An empirical model for drug traffic in the City of Sao Paulo

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This paper aims to empirically evaluate the determinants of the drug traffic in the City of Sao Paulo. The quantity of drug apprehended by the police is used as a proxy to the activity level of the market for drugs. These data are monthly, for the year 2001, and were obtained from the State of Sao Paulo Secretary for Public Safety and refer to all 93 police districts in which the City of Sao Paulo is divided and are available for each kind of drug (marijuana, cocaine, crack, etc). Since despite the existence of a continuously ongoing drug activity, there are months that no drug is apprehended, so a censored model such as, for instance, a TOBIT model is appropriate. Other variables to be included in the model are income, other crime rates, geographical location, etc.

Keywords: drugs, traffic, economics of crime, censored models, discrete models
JEL: K42, C1, C24, C25

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1. Some Theoretical Considerations

After the seminal work of Becker (1968) on Economics of Crime, several works ors have been written about drugs, the way they are consumed and some models for traffic. In this part of the article we will first show the problem in the way it is presented in the both sides.

Fernandez and Maldonado (1988 and 1999) wrote that the reasons for people doing traffic may be individual or social. The individual reasons are: psychic nature, as ambition, easy money or envy. Social reasons could be poverty, unemployment and low knowledge about the subject.

1.1 The supply case

In the work of Gaviria (2000), three premises are used:

a) criminals do crimes to people that lives next them, as this way the probability of being arrested is lower;

b) interaction of career criminals and local swindlers can improve the spread of the know how in crime

c) Daily contact of young with adult criminals results moral erosion and great tendency for crime.

Although there are others explanations for these questions. One of them we can find in Becker's (1968) seminal paper. The author wrote that criminals are rational, agents interested whose comportment can be better explained as a response to incentives. He also says that criminals will expand their activities if they are sure that the penalty they will suffer will be diminished. Other explanation can be found in an article of Ehrlich (1996) that tells about general equilibrium in the crime model: crime would be determined for supply and demand for crime. Models of Becker and Ehrlich are based in Microeconomic theory, considering negative feedbacks, i.e., the emphasis in how government and private expenses in drugs controlling, changes in criminal behaviour and the impact on combat expenses.

Romer (1993) wrote that local firms in poor countries generate flow of multinational knowledge of production, marketing and business. This way, it can be said that criminals that live in Colombia took cartels expertise for buying guns in international black market, and learned how to make money became by traffic into “clean money”, and identifying “connections” in local policy. Gaviria (2000) explained that a partial answer to this is that people form traffic became role models for one part of the population. Their actions were copied for many people and crime became a way of life. In this way we can say that authorities failed, since this promoted an increase of crime levels. Crimes in different cities suggested that crime in neighbor cities could be guided for similar forces.

In Becker, Murphy and Grossman (2004) we can find a supply analysis for illicit goods. This analysis shows as important variables the enforcements efforts government do against traffic (E) and a cost imposed to the addicted person (T).

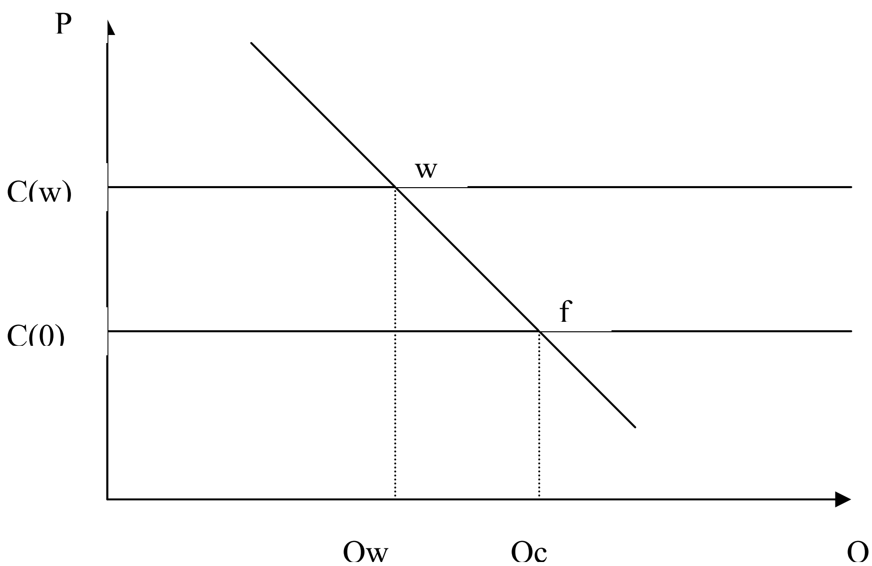
The equation considering these points is:

$$P_e = c(E) + T \qquad (1)$$

Without war against drugs, T = 0, E = 0 and $P_e = c(0)$. This way the equilibrium point f is showed in figure 1.

