low-income neighborhood. This can be easily generalized to allow for demand by residents of the local community. Without loss of generality, we restrict our attention to the case where only employed workers in the formal labor market are eligible to consume drugs.[32] We categorize the population of employed workers by their drug consumption status: "clean" workers (L^C) and "using" workers (L^D), with $\pi = L^D / L$ given exogenously ($1-\pi = L^C / L$).[33] Among those workers using drugs, some are active ($\tilde{A}_d$) whereas some are incarcerated, losing their employment income ($\tilde{I}_d$), where $\tilde{A}_d + \tilde{I}_d = L^D$. Denoting active and incarcerated external drug demanders as $\overline{A}_d$ and $\overline{I}_d$, respectively, we thus have: $\tilde{A}_d + \overline{A}_d = A_d$ and $\tilde{A}_d + \overline{A}_d = A_d$.

For the sake of simplicity, assume that the demand-side drug policy is nondiscriminatory

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[32] This assumption is innocuous, as drug dealers can always consume before supplying one unit to the market. To allow for unemployed to consume drugs, one can add non-labor income, which would induce complexity without changing the main results.

[33] One may allow for self-selection in drug consumption to pin down π, which would create complexity without generating much additional insight.

between local and external users. Further assume that clean and drug using workers are equally productive and that demand incarceration does not cause permanent loss of employment. Then, from the modified occupational choice rule, one can establish that demand-side drug policies now have direct influences on the drug price offer: it depends negatively on the flow arrest rate for drug demanders and positively on the flow release rate for drug demanders. Moreover, since an increase in the demand-side arrest rate (or a decrease in the demand-side release rate) lowers the residents' drug demand $\tilde{A}_d$, it creates an additional downward pressure on drug price by drug market equilibrium. Both effects lower the price incentive for drug dealing, thus reinforcing the effectiveness of demand-side drug policies. In other words, the consideration of endogenous drug demand by local residents grants the demand-side policy even greater advantages over the supply-side policy when the community government's objective is to minimize the active or the potential drug trade.[34]

One may then inquire what happens if long-term relationships between drug dealers and using workers are allowed as in Galenianos, Pacula and Persico (2009). In this case, dealers are encouraged to form long-term relationships in response to a tightened supply-side enforcement policy in order to reduce arrest exposure, thereby making such a policy even less effective compared to a demand-side policy. In other words, the consideration of possible long-term relationships between drug dealers and using workers grants the demand-side policy even greater advantages over the supply-side policy.

Intensive Margin of Drug Demand

One may inquire what happens if drug policy is allowed to affect directly the intensive margin of drug demand. This can be done by considering the following individual drug demand function $d(p) = D_0(\tau_d, \rho_d)p^{-\eta}$ and the aggregate demand is $D = A_d\, d(p)$. Then demand-side drug policy not only affect the extensive margin of drug demand via A_d but also the intensive margin via $d(p)$. This further strengthens the advantage of demand-side drug policy, so the implications of the drug arrest policies remain valid.

Neighborhood Externality

We now extend the model to include the externality that arises within a neighborhood from an increase in the number of drug dealers. One way to do this is to augment the value function for drug dealers to include a term that shifts the value according to the number of dealers that are in the community. This can be a positive shift if the stigma from engaging in illegal activity is lower, or, it can be negative if there are crowding-out effects such that the unit cost of doing business increases with the number of participants.[35] To incorporate both, the flow value received by an active dealer become pA_s^{γ}, where γ could be positive or negative, as argued above (when $\gamma = 0$, it reduces to the benchmark model). Occupational choice now leads to a drug price function that depends directly on the population of active drug dealers. As long as such an externality is not strongly positive, the implications of the drug arrest policies remain valid.

