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LAW ENFORCEMENT, THE PRICE OF COCAINE AND COCAINE USE

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Abstract—In this paper I investigate the relationship between law enforcement and the price and use of cocaine. I merge data from the Drug Enforcement Administration's (DEA) STRIDE (System to Retrieve Information from Drug Evidence) and MTF (Monitoring the Future). In particular, I apply a variety of grouped data estimators and relate these estimators to instrumental variables techniques, quasi-experiments, and classical experimental design.

I find no evidence that regional and time variation in DEA seizures of cocaine is helpful in explaining variation in either the demand or price of cocaine.

1. INTRODUCTION

One important component of U.S. drug policy is interdiction and the restriction of supply. It is widely held that such a policy is at least partially effective in reducing consumption through its alleged effect on the price of drugs. In the late 1980's and early 1990's one drug in particular, cocaine, has been the subject of a considerable amount of such enforcement activity.

However, there has been little effort made in obtaining reliable estimates of the efficacy of law enforcement in achieving any of its goals. Data on governmental activity regarding drug use and law enforcement is extremely difficult to obtain and, when it is collected, it does not appear to be collected with an eye toward its evaluation.

This essay investigates the relationship between law enforcement and the price of cocaine. Toward this end, data on law enforcement and price is used in combination with additional information on cocaine use in a simple empirical exercise to evaluate the participation elasticity of demand with respect to law enforcement. I use two data sets: System to Retrieve Information from Drug Evidence (STRIDE) which is collected by the Drug Enforcement Agency (DEA) and a special data set from Monitoring the Future (MTF) collected at the University of Michigan Institute for Social Research.

2. SUPPLY, DEMAND, AND THE "REDUCED FORM"

A primary reason for investigating the determinants of the price of cocaine is the presumed effect of the price on consumption and use. As it turns out, a focus on "demand" effects is also useful to empirically evaluate the effects of law enforcement on price. While I will not pursue a detailed study of the determinants of the demand for cocaine in this paper, recourse to demand side data is crucial for understanding the "supply" side of the market. In the following section, I will relate the notions of supply and demand to the task at hand with a simple statistical model.

2.1. A Simple Formal Model

Suppose we had a variable, "high-level seizures," that represented DEA activity that affected the supply of cocaine but influenced the demand of users only through changes in price. This would not be the case if, for example, users reduced the amount they demanded after hearing about a high-level seizure. However, let us assume for the moment that we have such a variable.

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To understand the strategy more analytically, consider the following simple model of demand for cocaine:[1]

$$q^d_{st} = \beta \log(p) + \phi Z, \tag{1}$$

where q^d is the quantity of cocaine demanded in state s at time t, p is the real price of cocaine, $\beta < 0$, and Z refers to the influence of other factors.

There is a corresponding supply equation:

$$q^s_{st} = \gamma \log(p) + \delta X, \tag{2}$$

where X is the level of DEA seizures $\delta < 0$, and $\gamma > 0$.

Equilibrium in the market for cocaine requires that:

$$q^d_{st} = q^s_{st}. \tag{3}$$

This problem is typically analyzed in the framework of "two-stage least squares." Sometimes the simple insight from two stage least squares is obscured and, therefore, I think it instructive to consider the more basic Ordinary Least Squares prediction of the model. For simplicity in exposition, let $\phi = 0$ and let X be a single factor. The assumption that $\phi = 0$ is an exclusion restriction. That is, we can assume that X has no independent effect on the demand for cocaine except through its impact on the supply (price) of cocaine. For example, think of X as representing the total weight of all cocaine seizures (excluding seizures related to purchases).[2]

Rewrite equation (2) as follows (dropping the subscripts for ease of exposition):

$$\log(p) = \frac{-\delta}{\gamma} X + \frac{1}{\gamma} q^s. \tag{4}$$

The interpretation of equation (4) is that factors leading to a decrease in supply (such as increased incidence of seizures) lead to *increases* in the supply price. Substituting (4) into (1) and using (3) results in the following "reduced form":

$$\begin{aligned} q &= \frac{-\delta\beta}{\gamma - \beta} X \\ &= \Pi_q X. \end{aligned} \tag{5}$$

Since $\beta < 0$, $\delta < 0$, and $\gamma > 0$, Π_q, the reduced form coefficient on X, is also negative. It is also useful to note the other reduced form equation:

$$\begin{aligned} \log(p) &= \frac{-\delta}{\gamma - \beta} X \\ &= \Pi_p X. \end{aligned} \tag{6}$$

Equation (5) has an intuitive explanation. If a policy such as increased law enforcement is hypothesized to work through its impact on the price and availability of cocaine, then the coefficient in an OLS regression of consumption on quantity of seizures (with all other relevant variables included) should be negative—the greater the amount of law enforcement activity, the lower the consumption. Likewise, equation (6) is also intuitive. To be coherent, increased enforcement must be positively correlated with the price.

