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# ILLICIT DRUG USE AMONG ARRESTEES AND DRUG PRICES

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## ABSTRACT

Previous studies, by relying on nationally representative surveys, have overlooked the important fact that use of addictive substances is not uniformly distributed; subgroups of hardcore users account for most of the drug consumption. This study employs the Drug Use Forecasting system to analyze the demand for cocaine and heroin by arrestees, employing objective indicators of use based on urinalysis. The data are repeated city cross-sections, and panel data methodologies are employed to control for policy endogeneity. Cocaine and heroin prices have a negative effect on the probability of use even among this group of heavy users. Results indicate that subjective, self-reported measures of participation are likely to be under-reported, which may impart bias to estimates of the price elasticity. The own-price cocaine participation elasticity is about $-0.17$, and the own-price heroin participation elasticity is about $-0.09$ for arrestees. This contemporaneous elasticity understates the full effect, and the long-run price elasticity is about twice the magnitude. Estimated cross-price elasticities indicate that cocaine and heroin are economic complements. While these findings show that higher penalties, enforcement, and supply reduction activities can discourage participation by heavy users, the elasticities are smaller in magnitude relative to the estimates in the prior literature.

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## 1. Introduction

The U.S. federal government spends approximately $19 billion a year on drug control activities (Office of National Drug Control Policy, 2003).[1] The portion of this budget allocated towards demand reduction, including treatment and prevention, has remained relatively stable over the past 15 years at around 31 %. Much of current drug control policy in the United States, however, focuses on supply-reduction programs aimed at stopping the flow of drugs and apprehending and punishing drug offenders. From an economic perspective, such drug enforcement, by raising the cost of supplying drugs to the U.S. market, acts as a non-monetary tax and increases the transaction price of drugs.[2] By the law of the downward-sloping demand function, the increase in price must reduce the consumption of illicit drugs. Hence, a critical question concerns the extent to which drug use responds to prices, especially heavy or problematic use. Since manipulating prices is one instrument of control that the public sector can exercise on the market for addictive unhealthy substances, empirical estimates of the relation between price variations and illicit drug consumption are key to informing and shaping public policy.

This paper estimates the empirical relationship between the prices of cocaine and heroin and objective indicators of their use. Cocaine and heroin prices are computed from the System to Retrieve Drug Evidence (STRIDE), comprised of purchases made by Drug Enforcement Administration (DEA) agents during undercover operations. The set of outcomes is the percentage of arrestees testing positive for each substance, derived from the Drug Use

[1] State and local spending on drug control amounted to an additional $16 billion in 2000.
[2] Costs for drug suppliers increase because: 1) they are forced to use underground distribution and transportation channels that can be hidden from authorities, 2) some drug shipments are captured by the authorities and destroyed, 3) suppliers are forced to use the threat of violence

Forecasting (DUF) program. Panel data methodologies are used to identify the empirical link between cocaine and heroin prices and these indicators of use.

While this study is related to the new and growing empirical literature dealing with the price sensitivity of illegal drug consumption, it improves upon the prior estimates in a number of ways. The illegal drug use indicators employed in much of the literature are based on self-reports and may be measured inaccurately. This is especially true for heroin use, which is virtually non-existent in national surveys.[3] In contrast, the indicators used in the present study are objective measures of cocaine and heroin participation, obtained via urinalysis.[4] Moreover, much of the literature, by relying on self-reported national surveys, does not consider consumption by certain subgroups like the homeless or arrestees, who may behave very differently from the population at large. The persons sampled in DUF are not representative of the general population. In particular, the focus is on persons arrested for any offense. These individuals are much more likely to be hardcore users of drugs than an individual selected at random. Thus, they also impose the heaviest costs on society and are the target of much illegal drug policy. Drug use trends based on national surveys may also paint an incomplete picture. For instance, results from the National Household Surveys of Drug Abuse show that past month illicit drug use declined steadily from 14.1 % in 1979 to 6.2 % in 1998. In contrast, more objective indicators of heavy drug consumption show an opposite trend. For instance, drug-related hospital emergency department episodes increased from 145 (per 100,000 people) in 1978 to 230 in 2001. There were a total of 19,698 deaths from drug-induced causes in 2000, an

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or other relatively costly methods to enforce their contracts rather than use the court system, and 4) because of fines and imprisonment.

[3] Less than 0.1 percent of the sample reported current heroin use in the 2002 National Survey on Drug Use and Health.

increase of 177 % from 1981. In 2000, the overall cost of drug abuse to society was estimated at $161 billion, an increase of almost 60 % from 1992. These trends suggest that while casual drug use may be declining, use among heavy consumers on the other tail of the distribution may be rising.

Many studies based on survey data also rely on the respondent's state of residence as the geographic unit. Consequently, when estimating the price elasticity of demand, these researchers have had to employ a state-average price despite the fact that there is considerable inter-city variation in drug prices even within a given state. This measurement error may lead to biased estimates. The present study overcomes this limitation by computing and merging drug prices at the city level. This analysis further exploits the time-series of city cross sections and estimates various fixed-effects specifications to control for unmeasured factors that may be correlated with price and consumption. In addition, lagged and lead price series are used in the context of panel data techniques to inform on the possibility of policy endogeneity. Another deficiency in the existing literature concerns cross price elasticities of demand. There are very few studies that analyze the effects of changes in the price of one drug on the consumption of another, and so estimates of these cross-price effects are limited. The present study estimates whether heroin and cocaine are substitutes or complements using the aforementioned objective drug use outcomes.

The remainder of the paper proceeds as follows. Section 2 reviews prior empirical studies dealing with the price sensitivity of the consumption of illegal drugs. Section 3 describes the data assembled for use in this study. Section 4 outlines the analytical models that guide the

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[4] Arrestees are also asked to report on their own drug use. Comparing these self-reports to the urinalysis data can inform on the magnitude and importance of any measurement error.

empirical specifications. Section 5 discusses the econometric strategy for estimating the models. Section 6 presents the price elasticities of demand for arrestees. Section 7 discusses these results and offers some concluding remarks.

## 2. Prior Studies

An editorial in Drug and Alcohol Review (1999) stated that while economics has a critical influence in the development of policies in other areas, "illicit drugs is one of the few remaining areas yet to be significantly influenced by advances in this discipline." Yet, there is a rapidly growing empirical literature by economists dealing with the price sensitivity of consumption of illegal drugs.[5] The inherent difficulty of measuring consumption and price of an activity that does not enter the official market is apparent. These demand studies primarily draw on illegal drug prices derived from local purchases made by drug enforcement agents while undercover. The studies typically combine these prices with self-reported measures of drug use from such national surveys as the National Household Survey of Drug Abuse and Monitoring the Future. The outcomes employed in these analyses are usually self-reported past year or past month participation and frequency of use given positive participation.

The early conventional view that the demand for addictive substances, such as illicit drugs, did not respond to price was increasingly challenged by subsequent studies. Silverman and Spruill (1977) implicitly estimate the long-run price elasticity of demand for heroin at –0.25, based on monthly aggregated data for 41 poor, non-white Detroit communities from November 1970 to July 1973. Van Ours (1995) analyzes data on opium consumption and the number of

[5] Economists have also studied various issues concerning the current policy towards illicit drugs versus a regime where drugs are legalized. See, for example, MacCoun and Reuter (2001), Miron (2001), Becker, Grossman, and Murphy (2003), Kuziemko and Levitt (2001), and Lee (1993).

opium users in the Dutch East Indies (now Indonesia) for the period 1923 to 1938. He estimates a short-run price elasticity of demand of –0.70 and a long-run price elasticity of demand of –1.00. Bretteville-Jensen and Sutton (1996) estimate the price-responsiveness for heroin to be –1.23, based on a sample of non-dealing heroin users who participated in a needle exchange program in Oslo, Norway.