With war against drugs concentrated in production and distribution combat, E>0, but T = 0, as there isn’t consumption penalties. In this case, the equilibrium is moved form point f to point w, as showed in figure 1.

Figure 1



Assume demand price elasticity ε <0, constant, we may do:

$$\Delta\%Q = \varepsilon\ \Delta\%c \qquad (2)$$

And the change in consumer expenses in drugs, when they become illegal is showed by:

$$\Delta\%R = (1+\varepsilon)\ \Delta\%c \qquad (3)$$

As consequence of competitive market, productors gain zero economic profit, what means that production costs and drugs distribution are equal to revenues obtained in their market as those obtained in free market (without war on drugs), and the illegal market (with war). So, the change in costs caused by the introduction of drugs combat in the market should be equal to the change of revenues obtained in this same market that, for equation (3) will be positive when demand is inelastic and negative otherwise.

Paradoxically, if demand for drugs is inelastic, the increase in severity for combating drugs will deliver to an investment increase of resources invested for suppliers in this market.

If we suppose that governments maximize social welfare, that depends of social evaluation of goods (and not of private evaluation that consumers does of them). From the point of view of suppliers and distributors, the best thing to do is take actions that avoid government combat.

Now we consider the variable Q, that is the amount of drugs consumed, P, the price of drugs, and F, the monetary factor attributed to loss of utility due to penalty. Also considering that the production function has constant returns on scale and that c is your cost in competitive market without taxes or combat (so, c = c(0)), A the amount of private expenses for avoiding government combat, and E the level of government enforcement in combat for one unity of the product and p(E,A) the probability of drug dealer being arrested, the unitary cost expected (v), will be calculated for the following expression:

$$v = \frac{c + A + p(E,A)F}{1 - p(E,A)} \quad (4)$$

If we define θ as the rate between the probability of being arrested and the probability of not being, i.e.:

$$\theta(E,A) = \frac{p(E,A)}{1 - p(E,A)} \quad (5)$$

And doing the necessaries changes in equation (4), we have:

$v = (c+A)(1+\theta)+\theta F$ (6)

When A includes all direct costs of operating an illegal firm, what means, for example, the cost of using a transport less efficient for calling less the attention or the costs of not having access to the laws for solving problems with contracts. The price of the equilibrium will exceed competitive price in a legalized market not only for this type of cost, but also for penalty costs expected, as variable θF.

In competitive equilibrium, a higher F doesn't have effect in expected profit as the market price increases reflecting the increase in expected costs due to the increase in penalties. Those drug dealers who can be able to run away form penalties will earn bigger profits.

The maximum point will be obtained when the unitary cost will be minim. As the variable controlled by drug dealers is A, there is an optimum level of A that is when the average minim cost is target. This average minim cost (v*) will be equal price:

$$P = v^* = (c+A^*)(1+\theta)+\theta F \ (\theta = \theta(E,A^*)) \quad (7)$$

If we do the derivate calc related to E, we obtain:

$$\frac{dP}{dE} = \left(c + A^* + F\right)\frac{d\theta}{dE} + \left[\left(1+\theta\right) + \left(c + A^* + F\right)\frac{d\theta}{dA}\right]\frac{dA}{dE} \quad (8)$$

Considering the envelope theorem, the second term on the right must be equal zero in the optimum point. So:

$$\frac{dP}{dE} = \left(c + A^* + F\right)\frac{d\theta}{dE} \qquad (9)$$

And if we take the logarithm of equation above, we obtain:

$$\frac{d\ln P}{d\ln E} = \frac{\varepsilon_\theta \theta\left(c + A^* + F\right)}{P} \qquad (10)$$

where ε_θ is the elasticity of θ due to E and, if we consider $\lambda = \theta(c + A^*+F)/P < 1$, we have:

$$\frac{d\ln P}{d\ln E} = \varepsilon_\theta \lambda \qquad (11)$$

And if the elasticity of demand for drugs will showed as ε_d, so we will have:

$$\frac{d\ln Q}{d\ln E} = \varepsilon_d \frac{d\ln P}{d\ln E} = \varepsilon_d \varepsilon_\theta \lambda \qquad (12)$$