It is possible that increased seizures also have a negative effect on demand for cocaine. If this is the case, then the coefficient estimated in equation (5) will be too negative. Note however, that even in the presence of a violation of the necessary exogeneity condition one should still expect a negative effect of law enforcement on consumption. In a sense, the "cards are stacked" in favor

[1] In other work, I have considered the problem that the demand for one drug is not independent of the demand for other drugs [1]. As will become clear, the success of this endeavor will not depend crucially on this issue.

[2] The appropriateness of this assumption will be discussed below.

of finding a negative effect. Although the bias on β (the relationship between demand and price) is not known *a priori*, the reduced form equation (5) is of independent interest.[3]

Furthermore, as is clear from the above discussion, in the case where seizures are the only instrument, the two-stage least squares estimator can be read off from the reduced form equations (5) and (6)—it is simply the ratio Π_q/Π_p. In sum, for this strategy to be coherent:

- The effect of increased seizures on the price of cocaine must be positive.
- The effect of price on cocaine use must be negative.
- The effect of seizures on the demand for cocaine must work its way solely through its effect on the price.

The first two assumptions are easily tested. The third prediction is more of a problem, although (with additional information) it can be tested. In particular, if the analyst has information on a different instrumental variable, which on *a priori* grounds is valid, then the third prediction can also be tested [3]. I do not have such a variable. However, as we will see, the first two predictions will be problem enough.

2.2. Empirical Strategy

I have already introduced two problems that will need to be addressed by any estimation procedure:

- Measurement Error in the explanatory variables;
- The endogeneity of price and consumption.

In this section, I suggest an estimation strategy which, in principle, can resolve both problems. Consider the following problem due to Wald [4].

Let X and Y refer the true (correctly measured) values and the following:

$$y_i = \alpha + \beta X_i + \epsilon_i \tag{7}$$

$$y_i^* = y_i + \eta_i \tag{8}$$

$$x_i^* = x_i + \mu_i \tag{9}$$

Let ϵ, η, μ, and x be all independent of one another, and be *iid* as $N(0,\sigma_\epsilon^2)$, $N(0,\sigma_\eta^2)$, $N(0,\sigma_\mu^2)$.

It is easy to show that the OLS estimate of β, $\hat{\beta}$, is biased:

$$\text{plim}\hat{\beta} = \beta\frac{\sigma_x^2}{\sigma_x^2+\sigma_\mu^2}. \tag{10}$$

This expression is a good basis for our intuition concerning *attenuation* bias. That is, measurement error in the explanatory variables imparts a bias in OLS estimates toward zero. The magnitude of bias depends on the ratio of the signal to sum of the signal plus noise. The greater the variance in the true X's, and the lower the amount of "noise", the smaller the bias.[4]

One simple solution due to Wald [4] is to group the data. Provided that the grouping is independent of the measurement error (but correlated with X), grouping the data can purge

[3] I do not consider purity in this paper. On empirical grounds this is harmless as including purity did little to modify the results in this paper. However, there are reasons to consider purity an additional (but unidentified) equation in the above system. Deaton [2] points out that it is, in general, not correct to merely adjust the price by purity. This is because purity potentially represents a *choice* on the part of the consumer. If the demand for purity is increasing in disposable income, then the magnitude of the relevant price elasticities will be *overestimated*. See his paper for details.

[4] Measurement error of the sort discussed immediately above is not a problem if it occurs in the dependent variable. In terms of equation (7) it is no different than relabeling ϵ to include this additional component and imparts no bias on OLS estimates.

estimates of attenuation bias. To illustrate, suppose the observations are put into two groups, G_1,G_2, of size N_1, N_2, respectively. It is easy to show that:

$$\beta_{\text{Wald}} = \frac{\frac{1}{N_1}\sum_{t\in G_1} y_i^* - \frac{1}{N_2}\sum_{t\in G_2} y_i^*}{\frac{1}{N_1}\sum_{t\in G_1} x_i^* - \frac{1}{N_2}\sum_{t\in G_2} x_i^*} \tag{11}$$

is a consistent estimate of β.[5] Note the close resemblance to classical experimental design. In classical experimental design, x is a dummy variable equal to 1 if the subject received the treatment, and 0 otherwise. In that case, the denominator of (11) is equal to 1, and the numerator is the difference between the treatment and control groups. The analogy to classical experimental design is also apparent from (10). If one is evaluating the effect of fertilizer on plant growth and one can only imperfectly control the amount of fertilizer, then it is clear why one would choose to put dissimilar amounts of fertilizer for the two groups of plants; that is, to maximize the variance in the "true X"—σ_x^2— in equation (10).