Several authors, in more recent studies, have estimated price elasticities using national survey data. Grossman and Chaloupka (1998) analyze the demand for cocaine by young adults (ages 17-29) in the Monitoring the Future (MTF) panels using the rational addiction framework. The data employed in their study consists of panels formed from nationally representative cross-sectional surveys of high school seniors conducted between 1976 and 1985, with the last follow-up conducted in 1989. Grossman and Chaloupka find that annual participation and frequency of use given positive participation respond negatively to the price of cocaine. The long-run price elasticity of participation is estimated at –1.00, and the long-run price elasticity of frequency given participation is estimated at –0.35. They also find that current consumption is positively affected by past consumption, consistent with the hypothesis that cocaine is an addictive good, and also positively affected by future consumption, consistent with the rational addiction model.

Chaloupka, Grossman, and Tauras (1999) estimate cocaine price elasticities for past month and past year outcomes based on the 1982 and 1989 MTF cross-sectional surveys of high school seniors. Their results indicate a price elasticity of past-year participation of –0.89 and an elasticity of past-month participation of –0.98. The corresponding frequency elasticities are –0.40 and –0.45 respectively. However, DiNardo (1993) finds that past-month participation by high school seniors does not respond to price in a similar MTF sample for the years 1977 – 1987.

Based on pooled data from the 1988, 1990, and 1991 National Household Surveys of Drug Abuse (NHSDA), Saffer and Chaloupka (1999a) estimate models for all ages. They find that the annual participation price elasticity for cocaine is –0.55 and that for heroin is –0.90. Monthly participation price elasticities for cocaine and heroin are –0.80 and –0.36 respectively. Using the same sample, Saffer and Chaloupka (1999b) estimate these price elasticities separately for demographic subgroups. They find that the cocaine price elasticity is insignificant for blacks and Asians, -1.83 for Native Americans, and between –0.5 and –0.8 for white males, Hispanics, women, and youth. For heroin, the price elasticity is estimated at –1.63 for white males, -0.62 for females, -0.36 for youth, and close to zero for all others. DeSimone and Farrely (2001) analyze data from 1990-1997 NHSDA. They estimate a past-year cocaine participation elasticity of –0.41 for individuals between the ages of 18 to 39. However, similar models for persons ages 12 to 17 do not yield significantly negative price effects.

While the weight of the evidence from these studies suggests that cocaine and heroin use do respond negatively to price, there is little consensus about the magnitudes of the own-price elasticities. Studies that investigate the cross-price responsiveness of various illicit substances are sparse. Saffer and Chaloupka (1999a, 1999b), based on NHSDA data, estimate demand functions for cocaine, heroin, marijuana, and alcohol that contain the money price of each substance except marijuana. Their results show that these substances are economic complements, such that an increase in the price of one decreases the consumption of all others.

The illegal drug use indicators in the studies just cited may be plagued by inaccuracies if self-reports are subject to response error, and such surveys also fail to capture many hardcore drug users.[6] Caulkins (1996) indirectly estimates cocaine and heroin participation price elasticities based on data from 1987 to 1991 for 24 cities represented in Drug Use Forecasting (DUF). He uses as outcomes the percentages of persons arrested and brought to booking facilities who tested positive for cocaine and heroin based on urine specimens. His price elasticity estimates are -0.39 for cocaine and -0.28 for heroin, for arrestees. Invoking assumptions concerning the fraction of drug users testing positive and arrests attributable to drug use, other causes, and drug spending, Caulkins imputes general participation price elasticities that are very large in absolute magnitude: -2.5 for cocaine and -1.5 for heroin. His models do not control for time trends. Furthermore, the city-level drug price is treated as endogenous and instrumented with the national price. Hence, the results reflect time-series variation between prices and the drug use outcomes. The models also do not control for any other variables that may have changed over time.

Crane, Rivolo, and Comfort (1997) employ aggregate time series from DUF in order to estimate the price elasticity of demand for cocaine ranging from -0.29 to -0.63. This study also fails to control for time trends. Hyatt and Rhodes (1995) find that cocaine price is negatively related to the fraction of arrestees testing positive for cocaine, from DUF. While this study adds city indicators to control for unobserved factors at the city level, it also does not control for time

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[6] Since drug use is significantly higher among respondents who live in households considered unstable, the NHSDA's bias towards sampling stable households is likely to overlook many heavy drug users. Many studies have documented that respondents in the NHSDA understate heavy drug use. The Substance Abuse and Mental Health Administration (SAMHSA) reports that virtually no heroin addicts respond in the NHSDA. A comparison of heavy cocaine users in the NHSDA with those in other sources shows a marked difference with respect to demographic characteristics. In the NHSDA, incomes are higher, unemployment is lower, and fewer respondents report using more than one drug. Estimates of heavy drug use reported in the NHSDA are also difficult to reconcile with other data sources maintained by SAMHSA. See Rhodes et al. (2001).

trends or any other factors that may have shifted over time. Furthermore, the price of cocaine is not adjusted for inflation. Since year indicators are not included, this leads to biased estimates.

All of these studies which employ DUF to measure the price responsiveness of cocaine and heroin estimate models that are misspecified due to lack of adequate controls. They also fail to check or control for the possibility that policies which affect drug prices may themselves be endogenous to the drug use outcomes. As a result, it is difficult to ascertain from these studies whether the negative correlation between the outcomes and price represents a true causal effect or whether it reflects a spurious correlation due to other unobserved factors. The specifications in this study include a full set of city and time indicators and interactions between city indicators and linear trends, along with various socio-economic variables, to control for unmeasured factors that may be simultaneously correlated with price and consumption. A first-differenced instrumental variables procedure is also implemented to account for potential endogeneity. None of the studies reviewed has combined this fixed-effects methodology with objective measures of drug use.

## 3. Data

The empirical work is based on objective outcomes related to cocaine and heroin consumption derived from the Drug Use Forecasting (DUF) program. The DUF program, which is maintained by the National Institute of Justice, was established in 1987 to investigate the level of drug use among booked arrestees in urban areas.[7] Adults, 16 years of age and older, who are arrested and brought to booking facilities in several cities across the U.S. are interviewed on a voluntary basis, within 48 hours of their arrest, and asked to provide urine specimens. The interview is usually conducted in about 20 minutes. Over 90 % of those approached agree to be interviewed, while 80 % of them agree to provide urine specimens. There are no marked differences between arrestees who agree and those who refuse to be interviewed with respect to ethnicity, age, gender, race, employment, or reason for arrest (Chaiken and Chaiken, 1992). Urine specimens are collected immediately after the interview and screening for various substances is conducted off-site. Urinalysis can generally detect the use of drugs within the past 48 to 72 hours.

While DUF does not sample all arrestees brought to booking facilities, Hunt and Rhodes (2001) suggest that it is reasonable to use the DUF sample to draw inferences about the general arrestee population. Moreover, Rhodes and McDonald (1991) estimated that in 1989 the DUF sample accounted for 90 % of cocaine consumption and virtually all of the heroin consumption in the U.S. While these figures should be interpreted with care, it is apparent that the population sampled by DUF includes more hardcore drug users. Because users involved in the criminal justice system account for the majority of drugs consumed, the overall elasticities of the drugs may be dominated by the price responsiveness of this sub-population (Caulkins, 2001). The data used in the present study are annual aggregates from 39 large cities for the period 1988 to 2000.[8] Until 1997, the DUF program collected information in 24 cities across the United States, although the number of sites varies from year to year. In 1998 the program was expanded to more cities, and a redesigned sampling frame based on probability based sampling of the adult

[7] See Hunt and Rhodes (2001) for a detailed description of the DUF program.
[8] The DUF cities are New York City, Washington D.C., Portland, San Diego, Indianapolis, Houston, Ft. Lauderdale, Detroit, New Orleans, Phoenix, Chicago, Los Angeles, Dallas, Birmingham, Omaha, Philadelphia, Miami, Cleveland, San Antonio, St. Louis, Kansas City, San Jose, Denver, Atlanta, Albuquerque, Minneapolis, Sacramento, Tucson, Anchorage, Des Moines, Laredo, Las Vegas, Oklahoma City, Salt Lake City, Seattle, Spokane, Honolulu, Albany, and Charlotte.

male population was fully implemented in 2000; it is currently the Arrestee Drug Abuse Monitoring system.[9]