And if law is imposed as a public good, so its costs will be independent of drugs level, i.e.:

$$C(E,Q) = C(E) \qquad (13)$$

But, if it is a purely private good, as the production function is, for hypothesis, of constant returns:

$$C(E,Q) = Q\ C(E) \qquad (14)$$

If we suppose that, in fact, they are a mix of both (public and private), and also consider the costs of penalties of those that been caught, that we will assume proportional to its total number (θQ). We will have:

$$C(Q,E,\theta) = C_1 E + C_2 Q E + C_3 \theta Q \qquad (15)$$

Choosing in correct way unities of E, will may have C(E) = E.

If the function of social value is V(Q), we have that the derivate, V_q will be minor that the price P if the social value of the drug is less that the private value that people wants to pay for it.

For making the well fare maximum, the government would choose a level E that would minimize w as follows:

$$\max w = V(Q(E)) - v(E)Q(E) - c(Q(E), E, \theta(E, A^*(E)))E \quad (16)$$

The first order condition results:

$$CMg_E = Vq\frac{\partial Q}{\partial E} - RMg\frac{\partial Q}{\partial E} \quad (17)$$

where CMg_E are the marginal costs of drugs combat and RMg are the marginal recipes obtained in this market.

If we assume that the marginal costs are equal zero, we will have:

$$Vq = RMg = P^*\left(1 + \frac{1}{\varepsilon_d}\right) \quad (18)$$

And,

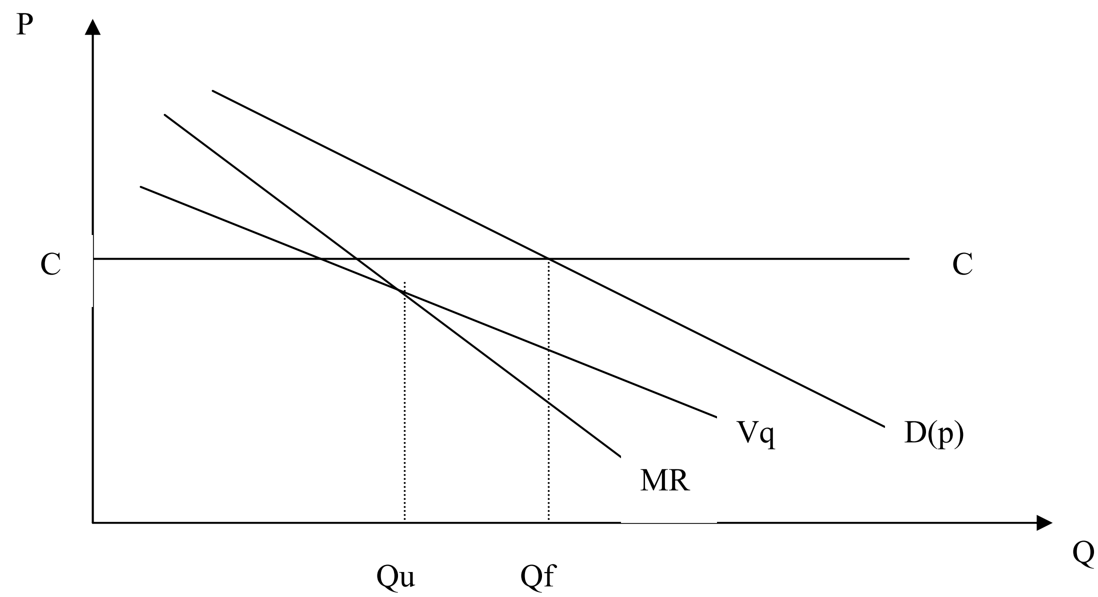
$$\frac{Vq}{P} = \left(1 + \frac{1}{\varepsilon_d}\right) \quad (19)$$

where the rate of V_q and P represents the relation of the social value of the drug and the private price.

This means that the optimum level of drugs combat could be zero if V_q is not negative and if demand is inelastic, causing marginal recipe negative.

If demand is elastic can not be social optimum decrease product if the good consume has social value positive. Intervention is more recommended when $V_q<0$. If demand is inelastic the marginal recipe will also be negative.