Multi-unit Drug Dealing

In our benchmark model, drug dealers are identical *ex ante* and each possesses exact one unit of drug at a point in time. While this greatly simplifies the analysis, it is natural to treat high-volume drug dealing as a more severe crime, and ask if such considerations alter the relative effectiveness of demand-side to supply-side policies. To address this concern, we consider two types of drug-selling activities: a low-volume drug dealer (type L) supplying one unit of drug and a high-volume dealer (type H) who supplies q > 1 units. While the structure and behavior of low-volume drug trade are exactly the same as previously described, incarcerated high-volume dealers are subject to a more severe penalty, specifically, a lower release rate $\rho_s^H = \alpha\rho_s < \rho_s = \rho_s^L$. As in some other models of criminal behavior, there is a "hide-in-the-crowd" effect, in the sense that the effective arrest rate is lower when the number of criminals is large. Denote the fraction of active dealers as β (to be

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[34] When the community government's objective is to maximize the community's aggregate income, the demand-side policy is still preferred as long as the income loss resulting from arresting drug using workers is not too large.

[35] Such external effects have been discussed extensively in the literature of crime, e.g., see İmrohoroğlu, Merlo and Rupert (2000) and papers cited therein.

determined endogenously in equilibrium). By normalizing $\tau_s^L = \tau_s$, the effective arrest rate facing each high-volume dealer can be specified as: $\tau_s^H = [(1-\beta)/\beta]\tau_s$, i.e., the effective arrest rate is inversely related to the relative size of the population. This creates another dimension to the occupational choice decision facing each resident (legitimate job, low-volume drug dealing and high-volume drug dealing) and the occupational choice rule requires: $J_U = J_{As}^L = J_{As}^H > 0$. These equalities determine the drug price function as well as the equilibrium fraction of high-volume active drug dealers. We can show that the additional penalty for high-volume drug dealing (higher α) discourages such an activity. Yet, due to the hide-in-the-crowd effect, the overall measure of the arrest rate (τ_s) generates a disproportionate deterrent effect on low-volume drug dealing, thereby resulting in a higher fraction of high-volume active dealers. If deterrence of more severe drug activities is an objective of the government, this suggests an additional disadvantage associated with supply-side drug policy.

Utility Cost of Incarceration

So far, the specification of occupational choice forces equal expected values of entering the formal labor sector and the illegal drug market in equilibrium, as indicated by (11). One limitation that is imposed in those value functions is that the cost of incarceration and unemployment are both zero. It's likely that the former creates a lower level of utility than the latter. Thus, there may be a utility cost, c, incurred by incarcerated drug dealers. That is, letting J_{As} denote the "gross" value facing a potential drug dealer, the corresponding "net" value can be written as $J_{As} - c$. Thus, occupational choice implies $J_U = J_{As} - c > 0$. By solving the drug price function, we obtain similar results as in the benchmark model. An additional finding is that the incarceration cost may be regarded as a policy instrument, which captures, for example, the cost of imprisonment. An increase in this cost raises the equilibrium price and lowers drug demand as well as active drug supply. The countervailing power of the dealer replacement effect is lower as well. If there is an otherwise costless increase in prison disutility then the effects of a rise in c are unambiguously good for any objective.

Social Costs of Drugs

In previous sections, we focus on a "small open" community of drug in which the social costs of drug is ignored throughout. Such costs can be measured by ψA_s with $\psi > 0$. We can then rewrite a worker's net flow value accrued from a successful match as $\theta Y - \psi A_s$. It can be easily shown that our main results remain qualitatively valid as long as ψ is not too large.

7. Concluding Remarks

We have developed an endogenous occupational choice model to examine the implications of both demand- and supply-side drug policies, from the point of view of a low-income community that is the site of the drug market. Our emphasis has been on inferences that are available about the effectiveness of the two policies under different types of demand functions and government objectives. Under a linear drug demand schedule, the demand arrest policy is likely to be more effective due to asymmetric effects on the negotiated drug price and the legitimate labor employment, especially when both arrest policies yield similar law enforcement spending effects. This asymmetry is absent in conventional canonical Walrasian models without market frictions. Compared to the objective of minimizing active drug selling, the deterrence of potential drug dealer entry results in a relatively lower optimal supply arrest rate while promotion of community's aggregate income leads to lower levels of both optimal drug arrest policies. Under a constant-elasticity drug demand schedule, the main conclusions concerning various local government objectives remain valid. However, the price elasticity of drug demand is a crucial determinant for comparing the effectiveness of demand and supply policies. In a society with severe drug problems so that drug demand is inelastic to price changes, demand-side arrest policy is preferred.