Results from urinalysis are used to compute the percentage of arrestees in each city testing positive for cocaine and the percentage testing positive for heroin.[10] Approximately 40 % of arrestees tested positive for cocaine in the sample, and approximately eight percent tested positive for heroin. In addition to the urine tests, respondents are also asked to report on their own drug use. Based on self-reports, variables measuring the percentage of arrestees who admitted using cocaine or heroin in the past 72 hours are also created. About 21 % of the arrestees reported using cocaine in the past 72 hours, and five percent reported using heroin. These figures show the extent of under-reporting in these self-reports. The arrestees are also asked to report whether they used cocaine and heroin in the past 30 days and the mean number of days that each drug was used. From these questions, variables measuring the percentage of arrestees reporting cocaine and heroin participation in the past 30 days and the mean number of days in each city that cocaine and heroin were consumed by users are created. About 28 % reported past month cocaine participation, and about six percent reported past month heroin participation. Conditional on positive participation, cocaine was used on about 23 days and heroin was used on about 17 days in the past month. Even from these self-reports, it is evident that the sample in DUF is more representative of the heavy users. For instance, based on the NHSDA in 1995, the average cocaine user consumed cocaine on 12 days and the average heroin

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[9] Restricting the data from 1988 to 1997 or deleting observations for the year 2000 does not affect the results. Models that include the number of arrestees in the DUF sample as a fraction of total arrests are estimated to account for the change in the sampling frame. Year effects will capture any other breaks in the data that have occurred over time.

[10] Urinalysis tests for all opiates instead of heroin specifically. While heroin is the most commonly consumed opiate, the class of opiates may also include other drugs such as morphine.

user consumed heroin on six days in the past month. Means for the DUF sample are presented in Table 1.

Additional covariates are also defined based on the individual arrestee data. These include the percent of arrestees in each MSA who are male, Black, other race, Hispanic, ages 16 to 24, ages 25 to 54, high school graduate, earned most of their income in the past month through full-time employment, are married, and whose most serious offense charge was drug-related. Since the outcomes are measured at the city or MSA level, additional MSA-level variables are created and included in all models. Personal income per capita is derived from the Bureau of Economic Analysis website and deflated by the national consumer price index reported by the Bureau of Labor Statistics. In order to capture local labor market conditions, the unemployment rate in each MSA is also included in all models. Data on unemployment are obtained from the Bureau of Labor Statistics, and in some cases also calculated from the March supplements of the Current Population Survey. Total MSA population is obtained from the U.S. Bureau of Census.

Indicators of local enforcement efforts are also appended to the DUF data set.[11] Variables measuring the probability of arrest for drug possession and drug sale are computed from the FBI's Uniform Crime Reporting System. Ideally, the probability of arrest is constructed by dividing the total number of arrests in each category by the total number of drug users and dealers in the MSA or some proxy for total drug activity. However, as there are no reliable estimates of the number of drug users and dealers by MSA, the denominator is proxied by total MSA population and in some cases by the total number of arrests. Variables measuring the total number of arrests in each MSA due to any drug possession, any drug sale or trafficking, any drug-related violation, sale or trafficking in cocaine or opiates, and sale or trafficking in marijuana are used to create the corresponding arrest rates.

Data on cocaine and heroin prices are computed from purchases made by undercover drug enforcement agents. Information on these purchases including cost, weight, and purity is recorded by the Drug Enforcement Agency (DEA) in their System to Retrieve Information from Drug Evidence (STRIDE). The advantage of STRIDE's transaction-level data is that they directly reflect prices on the street. These prices are expected to be relatively accurate because any unreasonable price offer by a DEA agent may raise suspicion on the dealer's part and endanger the agent. However, because the transactions are of varying size and quality, the cost of each drug must be standardized.

Standardized prices of one pure gram of cocaine and heroin in a given metropolitan area for a given year are derived in the following manner:

$$\text{(1)} \quad \text{Log Cost}_{ijt} = \pi_0 + \pi_1 (\text{log Predicted Purity}_{ijt} + \text{log Weight}_{ijt}) + \pi_{2j} \sum \text{MSA}_j + \pi_{3t} \sum \text{Year}_t + \pi_{4jt} \sum \text{MSA}_j * \text{Year}_t + \upsilon_{ijt}$$

The subscripts denote the $i^{th}$ transaction in the $j^{th}$ MSA for year t. Cost refers to the total cost of the purchase, weight is the total gram weight of the purchase, and purity is the weight of the pure drug found in the purchase as a fraction of the total purchase weight. MSA and Year refer to dichotomous indicators of each, and MSA*Year refers to indicators of the interaction between the two. Predicted Purity is obtained from a first-stage regression of actual purity on all of these other explanatory variables. The price of one pure gram of the drug in MSA j for year t is then imputed as:

[11] Data in the Uniform Crime Reports are available at the county level. To obtain MSA-level data, total arrests in each county are summed and aggregated for all counties represented in an

(2) $\exp ( \pi_0 + \pi_{2j} + \pi_{3t} + \pi_{4jt} )$ .

In the above procedure, purity is treated as endogenous because purchases may depend on expected rather than actual purity (Caulkins, 1994). Identification is achieved by constraining the coefficient on predicted purity to equal that on weight in the second-stage regression.[12] In this study, price series based on purity treated as exogenous and estimating (1) with the coefficients unconstrained were experimented with in all models. There are no material changes in the results or conclusions. STRIDE data are available from 1974 to 2001, and all years are used to impute the price series for the periods represented in DUF. Excluding outliers, there are 93,784 cocaine transactions and 40,957 heroin transactions.[13] In order to maximize the sample size in subsequent estimation, prices that are missing in any given MSA for any given year are imputed by the mean of the prices for all other available MSA's in that particular state.[14] Results are not sensitive to this imputation. All price series are deflated by the national CPI. The mean real price (in 1982-1984 dollars) of one pure gram of cocaine is \$80.47. The mean real heroin price is \$490.18.

One of the advantages of this study is that the drug prices are computed and merged at the city level. Many prior studies relying on national self-reported survey data used state-

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MSA. Using state-level arrest variables does not materially affect results.

[12] Equation (1) can be justified by defining the price of one pure gram of drug as: Price = Cost / (Pure Quantity of Drug) $^{\pi 1}$ , where pure quantity is purity times total weight. Here $\pi_1$ captures any non-linear effects of quantity on price, for example due to quantity discounts. In log-linear form, this is Log Price = Log Cost - π1 Log Purity - π1 Log Weight. It is assumed that the standardized price varies between cities and over time. Thus, Log Price = a + b MSA + c Year + d MSA*Year. Substituting this expression in the log-linear formulation results in an estimable form, equation (1).

[13] Transactions used in the imputation have a purchase cost of at least one dollar (zero cost represents seizures and are thus excluded) and purity between zero and 100 %.

[14] This imputation is more relevant for heroin prices due to more missing data; about eight percent of the DUF sample are affected by this imputation. For cocaine, a little over one percent of the DUF sample is affected.

average prices despite the fact that drug prices seem to vary widely from city to city. Granted that there may still be substantial intra-city variation in drug prices at any given time, the measurement error is likely to be much smaller than with state-level prices.

Kuziemko and Levitt (2001) find that STRIDE cocaine prices from 1986 through 1996 are positively related to state-level indicators of the certainty of punishment, measured by the per capita number of drug arrests, and the severity of punishment, measured by the fraction of drug arrests resulting in imprisonment. These findings suggest that illicit drug prices are responsive to enforcement and apprehension, instruments of current drug control policy. Basov, Jacobson, and Miron (2001) argue that due to the illicit, secretive nature of the drug trade, both production and sales are more labor intensive compared to legal markets. Most of these jobs are also likely to be filled by low-skilled employees, youths, or others with fewer outside opportunities. Their study shows that cocaine and heroin prices from STRIDE are positively related to the state-specific relative unskilled wage in a time series of states from 1974 to 1999. These two studies confirm that DEA drug prices do indeed reflect costs of retailing including expected penalties associated with this activity and labor costs.