Figure 2: elastic demand



Another relevant question is that most times war on drugs politics are partially effective. There are other high social costs, as resources expenses, official corruption and arrestment of productors and addicteds. Considering these points, many people defend partial or total drugs legalization.

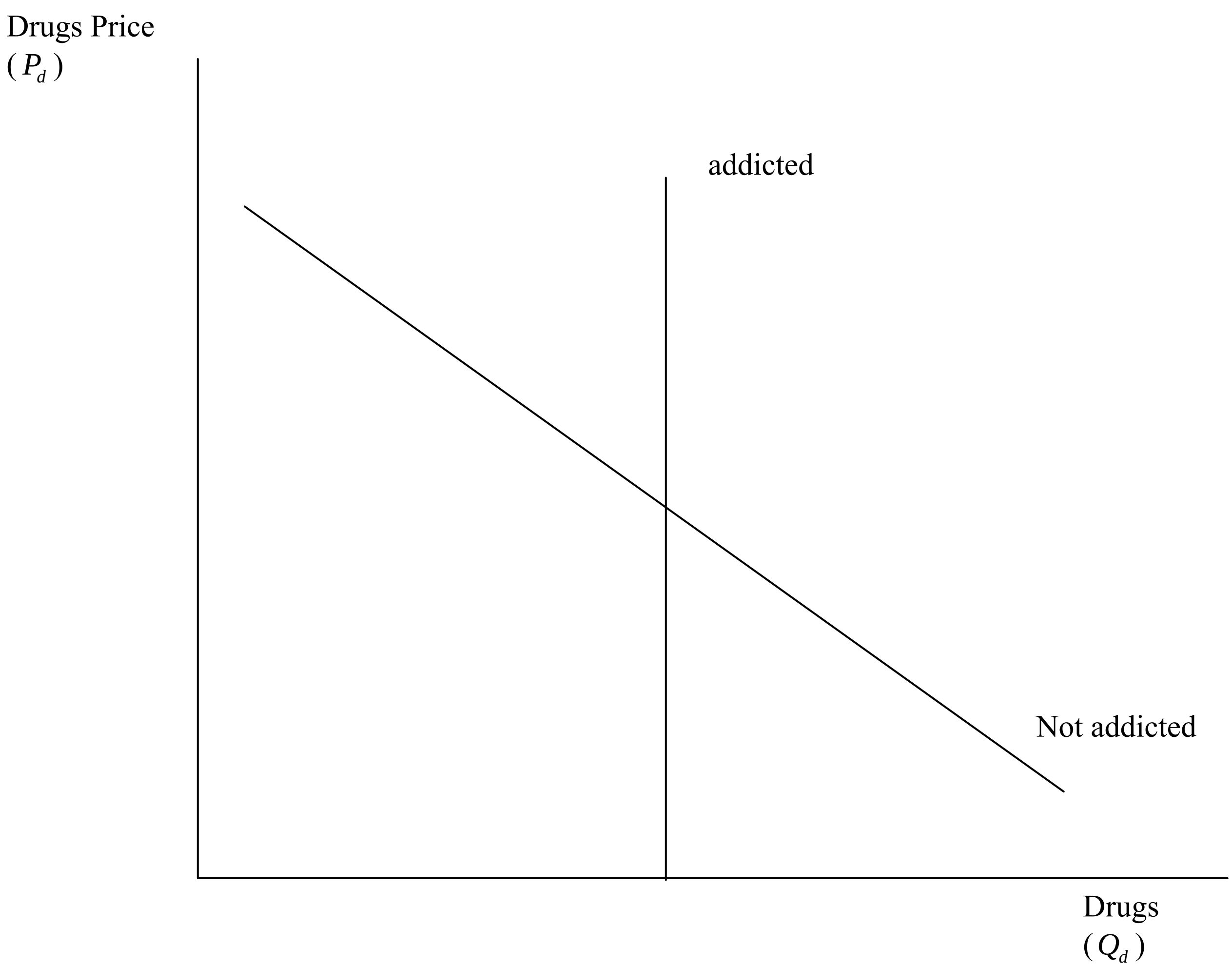
Another point of view that may be recorded is that illegal firms should be superior costs. For limit firms that wants to enter market, the prohibition acts as decreaser of market elasticity. If elasticity is minus than infinity, some firms have low costs, even if they are illegal and government must be more active.