Our model can be readily used for two important policy evaluations. One is to examine the effectiveness of employment policy on crime reduction and community welfare. Such analysis can then be compared to a recent empirical paper by Ihlanfeldt (2007) who documents that even a modest improvement in job access can lower inner-city young males' drug crime significantly. Another potentially interesting extension is to evaluate the consequences of a "legalized" drug market using our modified framework that allows for multi-unit sales. In this case, limited quantities of drugs are permitted for trade with an *ad valorem* tax, whereas excessive sales are subject to arrest and

conviction. It is then possible to examine the effectiveness of this sin tax relative to direct demand-side and supply-side arrest policies and to compare the results with findings in Becker, Murphy and Grossman (2006).

Despite providing a number of useful insights for drug policy recommendations, our model of course has its limitations. Among the most noticeable is the lack of human capital, or the ability to acquire it. Our framework shunts much of the labor market framework into the background, so that even if we allowed productivity and wages to depend on human capital the basic results would not change. An interesting extension would be to allow drugs to affect human capital negatively, due to their adverse physical and psychological effects as documented by DeSimone (2002). Another is to allow human capital to have positive wage effects and positive neighborhood externalities. The latter channel is likely to cause residents to under-invest in human capital, thus driving "too many" into the drug trade. In this case, not only will the effectiveness of the demand and drug arrest policies be different, but there may be a positive role for policies to prevent recidivism, or even a minimum wage policy, to play in correcting the incentive problem associated with human capital investment. Finally, it is possible to link the unemployed to drug activity as in the literature on crime (Raphael and Winter-Ebmer (2001). In this case, any policy reducing the incentive to work may generate larger effects resulting in more drug activity.

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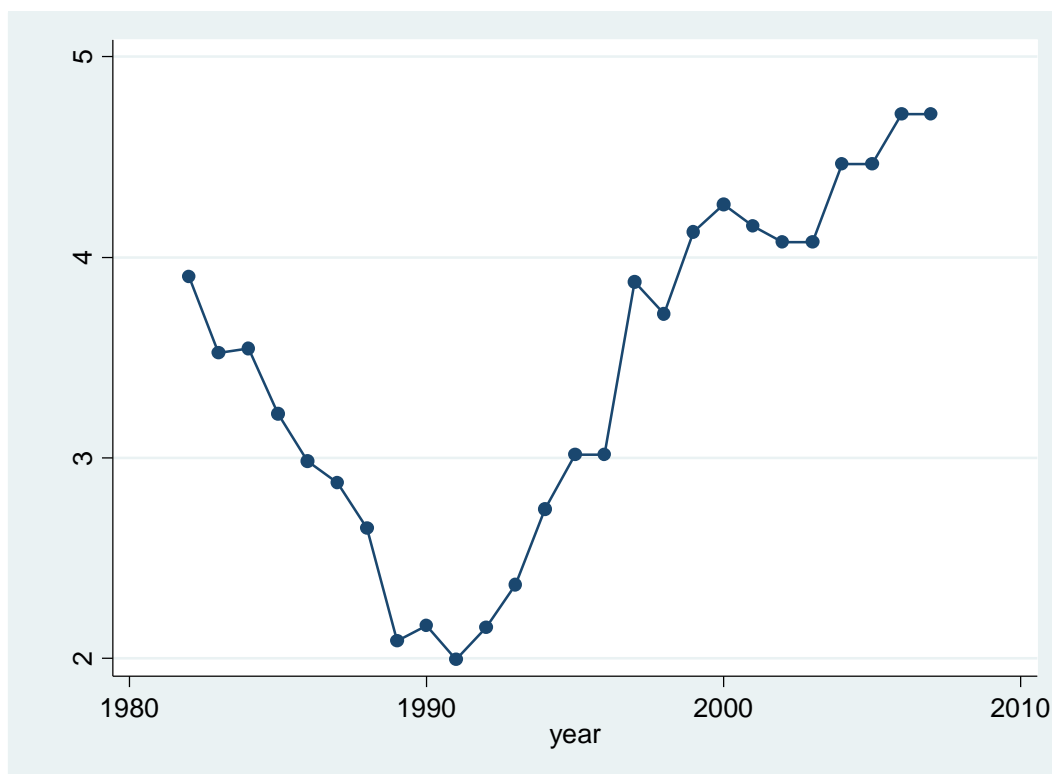
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19