## 4. Analytical Framework

The objective of this study is to assess the extent to which outcomes related to cocaine and heroin consumption respond to cocaine and heroin prices. Since illicit drugs are ultimately consumer goods, this question can be framed within the context of consumer theory and demand analysis. The utility function can be reformulated to explicitly take account of the addictive aspects of illicit drugs.

(3) $U_t = U_t\,(A_{1t}, A_{2t}, S_{1t}, S_{2t}, X_t)$

The individual's current utility depends on current consumption of the addictive goods ($A_1$ and $A_2$), the non-addictive good (X), and also on the stock of the addictive goods ($S_1$ and $S_2$) accumulated through past consumption. In addition to positive but diminishing marginal utility in A and X, the utility function also satisfies certain other restrictions. First, the stocks of addictive consumption positively affect current marginal utility of the addictive goods. This is the reinforcement effect by which past consumption of drugs stimulates current consumption.

(4) $U_{A1S1} = \partial_2 U_t / \partial A_{1t}\, S_{1t} > 0$

(5) $U_{A2S2} = \partial_2 U_t / \partial A_{2t}\, S_{2t} > 0$

Second, the stocks of addictive consumption negatively affect current total utility. This is the tolerance effect. Higher past addictive consumption lowers current utility, and hence a greater amount of current addictive consumption is required to obtain a given level of total utility. Alternatively, this can also reflect harmful addiction since past consumption of drugs can lower current utility due to detrimental health effects.

(6) $U_{S1} = \partial U_t / \partial S_{1t} < 0$

(7) $U_{S2} = \partial U_t / \partial S_{2t} < 0$

It is conceivable that there may also be cross-reinforcement effects so that the addictive stock of one drug may affect the current consumption of the other by affecting its current marginal utility.

(8) $U_{A1S2} = \partial_2 U_t / \partial A_{1t}\, S_{2t} \geq 0$

(9) $U_{A2S1} = \partial_2 U_t / \partial A_{2t}\, S_{1t} \geq 0$

Maximizing the above utility function in every period subject to a basic budget constraint derives a demand function where current consumption of the addictive good ($A_1$) is affected by its own price ($P_1$), the price of the other drug ($P_2$), income (I), and other characteristics (Y) such as the individual's age, gender, race, and education. Current consumption also depends on the addictive stocks ($S_1$ and $S_2$).[15]

(10) $A_t = \alpha_1 P_t + \delta_1 S_t + \beta_1 I_t + \beta_2 Y_t + \varepsilon_t$ .

(11) $A_{1t} = \alpha_1 P_{1t} + \alpha_2 P_{2t} + \delta_1 S_{1t} + \delta_2 S_{2t} + \beta_1 I_t + \beta_2 Y_t + \varepsilon_t$.

The parameter $\delta_1$ is hypothesized to be greater than zero due to the positive reinforcement of past addictive consumption on current consumption. This intertemporal complementarity between past and current consumption is the hallmark of economic models of addiction.[16] The own-price effect, $\alpha_1$, is hypothesized to be negative under the law of the downward sloping demand function. The cross-price effect $\alpha_2$ is positive if the two drugs are economic substitutes, negative if they are economic complements, and zero if the two drugs are independent. The cross-reinforcement effect $\delta_2$ may be zero or positive.[17]

## 5. Empirical Framework

In the model presented above, the key parameter of interest is $\alpha_1$, which quantifies the sensitivity of drug use to changes in its price. In estimating the addictive demand functions (10) and (11), since the accumulated addictive stock is unobserved, it can be proxied by past consumption outcomes. That is,

(12) $S_{it} = S\,(A_{it-1})$

[15] Equation (10) is based on a utility function with one addictive substance.

[16] This model is referred to as myopic addiction in the literature. Even though addiction is formulated explicitly through interactions between past and current consumption and has harmful effects in future periods, the individual is still myopic in that he is maximizing a single period utility function subject to a period budget constraint. See Becker and Murphy (1988) for a model of rational addiction wherein the individual maximizes a lifetime utility function comprised of a summation of discounted period utilities, similar to that specified in (3).

[17] In contrast to a cross-reinforcement effect, a cross-dampening effect would mean that (8) and (9) are negative; that is, an increase in the addictive stock of one drug lowers the current marginal utility of the other. In this case, $\delta_2$ is also negative. Since both cocaine and heroin

Substituting (12) into (10) and (11) yields:

(13) $A_t = \alpha_1 P_t + \delta_1 A_{t-1} + \beta_1 I_t + \beta_2 Y_t + \varepsilon_t$

(14) $A_{1t} = \alpha_1 P_{1t} + \alpha_2 P_{2t} + \delta_1 A_{1t-1} + \delta_2 A_{2t-1} + \beta_1 I_t + \beta_2 Y_t + \varepsilon_t$

Estimating equations with lagged dependent variables presents many econometric hurdles discussed later. Alternately, since demand in any period is a function of the price in that period, past consumption can be proxied by a series of past prices. With this substitution, the addictive demand functions can be formulated as:

(15) $A_t = \alpha_1 P_t + \lambda_1 P_{t-1} + \beta_1 I_t + \beta_2 Y_t + \varepsilon_t$

(16) $A_{1t} = \alpha_1 P_{1t} + \alpha_2 P_{2t} + \lambda_1 P_{1t-1} + \lambda_2 P_{2t-1} + \beta_1 I_t + \beta_2 Y_t + \varepsilon_t$

Since past consumption stimulates current consumption due to the reinforcement effect, the coefficients of own-lagged prices are expected to be negative. If there are cross-reinforcement effects, then the coefficients of cross-lagged prices are also expected to be negative. Statistically significant lagged price effects thus present indirect evidence of the addictive aspects of heroin and cocaine.

In this study, the addictive drugs considered are cocaine and heroin, and the set of outcomes from DUF is the percent of arrestees testing positive for cocaine or heroin use, which is a measure of the probability of participating in each drug. As such, it is a direct proxy for an arrestee's drug use. While the dependent variable is intended to measure a random arrestee's probability of participating in cocaine or heroin, DUF does not sample all arrestees. Therefore,

(17) Prob (Cocaine|Arrested)=Prob (Cocaine|DUF Arrestee)* Prob (DUF Arrestee|Arrested).

In log-linear form, this becomes,

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disrupt the flow of the neurotransmitter dopamine in order to produce feelings of pleasure and reward, a cross-reinforcement effect is theoretically more likely.

$$\text{(18)} \quad \text{Log Prob (Cocaine | DUF Arrestee)} = \text{Log Prob (Cocaine | Arrested)} - \text{Log Prob (DUF Arrestee | Arrested)}.$$

The outcomes employed in this study are the percentage of DUF arrestees who tested positive for cocaine or heroin, that is Prob (Cocaine|DUF Arrestee). Hunt and Rhodes (2001) note that inferences about the general arrestee population can be drawn from DUF. Nevertheless, some models include the number of DUF arrestees in each MSA as a fraction of total arrests (from the Uniform Crime Reports) to proxy for the Prob (DUF Arrestee|Arrested) and to control for changes in sample design between DUF and ADAM.

The data employed are a time-series of city cross-sections.[18] All regressions are estimated in logistic form, where the dependent variable is measured as the log of the odds ratio. Since the original outcomes are rates between zero and one, the logistic transformation ensures that the predicted rate or probability also lies in this range.[19] Panel-data techniques are employed to estimate the following models based on the above formulations:

$$\text{(19)} \quad \text{Log}\,(A_{it}/1\text{-}A_{it}) = \alpha_1 P_{it} + \lambda_1 P_{it-1} + \beta_1 I_{it} + \beta_2 Y_{it} + \mu_i + \eta_t + \nu_{it}$$

$$\text{(20)} \quad \text{Log}\,(A_{1it}/1\text{-}A_{1it}) = \alpha_1 P_{1it} + \alpha_2 P_{2it} + \lambda_1 P_{1it-1} + \lambda_2 P_{2it-1} + \beta_1 I_{it} + \beta_2 Y_{it} + \mu_i + \eta_t + \nu_{it}$$

The subscripts denote the $i^{th}$ MSA for year t. Y represents the vector of observable determinants of demand, besides price and income, and is proxied by the unemployment rate, various MSA-

[18] Models are estimated with MSA-aggregated rates, based on individual data, for two reasons. First, cocaine and heroin prices, the key variables of interest, are measured and merged at the MSA level. Thus, variation in drug use between individuals in a given MSA-year cell conditional on variation in MSA-level prices and other covariates is noise, and estimating models at the individual level will not add anything. Dow et al. (2003) also note that aggregation can ameliorate bias when omitted variables vary more at the individual-level than at the community level. This is likely the case in the present study where drug use is an individual behavioral choice affected by unobserved heterogeneity across individuals, and omitted community variables can be proxied with MSA effects and MSA-specific trends.