With higher combat expenses, change in productor costs is minor that in consumer costs, as price increases. Social costs, in this case, should be measured in changes of supplier costs.

1.2 The demand case

Escobar (1993) defines two types of consumers: the addicted that are characterized for a relation of dependence of drugs, and the not addicted, that are consumers that search drugs occasionally, and doesn’t present a compulsive relation with drugs. Social value inside the last type of consumer doesn’t percept that in this group could have a social problem of addiction to consume through the flow: use-abuse-addiction. Demand traffic for these two consumers follows the format:

Figure 3:



This way we see that for Escobar (1993) the demand for addicteds is inelastic, but the demand for not addicted has points of low and higher elasticity. There is also another way of considering consume of drugs between the analysis of social welfare. With this, we obtain the following equation form maximizing this variable:

$$\max I_{D,R,\beta} = W(D,R) - \beta(P_d D + P_r R - Y); D \rangle 0; R \rangle 0 \quad (20)$$

Where:

D = drugs

R = rest of goods available

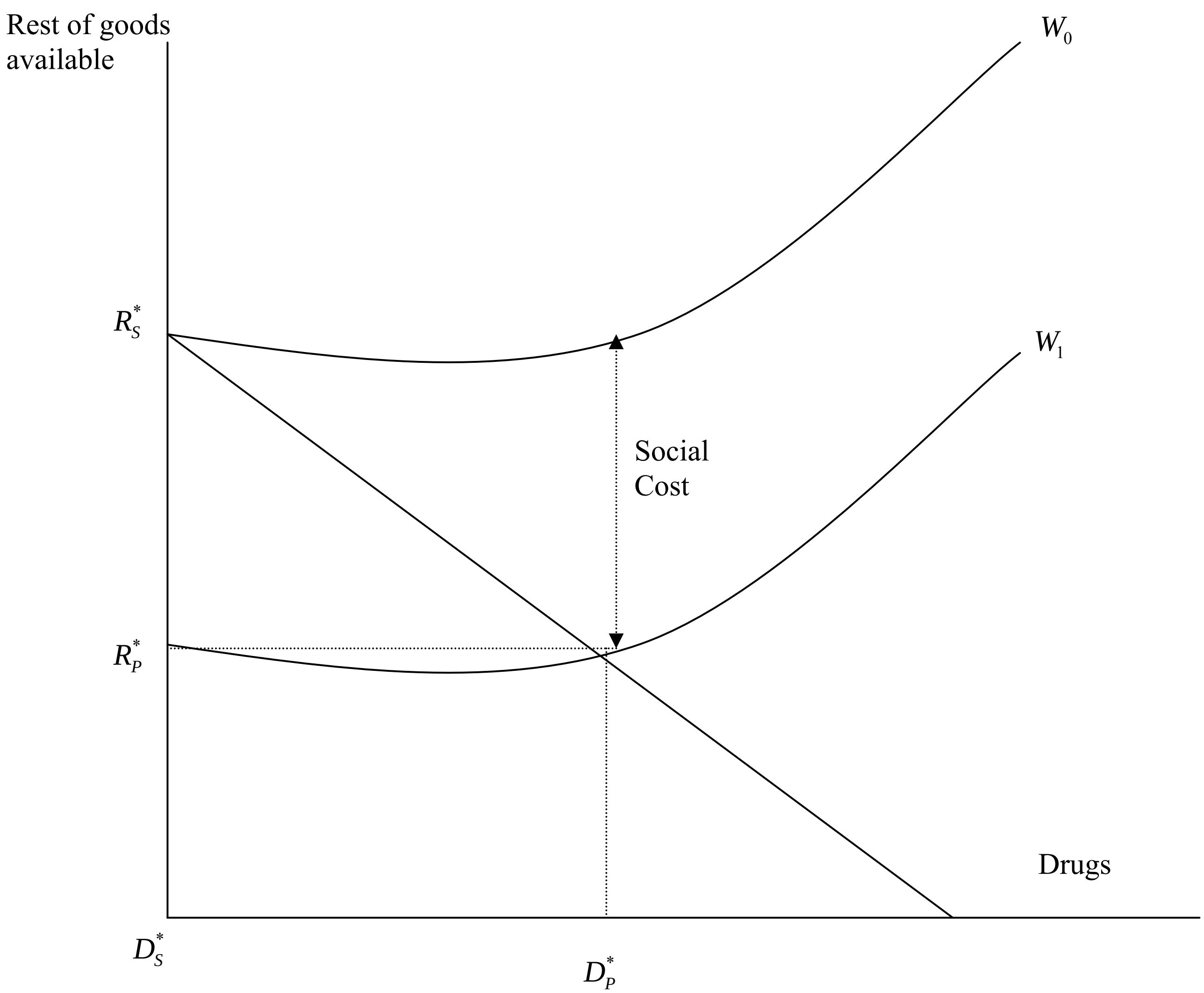
P_d = drugs price

P_R = rest of goods available price

Y = income

There is a maximum point of this well fare, although, Escobar (1993) points that there is a difference between the maximum well fare and private well fare. Figure 2 show the maximum well fare as W_0 and the private well fare of W_1, and we observe this in the figure below. The difference between the two curves can be considered as the social cost of combat, information of prevention and increase of number of addicteds.

Figure 4



The idea of an individual be engaged in consuming drugs sounds contradict the hypothesis of a rational, or at least, if it isn't completely rational, has a shorted view as it is maximizes its present utility without considering future consequences, maybe for problems of asymmetric information.

Although, Becker and Murphy (1988) say that is possible, if we maintain the hypothesis of consumer rationality, explain how someone can be addicted.

In the model of Becker and Murphy, the utility of an individual depends of two goods, x and y, that are distinguished as the follows: the current utility also depends on the past quantity consumed of x, but not depends on the past quantity consumed of y, so we can write this relation as equation 21:

$$u(t) = u[y(t), x(t), S(t)] \qquad (21)$$

where past quantity consumed of x affects current utility though a learning process measured by variable S, the reserve of what is called "consume capital", that may be modeled through a function of investment showed below:

$$\dot{S}(t) = x(t) - \delta S(t) - h[D(t)] \qquad (22)$$