Table 1: Comparative Static Analysis

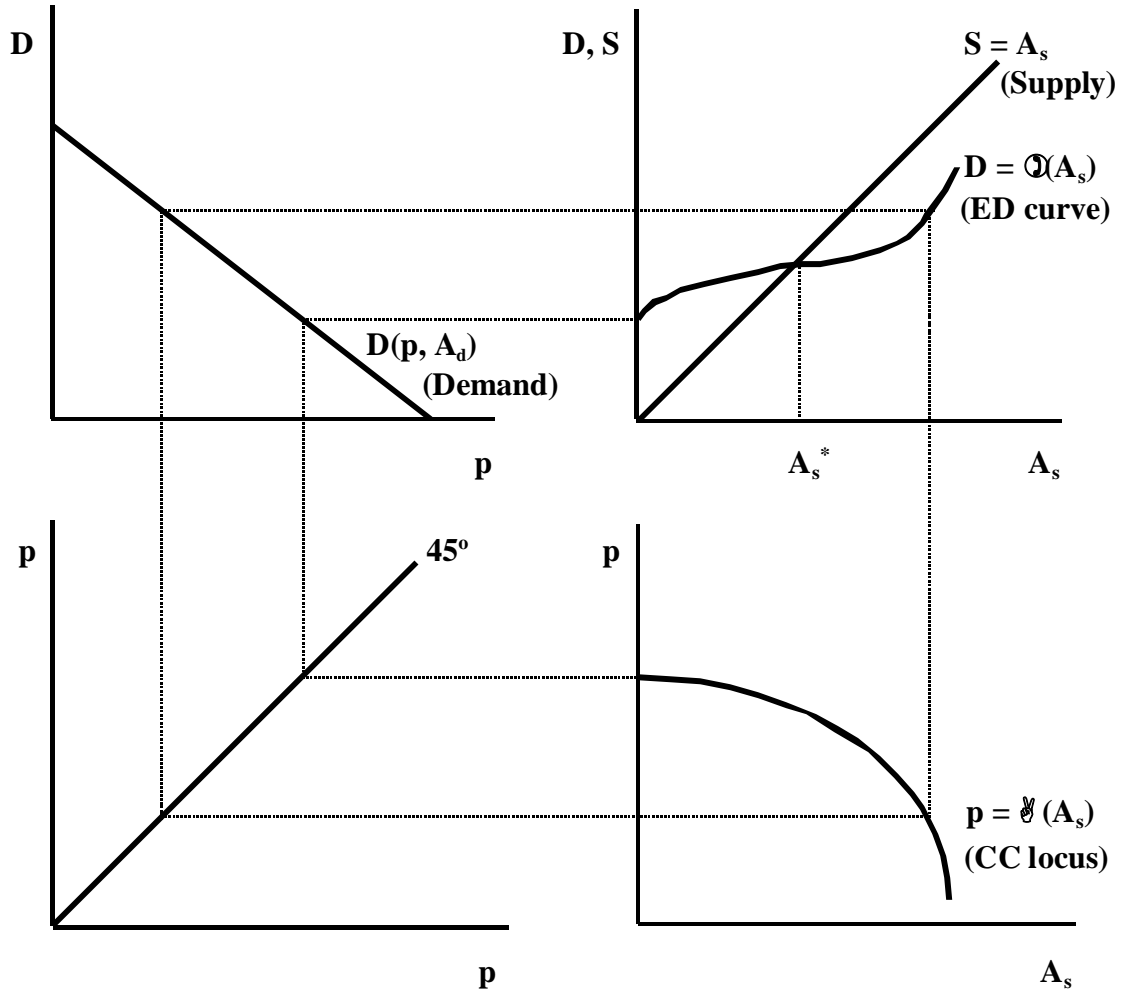| Endogenous Variable / Parameter		p	A_s	Q_s	L	Ω
Benchmark		**1.1788**	**0.2667**	**0.2957**	**0.6525**	**1.0554**
(i) Drug Demand Parameters						
B_0	$0.5725 \cdot 0.9$	1.1813	0.2223	0.2465	0.6981	1.1315
	$0.5725 \cdot 1.1$	1.1759	0.3111	0.3449	0.6069	0.9792
b	$0.1470 \cdot 0.9$	1.1777	0.2841	0.3150	0.6346	1.0254
	$0.1470 \cdot 1.1$	1.1798	0.2492	0.2763	0.6705	1.0854
D_0	$0.3861 \cdot 0.9$	1.1803	0.2398	0.2659	0.6801	1.1015
	$0.3861 \cdot 1.1$	1.1771	0.2936	0.3255	0.6248	1.0092
η	$0.65 \cdot 0.9$	1.1786	0.2695	0.2989	0.6495	1.0504
	$0.65 \cdot 1.1$	1.1790	0.2638	0.2925	0.6554	1.0603
(ii) Legitimate Labor Market Conditions						
δ	$0.0775 \cdot 0.9$	1.1855	0.2657	0.2946	0.6584	1.0650
	$0.0775 \cdot 1.1$	1.1721	0.2676	0.2967	0.6467	1.0459
θY	$1.6370 \cdot 0.9$	1.0584	0.2844	0.3153	0.6343	0.9212
	$1.6370 \cdot 1.1$	1.2991	0.2490	0.2760	0.6707	1.1955
(iii) Drug Policy Instruments						
τ_s	$0.0302 \cdot 0.9$	1.1745	0.2673	0.2935	0.6545	1.0597