[19] The elasticity of participation with respect to price is calculated as $\alpha_1$ (1-A)P. The marginal effect of price on participation is $\alpha_1$ (1-A)A.

level socioeconomic characteristics, and drug-related arrest rates. The disturbance is modeled with two-way error components where $\mu_i$ denotes the unobservable area fixed effects, $\eta_t$ denotes the unobservable time effects, and $\nu_{it}$ is the remainder stochastic error term. In an aggregated logistic regression, the variance of the error term is inversely proportional to $A_{it}(1-A_{it})n_{it}$ (Maddala, 1983). Thus, all models are weighted by $A_{it}(1-A_{it})n_{it}$ to correct for the heteroscedasticity. This formulation is followed in all estimations.

These fixed-effects procedures are inconsistent if city drug prices or the policies that determine them might depend on the level of substance use, or as is more likely the lagged level of substance use. This possibility is sometimes referred to as policy endogeneity. There are two critical issues. The first is that there is an unmeasured fixed effect that is correlated with right-hand-side variables. In the context of this research, the fixed effect may be city or state sentiment (e.g., religiosity) towards drug use that also influences drug prices and enforcement. The second issue is that price may be predetermined and not strictly exogenous because past shocks to drug use may be correlated with current prices. Thus, current price is predetermined if it is uncorrelated with the current disturbance term but correlated with past disturbances.

(21) $E(P_{it}\,\nu_{is}) \neq 0$ for $s < t$ and $E(P_{it}\,\nu_{is}) = 0$ for $s \geq t$

Consider the addictive demand equation (19). For convenience, $LO_{it}$ refers to Log $(A_{it}/1\text{-}A_{it})$, and the year effects and lagged effects are ignored.

(19a) $LO_{it} = \alpha_1 P_{it} + \beta_1 I_{it} + \beta_2 Y_{it} + \mu_i + \nu_{it}$

The area fixed effects can be removed by first differencing.[20]

[20] Fixed-effects estimation is equivalent to first-differencing if there are exactly two periods for each cross-section. Otherwise, including fixed effects is equivalent to a regression where all observations are transformed to deviations from the mean, where the mean is calculated for each cross-section over all periods. For this exposition, the distinction is not important.

(19b) $LO_{it} - LO_{it-1} = \alpha_1 (P_{it} - P_{it-1}) + \beta_1 (I_{it} - I_{it-1}) + \beta_2 (Y_{it} - Y_{it-1}) + (\nu_{it} - \nu_{it-1})$

If price is predetermined then the orthogonality assumption is violated since $P_{it}$ is correlated with $\nu_{it-1}$. The fixed-effects or first-differenced specification is no longer consistent.

In order to check for potential policy endogeneity, two informal tests are performed. First, following Model (1993), specifications with a series of lagged and leading prices are estimated. If changes in drug outcomes are caused by changes in enforcement or prices as opposed to changes in prices being causes by these outcomes, then larger outcomes should not occur until after any decreases in price and vice versa. In specifications with lagged and leading price series, only the coefficients on contemporaneous and lagged prices should be significant. The lead prices should be insignificant. If the leading prices are significant, however, then this could be evidence of policy endogeneity.[21]

A second informal test estimates specifications with various lagged enforcement variables to proxy for past shocks to demand that may also be affecting current prices. Consider the baseline demand equation again, where the disturbance term is divided into two components.

(19c) $LO_{it} = \alpha_1 P_{it} + \beta_1 I_{it} + \beta_2 Y_{it} + \mu_i + \nu_{it}$, where $\nu_{it} = \omega_{it-1} + \varphi_{it}$

Thus,

(19d) $LO_{it} - LO_{it-1} = \alpha_1 (P_{it} - P_{it-1}) + \beta_1 (I_{it} - I_{it-1}) + \beta_2 (Y_{it} - Y_{it-1}) + (\omega_{it-1} - \omega_{it-2}) +$

$(\varphi_{it} - \varphi_{it-1})$

Here, $\varphi_{it}$ is a pure stochastic disturbance term that is uncorrelated with all past, current, and future values of the explanatory variables. However, $\omega_{it-1}$ represents unobserved shocks to past

[21] Significant lead prices may also be construed as evidence of rational addiction. However in the present context, it is unlikely that users are able to forecast drug prices far in advance, as much as one year. See Gruber and Koszegi (2001).

demand that may also affect current prices, making price predetermined and statistically endogenous. This endogeneity is similar to omitted variables bias in an intertemporal context, and the composite error $\nu_{it}$ will also be serially correlated due to this omission. In other words, there are unmeasured factors $\omega$ that simultaneously affect past demand and current prices. Conditional on $\omega$, price is strictly exogenous with respect to the remainder disturbance term. Therefore, if variables measuring such shocks can be included in the models, then the coefficients on price can be analyzed to gauge the extent of such endogeneity. Past enforcement efforts may proxy for these shocks to some extent. For instance, higher arrest rates related to drug violations or sales may affect current drug consumption and also influence future drug prices. If the price effects are robust in specifications that control for these lagged enforcement variables, then it is likely that price is not predetermined and may be regarded as strictly exogenous. In addition, including city specific trends in the models may also control for some of these unobserved intertemporal shocks.

The possibility that price is not strictly exogenous is also treated explicitly in the estimation of the demand function.

(22) $\quad \text{Log}\,(A_{it}/1\text{-}A_{it}) = \alpha_1 P_{it} + \delta_1 \text{Log}\,(A_{it-1}/1\text{-}A_{it-1}) + \beta_1 I_{it} + \beta_2 Y_{it} + \mu_i + \eta_t + \nu_{it}$

Earlier, past addictive consumption was substituted out with past prices in order to bypass the problems associated with lagged dependent variables. The issues involved are very similar to those discussed above with predetermined covariates. A first-differenced specification of (22) gets rid of the unobserved fixed effect but also shows that orthogonality between the explanatory variables and the disturbance term is violated.

(22a) $\quad LO_{it} - LO_{it-1} = \alpha_1 (P_{it} - P_{it-1}) + \delta_1 (LO_{it-1} - LO_{it-2}) + \beta_1 (I_{it} - I_{it-1}) + \beta_2 (Y_{it} - Y_{it-1}) + (\nu_{it} - \nu_{it-1})$

Note that $LO_{it-1}$ is correlated with $\nu_{it-1}$ (as is $P_{it}$ if price is predetermined). Arellano and Bond (1991) show that the orthogonality conditions in a dynamic panel data model can be exploited to obtain valid instruments for ($LO_{it-1}$ - $LO_{it-2}$). Specifically, $LO_{it-2}$ is a valid instrument, since it is highly correlated with ($LO_{it-1}$ - $LO_{it-2}$) and uncorrelated with ($\nu_{it}$ - $\nu_{it-1}$) as long as the $\nu_{it}$ are not serially correlated.[22] In fact, following the same logic, all available lags of the dependent variable are valid instruments for ($LO_{it-1}$-$LO_{it-2}$), that is $LO_{it-2}$, $LO_{it-3}$, etc. All levels (lagged and current) of the strictly exogenous variables are also valid instruments.[23]

The Arellano-Bond estimator also allows for the possibility that one or more of the explanatory variables may be predetermined and endogenous, for instance price. In the case that price is predetermined such that $E(P_{it}\,\nu_{is}) \neq 0$ for $s < t$, all relevant lagged levels of the predetermined variables are used to instrument for the difference, ($P_{it}$ - $P_{it-1}$), following the same principles above. Lagged levels of the predetermined variables (and not the current levels) also enter the instrumental matrix for the differenced dependent variable ($LO_{it-1}$ - $LO_{it-2}$). If the drug price is not just predetermined but also purely endogenous such that $E(P_{it}\,\nu_{is}) \neq 0$ for $s \leq t$, then the orthogonality conditions allow levels of the drug price lagged two or more periods to serve as

[22] If the $v_{it}$ are not serially correlated, there is still first-order autocorrelation between the first-differenced errors. Thus, a test of no autocorrelation in $v_{it}$ translates to testing whether there is second-order or higher degree autocorrelation in the differenced errors. These tests are presented in the results.