It has long been known that the the estimator in equation (11) has an interpretation as an instrumental variables estimator.[6] This interpretation will be useful in the empirical work that follows. Start with the following model:

$$Y = X\beta + \epsilon, \tag{12}$$

where Y and ϵ are $n \times 1$ vectors and X is an $n \times k$ matrix of n individual observations of k explanatory variables. Instead of two groupings as before, consider the case where a variable G takes on g distinct values, with $g \geq 2$, and the data are ordered by the values of G. For example, in the empirical work below, each state $\times$ year combination would be stacked and G is merely the "state $\times$ year" from which the observation is taken.

It is also helpful to establish notation for a matrix Z, the columns of which are a set of indicators for each value of G. When the data are ordered by the values of G, Z has the form:

$$\begin{bmatrix} l_1 & 0 & 0 & \dots & 0 \\ 0 & l_2 & 0 & \dots & 0 \\ 0 & 0 & \ddots & & \vdots \\ \vdots & \vdots & l_j & \vdots & \\ 0 & \dots & \dots & \dots & l_r \end{bmatrix}$$

where l_j is a vector of n_j 1's and n_j is the number of individuals having the j^{th} value of G. One can then proceed with Two Stage Least squares on the original data using the matrix Z as a matrix of instrumental variables.

In this case, the Two-Stage Least Squares estimator is merely:

$$\beta_{\text{TSLS}} = (X'Z(Z'Z)^{-1}ZX)^{-1}X'Z(Z'Z)^{-1}ZY. \tag{13}$$

It is also useful to note that pre-multiplying the regression equation by $(Z'Z)^{-1}Z'$ transforms the original equation into an equation for the data grouped by values of G. OLS applied to this grouped data yields:

$$\beta_{\text{grouped}} = (\overline{X}'\overline{X})^{-1}\overline{X}'\overline{Y}, \tag{14}$$

where $\overline{X}$ is a $G \times k$ matrix of simple arithmetic means of X for the various groups.

It is easy to show, however, that this is the the same estimate of β as is obtained by the TSLS estimator described above. To relate this to the simple case in equation (11), the TSLS estimator is merely the most efficient combination of all the two-by-two combinations of grouping estimators.

[5]There are several examples of this type of estimator in the recent econometrics literature. A simple proof of the consistency of this estimator is available from Schmidt [5].

[6]See the very clear discussion by Deaton [6]. His paper goes on to note that the estimator suffers from a correctable attenuation bias, which results from the fact that the sample means above are "mismeasured" versions of their population counterparts. I follow Angrist [7] in ignoring this difficulty which vanishes as the number of observations in the cell increases. I also use Angrist's notation.

3. A BRIEF TOUR OF STRIDE

The data for price and enforcement come from STRIDE. The review in this section will be selective. The interested reader is referred to the review piece by Frank [8] for a more detailed discussion of STRIDE.

An observation in STRIDE contains information on the weight and purity of each seizure or purchase, the dollar value of each purchase, and additional information. An observation is a *purchase* if there is positive dollar value, and a *seizure* if there is no information on price. The database is not comprehensive. It does not record all government activity on purchases and seizures. This limitation is potentially important. However, it is the only source of data that allows breakdowns by state and year. The popular perception that cocaine has received more attention is confirmed by the display in Figure 1.[7] The number of purchases and seizures (observations in the STRIDE data) for cocaine has risen about five-fold, whereas activity on other types of drugs has remained virtually constant in comparison. However, it is not clear what to make of this observation. Has the DEA been more vigorous in its efforts to interrupt the supply of cocaine? Or has the DEA found it easier to collect cocaine as a consequence of rising demand for the substance? Although the correct answer may lie in between the two extremes, it is not possible to distinguish them with the data displayed in this fashion.

Turning specifically to cocaine, the number of observations that represent seizures (no price data) and purchases have increased together. Figure 2 presents the number of observations for both categories for the years in the STRIDE data set. The lines grow farther apart, indicating that seizures as measured by this simple metric have grown relative to purchases. Taking account of the average weight of purchases or seizures exacerbates this difference. In Figure 3 the average weight of purchases and seizures is plotted. This dichotomy between purchases and seizures is potentially useful and I attempt to exploit this in the empirical work below.