where $\dot{S}$ is the rate of change in S through the time, x is the gross investment in "learning", δ is the depreciation tax that measures the exogenous tax of disappearance of physical and mental effects of past consume of x and D.

Considering the given period of life, T, and a given discount rate of constant preferences σ, the utility function will be:

$$U(0) = \int_0^T e^{-\sigma t} u[y(t), x(t), S(t)]dt \qquad (23)$$

so we can see that the consumer behaviour toward the drugs will depend of the constants σ and δ.

The constant δ measures the tendency someone has to become addicted to good x. if the consume of x, otherwise, have negative consequences in the future, the consumer will tend to reduce the present consume of x, as the total utility of it – U(0) – will be reduced. The magnitude of this reduction depends on the tax of discount of preferences σ.

But if presents choices affect the future level of personal capital, among others, future utilities functions don't change just the levels of utility change.

2. Empirical Model

Data used in estimations could be divided into two big sets. One set, the "crime data", is originated from the State of Sao Paulo Secretary of Public Safety and it is available from CIS (Social Information Consortium).

Another data set, let's call it "social data" comes from two different sources: the Government of the City of Sao Paulo and IBGE (Brazilian Institute of Geography and Statistics).

Both data sets are for the year 2001, however there are some incompatibilities between them: while the "crime data" is monthly, "social data" is annual, so we must consolidate crime data in one year. Another issue is that crime data comes from the police districts of the City of Sao Paulo (there are 93 of them), while social data comes from the official city districts, a different division (there are 96 official city districts). We must either match crime data to the official districts or much social data to police districts. We chose the last one, since all of our dependent variables come from the crime data. For this purpose we use the same match as Sartoris (2000).

The variables in crime data are: the quantity of drug apprehended in each district (MARIJUANA, COCAINE and CRACK); the number of prisons, in general (PRISONS); the number of drug apprehensions (APREHEN); the number of crimes against property (PROPER); and the number of crimes against people (PEOPLE).

The variables in social data are: income, measured in minimum wage units (INCOME); the number of "favelas" – communities of very poor people living in poorly built houses – in each district (NFAV); the are occupied by the "favelas" (AREAFAV); population of age between 15 and 24 (POP1524); population of age between 25 and 44 (POP2544); population of age between 15 and 44 (POP1544).

Our first attempt is to estimate a model for apprehensions. The result of the estimation is shown in table 1.