[23] Studies have shown that drug prices are positively correlated with the costs of distribution and retailing, including the relative unskilled wage and the probability of apprehension for selling or trafficking in various drugs. Holding income and the arrest rate for drug possession constant, these variables should not affect the full price for users and thus should not affect demand. This suggests that they may be used as instruments for drug prices to deal with problems of any measurement error or policy endogeneity. However, in practical application, these instruments do not pass checks for instrumental validity in basic year-effects models since they are likely to be correlated with unobserved MSA-specific factors. In models with both year and MSA effects, these instruments pass the test for overidentification restrictions; however they are very weak and not strongly correlated with drug prices in the first stage. Since poor instruments exacerbate the problems, this method is not followed here.

instruments. Estimating (22a) via the Arellano-Bond method allows a direct estimation of the addictive demand function and yields short-run and long-run estimates of the price elasticities. It also provides a check for the robustness of the estimated elasticities from other specifications where the lagged dependent variable is proxied by lagged prices. Furthermore, it is also informative to note whether the price elasticity is sensitive to treating drug prices as strictly exogenous versus instrumenting them.

## 6. Results

Table 2 presents estimation of the baseline demand function for urinalysis based logistic cocaine and heroin use, which excludes the lagged effects. All specifications include the drug price, individual and MSA-level socioeconomic covariates, year effects and then progressively add MSA effects and indicators for MSA-specific linear trends. Specifications 1 through 4 present the models for cocaine use. Cocaine price is negative and statistically significant in all specifications, and the price elasticity ranges from -0.11 to -0.22. Specification 1, which includes year indicators, yields an elasticity of an arrestee's probability of recent (past 48 – 72 hours) cocaine participation with respect to own price of -0.20. Relative to whites, Blacks are more likely and arrestees of other race are less likely to use cocaine. Hispanics are more likely to use cocaine relative to non-Hispanics. Individuals ages 16 to 24 and ages 25 to 54 are also more likely to consume cocaine relative to older individuals. Being married reduces the probability of using cocaine. The coefficient on income is significantly positive, implying that health is a normal good. The arrest rate for drug possession has a negative effect on cocaine use. A higher probability of apprehension raises the full price of cocaine and reduces participation; the elasticity is estimated at -0.09. The coefficient of the log of the DUF arrest rate is significantly negative, consistent with equation (18). Specification 2 includes both MSA and year effects; here, only changes in the price of cocaine within a given MSA are relied upon for identification. Each MSA serves as its own control group, with the price in one year compared to the prevailing price in the same MSA for another year. The estimated price elasticity is robust at -0.22. Since there are some MSA-year cells for which the arrest rates are missing, most subsequent specifications exclude them in order to maximize sample size. Specification 3 shows that the elasticity is only negligibly affected (-0.19) by this exclusion. Specification 4 adds indicators of MSA-specific linear trends. This is a stringent test since only deviations around a linear trend, within each city, are used for identification. The price effect remains significant at the one percent level, and the elasticity decreases in magnitude to -0.11. The addition of MSA-specific linear trends causes the MSA-level covariates to lose joint significance. The largest gain in adjusted R-square results from the addition of MSA effects; including MSA-linear trends raises the adjusted R-square by a relatively small amount. In subsequent analyses, fixed-effects specifications without city-specific trends are preferred and used to more reliably pin down the price elasticity.

Specifications 5 to 8 present similar models for urinalysis based logistic heroin use. The estimated price coefficients are significantly negative in all cases. Specification 5 shows the effects of the individual and MSA-level covariates. These are generally similar to those discussed with the cocaine models. Males participate more in heroin, and Blacks and other races participate less. Arrestees who are otherwise employed full-time in the legal sector are also less likely to be heroin users. MSA-level income has a small positive effect on heroin participation, which disappears in subsequent models. Arrestees who have been booked on a drug-related charge have a higher probability of using heroin. The probability of apprehension, as proxied by the arrest rate for any drug possession, is significantly negative since it raises the full price of using heroin. The corresponding elasticity is estimated at -0.40. The DUF arrest rate is also negative and significant. Specification 2, which adds MSA effects, yields a heroin price participation elasticity estimate of -0.10. Adding MSA-specific linear trends diminishes the magnitude of the price elasticity to -0.05.

Table 3 presents separate results for drug and non-drug offenders in order to inform on the extent to which selection of drug offenders into the DUF arrestee sample affects the participation price elasticity. Compared to individuals whose most serious charge was non-drug related, drug offenders were more likely to use cocaine and heroin recently and in the past month. Drug-using offenders also had a higher frequency of use, consuming cocaine and heroin on slightly more days than non-drug offenders. Thus arrestees booked on a drug charge appear to be the heaviest among the heavy users. The price elasticities of cocaine and heroin use are estimated to be slightly lower for the drug offenders relative to the non-drug offenders, implying that heavier consumers are less price responsive. For cocaine use, the price elasticity ranges from -0.12 to -0.17 (compared to -0.20 to -0.28 for non-drug offenders), and for heroin use, the price elasticity ranges from -0.07 to -0.15 (versus -0.14 to -0.19 for non-drug offenders). Specifications 5 and 6 further restrict the sample of non-drug offenders to those booked only on misdemeanor charges. The cocaine price elasticity of -0.20 and the heroin price elasticity of -0.08 are similar to those estimated for all non-drug offenders. Furthermore, elasticities based on samples that exclude individuals booked on drug-related charges are highly similar to those based on the sample of all arrestees. This is not surprising given that individuals arrested for a drug-related charge comprise only about 18 % of the total DUF sample and thus do not contribute much to the overall elasticity measures computed for all arrestees. All subsequent estimations employ the full sample of arrestees.

Table 4 estimates the demand function under the addiction framework, given by equation (19), where the addictive stock is proxied by one- and two-year lagged prices. The contemporaneous prices are negative and significant in all specifications, for both cocaine and heroin, including those with MSA-linear trends. The inclusion of lagged prices does not substantially reduce the magnitude of the current price elasticity. The short-run cocaine price elasticity is estimated at -0.18, and the short-run heroin price elasticity is estimated at -0.08. The elasticity of participation with respect to lagged price, holding current price constant, has a magnitude almost as large as the current price elasticity. The one-year lagged cocaine price elasticity is about -0.15, and the two-year lagged cocaine price elasticity is about -0.14. For heroin, the one-year lagged price elasticity is about -0.15, and the two-year lagged price elasticity is about -0.05. The coefficients on the contemporaneous and the lagged prices can be used to calculate the long-run price elasticity of the probability of participating in each drug. The long-run price elasticity measures the full current and future effects of a change in current price. For both drugs, it has a magnitude which is more than double the short-run price response, about -0.45 for cocaine and -0.21 for heroin.

Models 4 and 5 in Table 4 provide a check for policy endogeneity. These models add the one-year leading price in addition to the current and lagged prices. Significant leading price effects may indirectly inform on the presence of policy endogeneity or any specification bias. The current price effect for both cocaine and heroin use is negative and significant in all cases. The contemporaneous price elasticity for cocaine participation is about -0.18; for heroin, it is -0.09. These magnitudes are highly similar to the estimates reported above and are not sensitive to the inclusion of the lead prices. The lagged prices are significant as a group in all specifications, while the lead prices are insignificant. The contemporaneous as well as the long-run price elasticities remain robust to the inclusion of the lead prices, and current cocaine or heroin use does not seem to be affected by future prices.