4. STRIDE AND THE PRICE OF COCAINE

Figure 4 represents three differences in recording the price over other presentations I have encountered.

First, the price is measured in *real* rather than nominal terms using the CPI (Consumer Price Index). [8] Second, state variation, and variation in average size and purity of purchases are controlled for using regression techniques. This involves running a regression of the unit price of cocaine (one gram) on a vector of explanatory variables including the size of the purchase and its purity. Third, standard errors are presented.[9]

Several things are immediately clear. First, STRIDE is an extremely noisy source for information on prices. Second, the price of cocaine has not varied much over the period. The 1987 price is well within the standard error bounds of the 1977 price. Year to year changes in the price are not very significant. It is worth noting one important difference in this display of prices. Many researchers (see [9]) focus on the value of real price per *pure* ounce. Viewed from the approach taken in this paper, this is equivalent to forcing the elasticity of the real price per pure ounce with respect to purity to be equal to -1. In other words, this forces the researcher to assume that two ounces of 50 percent pure cocaine sell for the same price as one ounce of 100 percent pure cocaine. While this might be intuitively appealing, I see no reason to force this relationship on the data, and hence allow the data to estimate this elasticity.

To get an idea of the sources of variation in the data, Table 1 shows the results of a simple variance decomposition. The primary source of variation in the data is not the state in which it was collected, nor the year. Over three quarters of the variation in the data can be explained by variations in the size of the purchases. In earlier work [10] I document that this simple variance

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[7] I have made some minor deletions to the data set. In particular, any data for which the purity was greater than 100 percent or less than or equal to zero percent have been deleted. Also deleted are observations for which the net amount collected is less than zero. Not all these deletions are *necessarily* "harmless." Caulkins [9] for instance includes observations which have zero recorded purity.

[8] Here and elsewhere, the CPI base is 1982–1984 = 100.

[9] The regression used was log real price of cocaine on a complete set of year and state dummies, log weight of purchases, and percent purity. The prices are normalized by setting purity at the sample average (57 percent), using New York as a base, and setting log weight equal to zero.

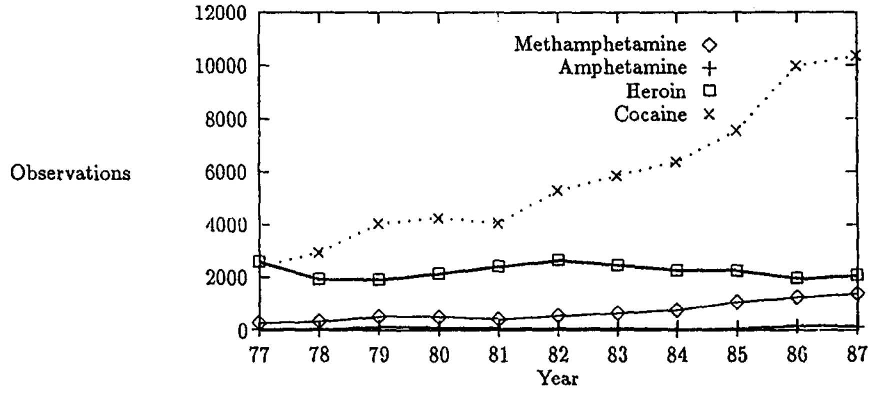

Figure 1. Purchase or seizures by type of drug.

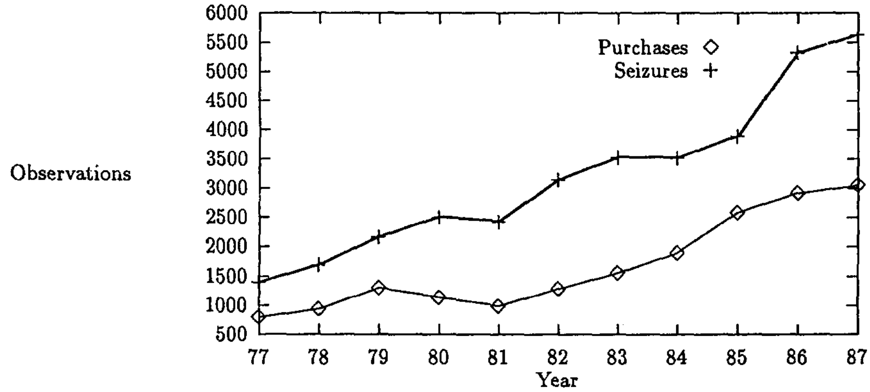

Figure 2. Purchase *versus* seizures—cocaine.