Table 1- dependent variable: APREHEN

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-13.31071	13.72883	-0.969545	0.3351
PRISONS***	0.212859	0.028800	7.390957	0.0000
INCOME	1.276020	0.864343	1.476289	0.1436
AREAFAV	-0.002180	0.001932	-1.127977	0.2625
NFAV	0.949855	0.978749	0.970479	0.3346
POP1524	-0.001171	0.001694	-0.691227	0.4913
POP2544	0.000538	0.001039	0.517806	0.6060
PEOPLE***	0.029406	0.009055	3.247415	0.0017
PROPER***	-0.006957	0.001999	-3.479856	0.0008
R-squared	0.622519	**Mean dependent var**		41.08602
Adjusted R2	0.586569	**S.D. dependent var**		33.28260
S.E. of regression	21.40025	**Akaike info criterion**		9.056448
Sum squared resid	38469.55	**Schwarz criterion**		9.301538
Log likelihood	-412.1248	**F-statistic**		17.31599

*significant at 10% level.
**significant at 5% level.
***significant at 1% level.

Since AREAFAV is obviously correlated to NFAV, let's try using just one of them, which can be seen in tables 2 and 3.

Table 2 - dependent variable: APREHEN (excluding NFAV)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-17.10382	13.15622	-1.300056	0.1971
PRISONS***	0.218948	0.028099	7.792140	0.0000
INCOME*	1.466101	0.841571	1.742102	0.0851
AREAFAV*	-0.000312	0.000171	-1.824015	0.0717
POP1524	-0.000899	0.001670	-0.538314	0.5918
POP2544	0.000417	0.001031	0.404477	0.6869
PEOPLE***	0.030027	0.009030	3.325404	0.0013
PROPER***	-0.007371	0.001953	-3.774949	0.0003
R-squared	0.618287	**Mean dependent var**		41.08602
Adjusted R2	0.586852	**S.D. dependent var**		33.28260
S.E. of regression	21.39293	**Akaike info criterion**		9.046093
Sum squared resid	38900.88	**Schwarz criterion**		9.263951
Log likelihood	-412.6433	**F-statistic**		19.66862

*significant at 10% level.
**significant at 5% level.
***significant at 1% level.

Table 3 - dependent variable: APREHEN (excluding AREAFAV)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-17.71366	13.18330	-1.343644	0.1826
PRISONS***	0.219859	0.028168	7.805181	0.0000
INCOME*	1.503106	0.841916	1.785340	0.0778
NFAV*	-0.149824	0.086722	-1.727625	0.0877
POP1524	-0.000887	0.001678	-0.528635	0.5984
POP2544	0.000411	0.001034	0.397596	0.6919
PEOPLE***	0.030014	0.009054	3.315146	0.0013
PROPER***	-0.007428	0.001958	-3.792923	0.0003
R-squared	0.616802	**Mean dependent var**		41.08602
Adjusted R2	0.585244	**S.D. dependent var**		33.28260
S.E. of regression	21.43451	**Akaike info criterion**		9.049976
Sum squared resid	39052.24	**Schwarz criterion**		9.267834
Log likelihood	-412.8239	**F-statistic**		19.54532

*significant at 10% level.
**significant at 5% level.
***significant at 1% level.

The results improve in both tables, but there is a slight advantage to the model including AREAFAV.

We could also use the population from 15 to 44 years old, instead of separating in two groups.

Table 4 - dependent variable: APREHEN (with POP1544)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-18.96802	12.53429	-1.513290	0.1339
PRISONS***	0.218806	0.027972	7.822228	0.0000
INCOME*	1.667438	0.730398	2.282917	0.0249
AREAFAV*	-0.000325	0.000168	-1.938990	0.0558
POP1544	-8.46E-05	8.70E-05	-0.972730	0.3334
PEOPLE***	0.029945	0.008988	3.331743	0.0013
PROPER***	-0.007281	0.001935	-3.762348	0.0003
R-squared	0.617216	**Mean dependent var**		41.08602
Adjusted R2	0.590510	**S.D. dependent var**		33.28260
S.E. of regression	21.29800	**Akaike info criterion**		9.027389
Sum squared resid	39010.01	**Schwarz criterion**		9.218015
Log likelihood	-412.7736	**F-statistic**		23.11164

*significant at 10% level.
**significant at 5% level.
***significant at 1% level.

The age variable is still non significant, but there is a slight improvement in the results.

The estimation suggests that drug apprehension tend to happen more on districts with more crimes against people and less on districts with more crimes against property. That result could be income related if the model itself was not controlled by income. Since income is also significant, it could mean that the spatial distribution of traffic is more associated to crimes against people, indicating that one kind of crime must affect the other.