Since this is not a definitive test, it would be reassuring if other specification checks also confirm that policy endogeneity is not likely or does not substantially alter inferences. Table 5 presents specifications that include lagged drug enforcement measures in order to control for any unobserved shocks to past drug-related outcomes that may affect current prices. One set of lagged enforcement variables includes one-year lags of the arrest rate for any drug violation and the arrest rate for selling or trafficking in any drugs. The second set includes one-year lags of the arrest rate for any drug violation, the arrest rate for selling cocaine and opiates, and the arrest rate for selling marijuana. The third set includes both one- and two-year lags of the arrest rate for any drug violation and the arrest rate for selling or trafficking in any drugs. The final set includes one- and two-year lags of the arrest rate for any drug violation, the arrest rate for selling cocaine and opiates, and the arrest rate for selling marijuana.

The top panel of Table 6 presents these results for recent cocaine use. Specifications 1-4 include MSA and year effects in addition to the other covariates, and specifications 5-8 also add MSA-specific linear trends. The lagged enforcement variables as a group are significant in all models. The cocaine price elasticity is significantly negative in all specifications and is robust to the inclusion of the lagged arrest rates. It decreases only marginally and ranges from -0.10 to -0.19.

The bottom panel presents the same models for recent heroin use. Heroin price is negative and significant in all cases, and the lagged enforcement measures are significant in all but one of the models. The price elasticity remains robust and lies between -0.08 and -0.13. Overall, these checks show that the drug participation price elasticities are not sensitive to the addition of leading prices or lagged arrest rates, which may be capturing to some extent unobserved shocks simultaneously affecting past drug uses and price.[24]

All of the models presented thus far have included only the relevant drug's own price. Table 6 estimates the cross-price model derived in equation (20), with and without lagged prices. Specifications 1-4 present the models for recent cocaine use. Current cocaine price is significantly negative in all models as is the one-year lagged cocaine price. The contemporaneous cocaine participation own-price elasticity is estimated at -0.20. Current heroin price is also negative and significant in the full fixed effects models, with a cross-price elasticity of -0.03. The one-year lagged cross-price elasticity is estimated at -0.04. This suggests that cocaine and heroin are not only current economic complements but also intertemporal complements. This is consistent with a cross-reinforcement effect wherein past heroin consumption motivates current cocaine consumption by raising the current marginal utility of cocaine use. Specifications 5-8 present similar models for heroin use. The current own price elasticity is not affected by the inclusion of the current and lagged cocaine prices, and is estimated at -0.09. The lagged heroin price effects are also significant, with a corresponding elasticity of about -0.17. However, the cross price effects are imprecisely estimated in these models. Symmetry of compensated cross-price effects for cocaine use and heroin use should not be expected because these are demand functions at the extensive margin, measuring the decision to participate in the consumption of a given drug.[25]

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[24] The elasticities are more affected in non-fixed effects models (not shown), suggesting that the full fixed effects and the city-specific trends are capturing much of the variation in such factors and other unobserved non-contemporaneous shocks.

[25] In the case of an interior solution, symmetric cross-price effects result from Young's theorem applied to a small neighborhood around a given interior point where both X and Y are consumed. In the case of an exterior solution, the comparison of cross-price effects involves the comparison of neighborhoods around two points, one where X is consumed but Y is not and

One of the advantages of DUF is that the indicators of drug use based on urine specimens are objective and more accurate than self-reported indicators, which may be plagued by measurement errors due to misreporting. Such inaccuracies in self-reported data may have biased prior estimates of the price elasticity of demand. The extent of this measurement error can be gauged in DUF because arrestees were also asked to report on their own cocaine and heroin use in the past 72 hours.[26] Looking at the simple means, there seems to be vast under-reporting in the self-reported data. About 41 % of the arrestees tested positive for cocaine use whereas only 21 % admitted to using cocaine recently. Over eight percent of the arrestees tested positive for heroin whereas only five percent admitted to its use in the last three days. While most agree that survey data are plagued with misreporting, it is unknown to what degree and whether the misreporting is systematic. It is likely that hardcore drug users are more likely to under-report, and that recent use is more likely to be under-reported than past month or past year use. At least for the sample of arrestees, it can be assessed whether the elasticities and marginal effects are sensitive to such measurement error. The participation-price elasticity can differ because of differences in mean participation as well differences in the marginal response. Under-reporting, by reducing the measured mean participation, results in larger magnitudes of the elasticity, ceteris paribus. However, it is also likely that the marginal response may be different between those who accurately report drug use and those who do not. Since the sign of this difference is not known a priori, this effect may either raise or lower the elasticity.

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vice versa. In the absence of requisite restrictions on the utility parameters, symmetric cross-price effects for the participation decision are not a necessary property of such demand functions.

[26] These questions were only asked from 1989 to 1999.

Table 7 presents models for both the urinalysis-based indicators of drug use and the self-reported measures. The top panel estimates the same logistic specification used thus far, and reports both the elasticity and the marginal effect for cocaine and heroin use. Comparing the specifications for the objective and self-reported indicators of cocaine use, the marginal effect of price is somewhat larger for the urinalysis based indicators. However, the large under-reporting raises the absolute elasticity. For heroin participation, the marginal price response is not much different between the two sets of outcomes. The under-reporting again causes the absolute magnitude of the self-reported elasticities to be larger. The bottom panel estimates a double-log demand function so that the estimated price coefficient also represents the elasticity. The price elasticities with respect to self-reported cocaine participation and heroin participation are again higher. Overall these results suggest that self-reported data are plagued by under-reporting, which in the case of heavy users is likely to be substantial. Such under-reporting tends to impart an upward absolute bias, yielding cocaine price elasticities that are as much as two times the magnitude and heroin price elasticities that are as much as three times the magnitude relative to those based on objective indicators.

Defining the percentage of arrestees in each MSA who under-report as the difference between the objective and the subjective participation measures, models show that the rate of under-reporting is significantly negatively related to the own drug's price conditional on other observed covariates. This means that the rate of under-reporting is higher in those cities with lower drug prices and presumably higher consumption. This negative correlation between under-reporting and drug prices implies that the measurement error is systematic. It is also consistent with the direction of the bias in the elasticities estimated with the self-reported data and the hypothesis that more heavy drug users are less price responsive.

Models of addiction suggest that current use is a direct and positive function of past use due to the reinforcement effect. Earlier, the addictive stock was proxied by a series of past prices due to problems associated with including a lagged dependent variable as a regressor. The significance of lagged price effects is evidence of this addiction framework. Table 8 directly estimates the demand function under addiction expressed in equation (22) by the Arellano-Bond (A-B) procedure, which as explained in section 5 is a first-differenced instrumental variables estimator.[27]

The top panel of Table 8 presents the results for logistic cocaine use. Specifications 1-3 exclude year effects, and specifications 4-6 include them. The one-year lagged cocaine use is positive and significant at the one percent level in all models. This is consistent with the addiction paradigm. Cocaine price is negative and significant in all specifications. Specification 1 and 4 treat the cocaine price as strictly exogenous. Specifications 2 and 5 treat it as a predetermined variable and account for an endogenous policy response. Specifications 3 and 6 treat the price as a pure endogenous variable and account for the simultaneity of supply and demand.[28] Specifications 1-3, which exclude year effects, are only presented for comparison.

[27] Baltagi et al. (2000) estimate demand specifications for cigarettes using various dynamic panel-data estimators. Also see Baltagi and Levin (1986). Anderson and Hsiao (1981, 1982) discuss these estimation techniques. Baltagi (1995) provides a good overview of these estimators.