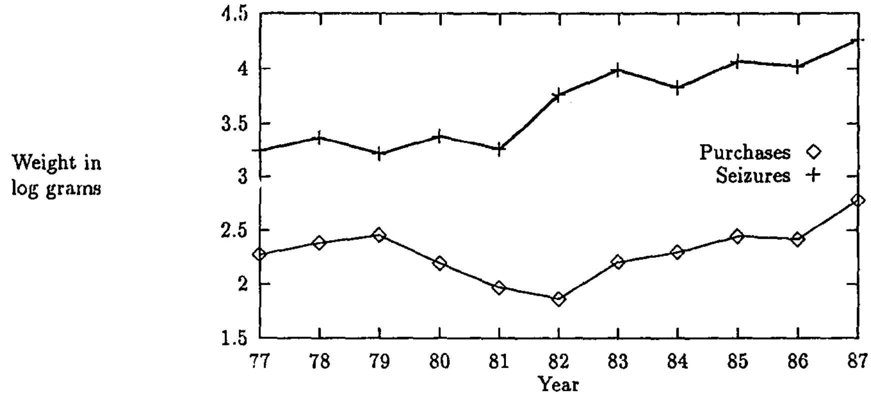

Figure 3. Average log weight of purchases and seizures of cocaine.

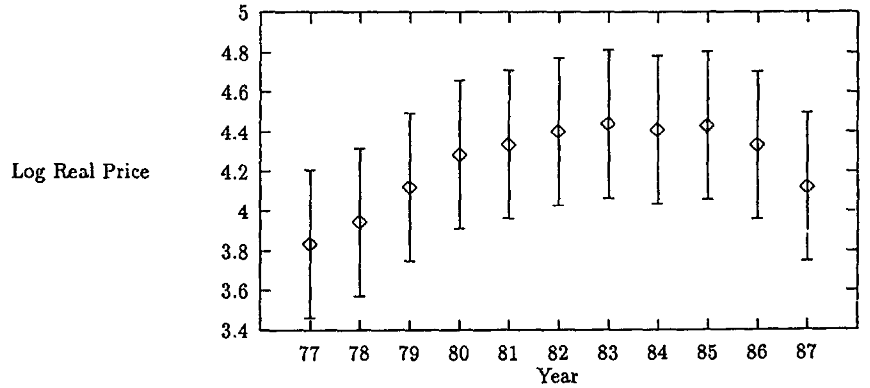

Figure 4. Time series plot with one standard error bounds.

Table 1. Analysis of variance for cocaine price.

Source	Number of obs=	18468	R^2=	0.4259	
	Root MSE=	.5422	Adj R^2=	0.4240	
Source	Partial SS	df	MS	F	Prob F
Model	4015.789	62	64.770	220.27	0.0000
lweight	2942.876	1	2942.876	10007.80	0.0000
purity	29.325	1	29.325	99.73	0.0000
state	231.385	50	4.627	15.74	0.0000
year	472.317	10	47.231	160.62	0.0000
Residual	5412.141	18405	.294		
Total	9427.931	18467	.510		

decomposition is adequate to the task at hand. As others have noted, a very simple behavioral model can be used to "rationalize" the use of this specification.[10] For the purposes in this paper, however, the model is not intended to be behavioral. I am merely using this parsimonious representation to remove the effect of size of purchases on estimates of the state-year means of the data.

To those who are more descriptively inclined, most of the variation is accounted for by where, in the distribution chain, the drug is purchased. "Noisiness in the data" is surely a problem, but the problem of coming up with precise estimates of state and year-to-year variation is largely made difficult by the tremendous variation in the size of purchases.

The anova in Table 2 provides information on the impact of potential outliers. Deleting those observations whose value of Cooks-D was in the 99 percentile or higher had almost no influence on the variance decomposition.[11] The R^2 rises to about .5 after deleting these observations but the components of variation retain their relative share. The estimates of the state-year means between the two specifications (deleting outliers, versus keeping them in) have a correlation of 98 percent.[12]

Table 2. Analysis of variance for cocaine price (potential outliers deleted).

	Number of obs=	18283	R^2=	0.541	
	Root MSE=	.373	Adj R^2=	0.539	
Source	Partial SS	df	MS	F	Prob F
Model	2986.746	62	48.173	346.07	0.0000
lweight	1954.899	1	1954.899	14043.66	0.0000
purity	18.0469	1	18.047	129.65	0.0000
state	172.583	50	3.452	24.80	0.0000
year	496.580	10	49.658	356.73	0.0000
Residual	2536.252	18220	.139		
Total	5522.999	18282	.302		

5. THE DATA

5.1. *Monitoring the Future*

Since the source of the consumption data I use, the Monitoring the Future data (henceforth MTF), is well-described in other published work [12], only a brief synopsis is provided here.