Surprisingly, the variable for "favelas" is negatively associated to the number of apprehensions. The sign for number of prisons is, however, the same as expected, i.e., districts with more police activity, possibly with more efficiency in the police work, has more apprehensions.

Tables 5, 6 and 7 show the estimations for the quantity of drugs apprehended (marijuana, cocaine and crack). Since not all districts had crack apprehension, that is a censored variable, so a Tobit estimation is more appropriate[1].

Table 5 – dependent variable: MARIJUANA

Variable	Coeff.	Std. Error	t-Statistic	Prob.
C	64535.15	35887.30	1.798273	0.0756
PRISONS	-12.47349	80.08841	-0.155747	0.8766
INCOME	-2041.250	2091.224	-0.976103	0.3318
AREAFAV	0.464987	0.480505	0.967705	0.3359
POP1544	-0.407772	0.249068	-1.637190	0.1052
PEOPLE	-14.76285	25.73357	-0.573681	0.5677
PROPER	2.367640	5.540894	0.427303	0.6702
R-squared	0.040401	Mean dependent var		15854.19
Adjusted R2	-0.026547	S.D. dependent var		60185.28
S.E. of regression	60978.93	Akaike info criterion		24.94673
Sum squared resid	3.20E+11	Schwarz criterion		25.13736
Log likelihood	-1153.023	F-statistic		0.603468

*significant at 10% level.
**significant at 5% level.
***significant at 1% level.

[1] See Maddala(1983).

Table 6 – dependent variable: COCAINE

Variable	Coeff.	Std. Error	t-Statistic	Prob.
C	1305.785	1117.071	1.168936	0.2457
PRISONS	0.504475	2.492928	0.202362	0.8401
INCOME	-29.37098	65.09396	-0.451209	0.6530
AREAFAV	-0.002255	0.014957	-0.150742	0.8805
POP1544	-0.005680	0.007753	-0.732629	0.4658
PEOPLE	0.561790	0.801014	0.701348	0.4850
PROPER	-0.127575	0.172473	-0.739684	0.4615
R-squared	0.021495	Mean dependent var		657.4516
Adjusted R2	-0.046773	S.D. dependent var		1855.213
S.E. of regression	1898.104	Akaike info criterion		18.00738
Sum squared resid	3.10E+08	Schwarz criterion		18.19801
Log likelihood	-830.3433	F-statistic		0.314860

*significant at 10% level.
**significant at 5% level.
***significant at 1% level.

Table 7 – dependent variable: CRACK (Tobit estimation)

Variable	Coeff.	Std. Error	z-Statistic	Prob.
C	-567.1111	861.2972	-0.658438	0.5103
PRISONS	-0.459071	2.047022	-0.224263	0.8226
INCOME	62.84044	47.90526	1.311765	0.1896
AREAFAV	0.012360	0.011541	1.071006	0.2842
POP1544	0.001481	0.006005	0.246649	0.8052
PEOPLE	-1.453315	0.776251	-1.872223	0.0612
PROPER	0.010460	0.133553	0.078320	0.9376
R-squared	0.056032	Mean dependent var		93.10753
Adjusted R2	-0.021707	S.D. dependent var		575.3098
S.E. of regression	581.5203	Akaike info criterion		5.780074
Sum squared resid	28744094	Schwarz criterion		5.997932
Log likelihood	-260.7735	Hannan-Quinn criter.		5.868039

*significant at 10% level.
**significant at 5% level.
***significant at 1% level.

None of the regressions above show any significance whatsoever, with only one except for the variable crimes against people in the crack model. These results are probably due to the erratic behavior of the quantity variables.

Final remarks

In our attempt to build a model for drug traffic in the city of Sao Paulo, we have more successful when using the number of apprehensions, rather than the apprehended quantity.

Drug traffic responds positively to income, which is expected, since as well as in any other market, the higher income is, higher is the demand and bigger the market. However, it is negatively related to the area of “favelas”, which is surprising, since bigger “favela” areas tend to stimulate crime due to difficulties of law enforcement activity.

Police efficiency also seems to explain drug apprehensions. They are also specifically related to different kinds of crimes, positively to crimes against people, and negatively to crimes against property. This result suggests that law enforcement efforts in combat drug traffic and crimes against people must be, at least in part, a conjoint task.

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