	$0.0302 \cdot 1.1$	1.1831	0.2660	0.2979	0.6505	1.0511
τ_d	$0.0050 \cdot 0.9$	1.1792	0.2670	0.2960	0.6522	1.0552
	$0.0050 \cdot 1.1$	1.1784	0.2663	0.2953	0.6528	1.0556
ρ_s	$0.2778 \cdot 0.9$	1.1811	0.2663	0.2985	0.6499	1.0510
	$0.2778 \cdot 1.1$	1.1766	0.2670	0.2934	0.6546	1.0589
ρ_d	$0.5464 \cdot 0.9$	1.1788	0.2662	0.2952	0.6530	1.0561
	$0.5464 \cdot 1.1$	1.1788	0.2670	0.2961	0.6521	1.0548

Note: Other parameters are fixed at their benchmark values.

**Figure 1: Ratio of Arrests for Drug Possession to Arrest for Sale/Manufacture
1982-2007**

Source: Derived from U.S. Department of Justice, Bureau of Justice Statistics, *Drug and Crime Facts.*
http://www.ojp.usdoj.gov/bjs/dcf/tables/salespos.htm

Figure 2: Steady-State Equilibrium with Balanced Government Budget and Linear Drug Demand

D | D, S

S = A_s
(Supply)

$D = \mathbb{Q}(A_s)$
(ED curve)

$D(p, A_d)$
(Demand)

p | A_s^* | A_s

p | 45° | p

$p = \mathbb{V}(A_s)$
(CC locus)

p | A_s

Appendix

This appendix presents the mathematical details for our discussion of model extensions in Section 6.