[10] See Caulkins and Padman's study [11].

[11] Cook's-D is a measure of "influence." Deleting observations with high values of Cook's D is an attempt to delete observation that perhaps exert "undue" influence on the coefficient estimates. Cook's D is defined as follows: $D = \frac{he^2}{ns^2(1-h)^2}$: where $h = x_i(X'X)x_i'$, n is the number of explanatory variables, and e^2 is the squared residual.

[12] The state year means were also not substantially different with purity included or excluded.

MTF is a representative sample of high school seniors from high schools across the United States. The survey instrument has questions on demographic characteristics, family background, and legal and illegal drug use. It utilizes a multi-stage cluster sampling procedure which is designed to produce a sample representative in terms of sex, SMSA, and the broad (4 category) census regions. Since MTF was intended, *inter alia*, to collect information on illegal drug use, extra attention was paid to ensure informative responses to obviously sensitive questions. A typical year has responses from about 15,000 individuals.

In the present context, the focus on high-school seniors is somewhat limiting. It would be interesting to consider the entire population; however, there is no data set that has been made accessible to researchers which has the necessary information. For instance, currently, only three years of the National Household Drug Abuse Survey are available. Furthermore, the NHS survey has very limited geographical information which makes it difficult to match with the price data from STRIDE.

A well-known deficiency is that the MTF survey excludes high school dropouts. This is an interesting subgroup to analyze, but again no data exist to researchers (or policy makers) that allow useful inference on the effects of law enforcement or price on consumption.

A further deficiency of the public use version of MTF (like the NHS survey) is the lack of state of residence codes (only codes for the broad census regions are included). As a safeguard for confidentiality of the respondents, data with these codes are not generally made available to researchers. However, for this project, the authors of Monitoring the Future have graciously provided me with state-year tabulations of a subset of the variables in the data set, and it is these tabulations that comprise the data I analyze in this paper.

5.2. Combining the Consumption and Price Data

The data set that I use for the analysis that follows is summarized in Table 3.[13] The data set has 344 state $\times$ year means.[14] The variables used in the analysis are quite standard. The unemployment rate is the state unemployment rate for males older than 16, and comes from tabulations of the Current Population Survey. Job and other income are income from work, and income from gifts and allowances, respectively. Also included are variables which indicate whether the high school senior is older or younger than eighteen years of age. A variable which equals the proportion male is also included. The inclusion of the legal minimum drinking age for liquor is included to control for possible effects of substitution between alcohol and cocaine. In previous and continuing work, I have considered the effect of drinking ages on the consumption of psychoactive substances other than alcohol [1, 13].

The STRIDE data is the source for the log real price of cocaine. As before, I first run a preliminary regression where I regress the log real price on the log weight of the purchase. I then take the state $\times$ year means that obtain from removing the estimated impact of purity and weight of purchase.[15] The other source of identifying information comes from the portion of STRIDE where there is no price information—seizures. I calculate the sum of the weight of seizures and then take logarithms. I *do not* use the weight of the purchases in this calculation; to do so would almost certainly introduce a spurious correlation between price and weight. The idea of separating the data set in this fashion is to use the seizure data as an *independent* source of information on the extent of enforcement. While it is certainly only an imperfect proxy, it is not clear that there exists a better measure. At a minimum, since enforcement efforts are undertaken by agencies other than the DEA, it certainly measured with error. While it would be better to have a measure that is measured with less error, it is only necessary that the instrumental

[13] I also experimented with other variables for the analysis including mother's education and a fuller set of age dummies; the analysis is robust to the inclusion or exclusion of these other variables. I also run the regressions unweighted. The results are not sensitive to weighting.

[14] The reduced size of the sample is the result of the fact that to be included in the analysis I required observations on consumption, price, *and* seizures. Since coverage is incomplete in both STRIDE and MTF, the resulting data set is the intersection of both.

[15] I use a regression of log real price on log weight of purchase, purity, and a complete set of state and year interactions. The estimates are merely the coefficients on these interaction terms. The results are not sensitive to treatment of purity since the estimated impact of purity is small—this results from the comparatively low amount of variation in reported purity.

Table 3. Summary of data used in analysis.

Variable	Mean	Standard Deviation
Percent Using in last 30 days	.0446	.0335
Unemployment Rate	.0736	.0222
White	.8574	.1794
< 18	.0151	.0159
> 18	.2677	.0867
% in SMSA	.6656	.3531
Drinking Age	20.11	1.194
Male	.4864	.0651
Father ($<$ high school)	.2217	.0932
Father ($>$ high school)	.4144	.1354
Other Income	9.521	2.797
Job Income	35.01	7.059
Real Price of Cocaine	4.842	.2707
Log Total Weight Seized (grams)	8.794	3.000

variable is orthogonal to the error; misspecification in the first stage equation does not induce bias.

This also underscores the importance of having both regional and time series variation in "treatments." To use a common statistical metaphor, if we wanted to investigate the efficacy of different amounts of fertilizer on plant growth, we would wish to have as much variation across our plots as possible. If the same plots of land are always given the same amount of fertilizer then it will be hard to disentangle the effects of the fertilizer from the random variation in, say, the soil quality across plots.

6. RESULTS

6.1. The Limitations of Time Trends

This instrumental variables interpretation is also useful in thinking about the "quasi-experiment" that is necessary to make useful inferences about the relationship between consumption and price. The most common temptation in looking at the relationship between price and consumption is to treat the two as representing movements along a stable demand curve. For instance, one might compare annual changes in price to annual changes in the proportion of individuals who report using cocaine.

In light of the discussion in Section 2.2 , it is very simple to specify the conditions under which that would be a valid inference. In particular, the assumption of a "stable demand curve" means that year dummies can be excluded from the "demand" equation in the structural model (i.e. there is no year-to-year variation in the demand for cocaine) but belong in the structural supply curve. This assumption is also necessary for the inference that rising prices reflect decreased availability (supply). To illustrate the approach, and bring into sharp focus its limitations, I use data from the Monitoring the Future Survey and STRIDE, I plot the 30 day prevalence rate for high school seniors against the log real price of cocaine in Figure 5.[16] The solid line is the regression coefficient from the "means-on-means" regression.[17] Far from being a downward sloping demand curve, the curve is well determined and upward sloping!

While we could of course choose to dispense with the "Law of Supply and Demand," perhaps a more useful approach would be to re-examine the assumptions necessary for this exercise to be valid. Table 4 summarizes the yearly average used to calculate the aforementioned grouped regression. While it is true that the general direction of the trend is upward for both time series, the upward trend is very small for the price of cocaine. The 30 day prevalence rate on the other

[16]The yearly means for the 30 day prevalence rate are the unweighted means from the Monitoring the Future Sample. The log real prices are the same as those used in Figure 4.

[17]The fitted coefficient is .0331224. It is not mathematically equivalent to a pure means on means estimator since I have partialled out the state effects from the price data, but not from the MTF data. I also use the complete MTF data set, not merely the matching observations.

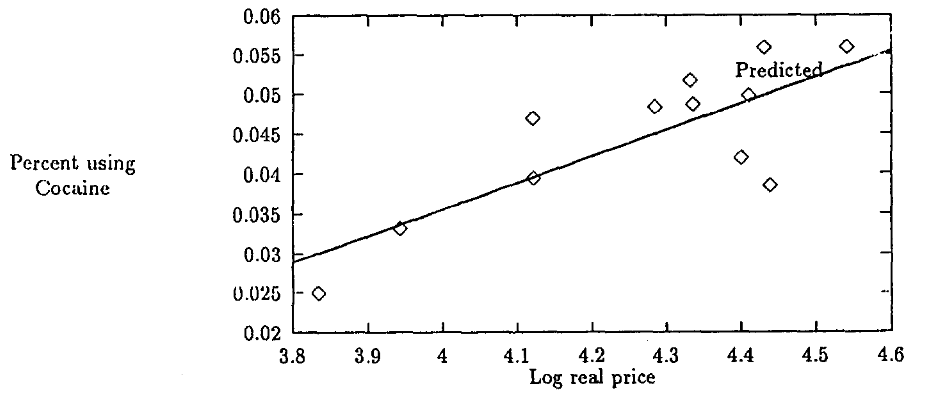

Figure 5. Time series plot with year dummies.

Table 4. Data used in Figure 5.

Year	Log Real Price	30-day Prevalence Rate
77	3.835	.0249
78	3.943	.0332
79	4.121	.0470
80	4.285	.0484
81	4.336	.0487
82	4.401	.0420
83	4.439	.0385
84	4.411	.0497
85	4.431	.0558
86	4.333	.0517
87	4.122	.0395

hand appears cyclical (its lowest values correspond to downturns in the business cycle) and rises quite dramatically over the period. Comparing 1977 to 1986, for instance, the percent change in real price is about 50 percent. The equivalent calculation for the prevalence rate is 107 percent. If one wants to believe in the existence of a demand curve in spite of these numbers, then one might wish to assert, for example, that there has been a small rightward shift in the supply curve and a large upward shift in the demand.