(i)   Endogenous Drug Demand

Denoting J_L^C, J_L^A and J_L^I as the value for clean workers, active users and incarcerated users, respectively, we can then specify:

$$rJ_L^C = w + \delta(J_U - J_L^C)$$

(A1)

$$rJ_L^A = w + \delta(J_U - J_L^A) + \tau_d(J_L^I - J_L^A)$$

(A2)

$$rJ_L^I = \rho_d(J_L^A - J_L^I)$$

(A3)

where J_U is given by (9b) with $J_L = (1-\pi)J_L^C + \pi J_L^D$. Under positive demand arrest and finite demand release, straightforward manipulations yield:

$$J_L^C = \frac{w + \delta J_U}{r + \delta}$$

(A4)

$$J_L^A = \frac{w + \delta J_U}{(r+\delta) + r\tau_d/(r+\rho_d)} < J_L^C$$

(A5)

$$J_U = \mu w \left[\frac{(r+\mu)(r+\delta)}{1 - \pi + \pi(r+\delta)/[(r+\delta) + r\tau_d/(r+\rho_d)]} - \mu\delta \right]$$

(A6)

(ii)   Neighborhood Externality

The value function of an active dealer is modified as:

$$rJ_{As} = pA_s^\gamma + \tau_s(J_{Is} - J_{As})$$

(A7)

Occupational choice yields:

$$p(A_s; w, \mu, \delta, r, \tau_s, \rho_s) = \frac{\mu}{r+\delta+\mu} \frac{r+\rho_s+\tau_s}{r+\rho_s} wA_s^{-\gamma},$$

(A8)

This together with the drug market equilibrium condition under linear demand schedule implies:

$$A_s = \frac{\rho_d}{\rho_d + \tau_d} - b \frac{\mu}{r+\delta+\mu} \frac{r+\rho_s+\tau_s}{r+\rho_s} wA_s^{-\gamma}$$

(A9)

(iii)   Multi-unit Drug Dealing

For the modified occupational choice rule, J_{As}^L is as in (10c) and

$$J_{As}^H = \frac{r + \alpha\rho_s}{r + \alpha\rho_s + \tau_s(1-\beta)/\beta} \frac{pq}{r}.$$

(A10)

The equilibrium fraction of high-volume active drug dealers can then be derived as:

$$\beta = \frac{1}{1 + (r+\alpha\rho_s)[(q-1)/\tau_s + q/(r+\rho_s)]}.$$

(A11)

23

(iv)   Utility Cost of Incarceration

The modified occupational choice gives the drug price function as follows:

$$p(w, \mu, \delta, r, \tau_s, \rho_s) = \frac{\mu}{r + \delta + \mu} \frac{r + \rho_s + \tau_s}{r + \rho_s} w + c.$$

(A12)

(v)   Social Costs of Drugs

The modified occupational choice rule becomes:

$$p(w, \mu, \delta, r, \tau_s, \rho_s) = \frac{\mu}{r + \delta + \mu} \frac{r + \rho_s + \tau_s}{r + \rho_s} (w - \psi A_s),$$

(A13)

Drug market equilibrium under linear demand schedule gives:

$$A_s = \left(1 - b\psi \frac{\mu}{r + \delta + \mu} \frac{r + \rho_s + \tau_s}{r + \rho_s}\right)^{-1} \left[\frac{\rho_d}{\rho_d + \tau_d} - b \frac{\mu}{r + \delta + \mu} \frac{r + \rho_s + \tau_s}{r + \rho_s} w\right]$$

(A14)

A sufficient condition to ensure the validity of our results is $\dfrac{b\psi\mu}{r + \delta + \mu} \dfrac{r + \rho_s + \tau_s}{r + \rho_s} < 1$, which holds true if

ψ is not too large.

24