6.2. The Relationship Between Law Enforcement and Price

With the previous sections in mind, I am able to discuss some of the results. Table 5 presents the bad news. The table reports the results of a simple analysis of covariance. After controlling for state and year effects, the effect of seizures on the price of cocaine is small and insignificantly different from zero. This analysis of covariance is identical to the reduced form regression of price that results from the structural model described above with only price, and state and year effects in the demand equation.

I present this first-stage regression so as not to obscure the source of difficulty in analysis. Table 6 should make the point abundantly clear. The table is organized as follows. The first column is the coefficient on price with the fraction reporting use of cocaine in the last 30 days as the dependent variable. The next three columns indicate the use of other covariates. The final two columns report the coefficients on log weight seized in the first-stage regressions. Π_q and Π_p indicate whether the proportion of those using or price is the dependent variable. (This is consistent with the notation developed above.) The specifications are ordered by the number of included covariates or dummy variables. The TSLS estimates use log weight seized as an instrumental variable.

Considering the OLS estimates in the first three rows of the table, there appears to be little evidence in favor of an effective role for law enforcement over the sample period studied. Without exception, the estimates are economically small and not significantly different from zero.[18]

[18]There is a possibility that law enforcement has some temporary effect on the price. The remarks in this section

Table 5. Relationship between law enforcement and price.

	Number of obs=	466	R^2=	0.520	
	Root MSE=	.224	Adj R^2=	0.448	
Source	Partial SS	df	MS	F	Prob F
Model	22.049	61	.361	7.19	0.0000
Log total weight seized	.0244	1	.0244	0.48	0.487
state	3.683	50	.074	1.46	0.0261
year	15.635	10	1.564	31.08	0.0000
Residual	20.323	404	.0503		
Total	42.372	465	.091		

Table 6. Estimates of the participation elasticity of demand (standard errors in parentheses).

Estimate	Estimation Technique	State/Year Dummies	Other Covariates	Π_p	Π_q
−.005 (.006)	OLS	No	No	—	—
−.002 (.007)	OLS	Yes	No	—	—
−.001 (.005)	OLS	Yes	Yes	—	—
0.746 (1.13)	TSLS	No	No	.003 (.005)	.0025 (.0006)
−.014 (.018)	TSLS	Yes	No	−.005 (.006)	.0002 (.0008)
−.029 (.113)	TSLS	Yes	Yes	−.006 (.006)	.0001 (.0007)

Turning to the TSLS estimates in the antepenultimate row, one of the estimates is actually large and positive. A possible explanation is that, at current levels, law enforcement has very little effect on the price of cocaine and that the positive relationship reflects that—law enforcement efforts are directed at where the "problem" is most severe. The last rows provide no evidence consistent with a significant effect of law enforcement on either the price of cocaine or the demand. Although the point estimates in the first column are indeed negative, the coefficient estimates on log weight seized (Π_p and Π_q) are exactly the opposite sign for the model to be consistent. The relationship between seizures and price is *negative* whereas the relationship between seizures and quantity consumed is *positive*. Again the results are consistent with the hypothesis that law enforcement efforts are directed toward where the problem is most severe and that there is no exogenous variation—enforcement merely mirrors demand. For instance, if variations in price reflect only variations in the demand for cocaine (and not supply changes) it is perhaps not surprising that DEA activity is lowest where demand (price) is lowest.

7. CONCLUDING REMARKS

In short, I have failed to find any significant effects of law enforcement on the price of cocaine faced by users. I looked for effects of law enforcement on the price of cocaine, and for effects of law enforcement on the participation of high school seniors in cocaine use.

One explanation is that the effect of law enforcement activity on the price of cocaine is very small. Kleiman [14], for instance, argues that drug and other asset seizures account for a very small fraction of the cost of supplying illegal drugs; it would not be surprising then that fluctuations in the amount of cocaine seized would not be highly correlated with major changes in the supply price of cocaine. Another non-mutually exclusive explanation, that is consistent with the evidence provided in this paper, is that the seizures of cocaine recorded in the STRIDE data

refer to more permanent changes that might reasonably be observed across years, and not necessarily within a given year.

are not highly correlated with effective law enforcement activity; federal efforts, for instance, might displace more "effective" local law enforcement efforts. Not to be ignored is the possible endogeneity of enforcement and supply—that is, higher supply calls forth greater enforcement.

The analysis also suggests that, if policy makers were interested in evaluating the efficacy of law enforcement in raising the price of cocaine to end users, passive observation of current efforts is unlikely to be adequate. Instead, it would probably be helpful to (partially) design both the enforcement activity and the data collection with a mind to its evaluation.

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