[28] It is generally assumed that the U.S. supply of cocaine and heroin is infinitely elastic, that is suppliers are able to satisfy any market demand at the current price. This assumption is invoked in virtually all empirical studies of the demand for drugs. Cocaine and heroin are basically agricultural products that are inexpensive to produce and require minimal processing. Rhodes et al. (2001) note that cocaine, for instance, is fairly easy to transport and only about 300 metric tons satisfy entire U.S. market demand. The largest costs involved in producing, transporting, and distributing cocaine are the costs of operating in the illegal sector. Miron (2001) suggests that the black market price of cocaine is as much as 5 times higher and that of heroin as much as 19 times higher than prices that would prevail in a legalized regime. The amount of coca harvested exceeds the amount shipped by a substantial amount. This implies that suppliers can draw on this excess capacity to satisfy any expansions in market demand

For these models, the test of overidentifying restrictions for instrumental validity can be rejected at the 10 % significance level. The instrumental matrix passes the validity check more readily in the models with year effects. From these specifications, the short-run or contemporaneous cocaine price elasticity is estimated to be between –0.09 and –0.12. A model with a lagged dependent variable can be derived from a distributed lagged model where current consumption depends on all past values of price and the effect of successively distant lags diminish geometrically. In this case, the long-run price elasticity can be calculated as the current price elasticity times ($1/1-\delta_1$) where $\delta_1$ is the coefficient of lagged drug use. It measures the total impact of a change in price on participation after all the lagged effects have been felt. The long-run cocaine price elasticity is estimated between –0.16 and –0.22. Note that this long-run elasticity is much smaller than that implied from the reduced-form myopic addiction models that include a series of lagged prices. The reason is that these models do not show any evidence that lagged prices have a substantially smaller effect than current prices, at least for the one and two-year lags. That is, the price coefficients are not restricted to follow a geometrically decaying pattern.

Treating the cocaine price as predetermined or endogenous and instrumenting for it does not substantially alter the results. It should also be noted that there is no evidence of autocorrelation in any of the models; no autocorrelation in non-differenced errors is equivalent to no autocorrelation beyond the first order in first-differenced errors. This is a necessary condition for the validity of past levels as instruments for current differences in the A-B procedure. If

without increasing their per unit cost. Basov, Jacobson, and Miron (2001) similarly note that the U.S. is also a relatively small market for opiates. All of these considerations point to the domestic supply curves for cocaine and heroin being highly elastic. However, simultaneity and policy endogeneity is interpreted as an intertemporal omitted variables bias, then it will lead to impure serial correlation in the disturbance term. The lack of serial correlation suggests that policy endogeneity is not likely. This is consistent with the inferences drawn from the prior checks for such specification bias.

The bottom panel of Table 8 presents similar estimation for logistic heroin use. Lagged heroin use is significantly positive in all specifications. The short-run heroin price elasticity is estimated to be between –0.06 and –0.11, and the long-run price elasticity is between –0.09 and –0.17. Overall, these results confirm the strong addictive aspects of cocaine and heroin. Magnitudes of the current price elasticity for heroin are very similar to those estimated in the earlier models with and without lagged prices. Furthermore, the errors are non-autocorrelated, and explicitly treating price as a predetermined or endogenous variable does not substantially alter the elasticities.

## 7. Conclusions

The objective of this study was to estimate the empirical relationship between the prices of cocaine and heroin and objective indicators of their use. By employing data on cocaine and heroin use based on urine specimens this study bypasses any measurement errors prevalent in survey data due to misreporting. The persons sampled in DUF constitute an important subgroup of hardcore drug users, which is often not captured by national surveys. Since these persons are more likely to be serious users, impose the heaviest costs on society, and are the targets of much illegal drug policy, studying their addictive consumption behavior is very important from a public policy stance.

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the more relevant consideration of policy endogeneity are directly addressed with the Arellano-Bond methodology.

The key conclusion that emerges from this study is that cocaine and heroin prices have a significantly negative effect on the probability of use for arrestees. The elasticity estimates that emerge are robust in virtually all of the specifications tested. Results from DUF indicate that the own-price cocaine participation elasticity ranges from -0.11 to -0.23, and the own-price heroin participation elasticity is between -0.07 and -0.12. These elasticities are significantly smaller than those estimated in prior studies. This is not surprising since the arrestee population is more likely to be addicted to drugs than the population at large and thus may be less responsive to price. Indicators based on urinalysis are also more likely to pick up participation in heavy consumption, which may be less responsive to price. Furthermore, the data from DUF show that self-reports of drug use are biased downwards, and this may impart an upward absolute bias to the estimated elasticities. These elasticities are also smaller in magnitude than those obtained from other studies of DUF. However, all of these other studies are plagued with specification errors, inadequate controls, and bias due to unmeasured factors. The present study uses the time series of repeated city cross-sections to estimate full fixed-effects specifications that control for unmeasured factors, policy endogeneity, and simultaneity. It also adds to the limited literature on cross-price elasticities; the results suggest that cocaine and heroin are likely economic complements.[29] The results also show the presence of significantly negative own and cross-price effects but insignificant lead-price effects.

The contemporaneous elasticity understates the full effect, since the long-run price elasticity is about twice the magnitude. In a fixed population of arrestees, the elasticity estimates from this study imply that a 10 % increase in the current price of cocaine in the U.S. will prevent about 63,187 arrestees from currently using cocaine and deter an additional 103,627 arrestees in future periods. A corresponding increase in heroin price will prevent about 7,093 arrestees from consuming heroin in the current period and deter an additional 14,840 arrestees subsequently.[30] Approximately 13.8 % of cocaine and heroin users consume both drugs. Taking multiple users into account, a 10 % increase in cocaine and heroin price will thus deter approximately 165,842 arrestees from using drugs. Total societal costs from drug abuse were estimated at $160.7 billion for 2000 (ONDCP, 2001). In the Drug Abuse Warning Network, about 46 % of all hospital emergency department drug-related episodes involved cocaine or heroin in 2000.[31] Applying this proxy share for health-related costs, total costs from cocaine and heroin abuse amount to approximately $73.9 billion. For that same year, there were a total of 13.8 million federal, state, and local arrests in the U.S. About 30.5 % of the DUF sample tested positive for either cocaine or heroin, or both. Ignoring multiple arrests in a year, this implies that there were approximately 4.2 million cocaine or heroin using arrestees in 2000. Assuming that these drug abusing arrestees are fully responsible for all of the costs from drug abuse, the social cost of one such drug user is $17,539.[32] Thus a 10 % increase in both cocaine and heroin prices will reduce social costs by $2.9 billion. Simple time-series estimates and prior studies suggest that a 10 % increase in drug prices requires an increase in total drug control spending of at least $2 - $3 billion or

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[29] This is consistent with the studies by Saffer and Chaloupka (1996a, 1996b) and Dave (2004).
[30] These estimates are based on Table 4 and the total number of arrests (13,814,843) and arrestee drug prevalence in 2000. If the cross-price effects are negative, then more arrestees will be deterred from using cocaine and/or heroin. It is also assumed that increases in drug prices do not affect arrests. If enforcement efforts that raise the price of drugs also raise the total number of arrests, then less arrestees will be deterred from drug participation.
[31] This is likely an overestimate because episodes may involve multiple drugs. For instance, only 28 % of cocaine episodes involved solely cocaine. See Dave (2004).
[32] Rhodes and McDonald estimated that the sample represented in DUF accounts for as much as 90% of total cocaine consumption and virtually all of the heroin consumption in the U.S.

between $12,060 to $18,090 per deterred user.[33] Thus, it is not readily apparent that further enforcement and interdiction driven increases in drug prices are necessarily cost-efficient. The share of law enforcement has steadily risen from 36 % to 53 % over the past 15 years. In contrast, resources allocated towards shifting demand, such as treatment and prevention, have remained stable at only about one-third of the total budget over this period. Requisite caveats notwithstanding, the low magnitudes of the participation price elasticity suggest that a more demand-driven drug control policy may well be worth considering in future allocation of the drug control budget.[34]

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[33] Total drug control spending in the U.S. amounted to $35 billion in 2000. Miron (2001) estimates that the black market price of cocaine is about 4 times larger and that of heroin is about 14 times larger than the price in a legal market. A crude extrapolation implies that an increase in the drug control budget of $2 - $3 billion will raise the price of both drugs by about 10 %. Time series regressions of cocaine and heroin prices on total drug control spending, after accounting for linear and quadratic trends, suggest a similar increase in spending of $2 billion.
[34] This analysis does not consider the price response at the intensive margin. However, prior studies have shown that the consumption elasticity for users is a very small share of the total price response. See Grossman et al. (2002). Models estimated on the DUF sample, based on self-reported past month participation and frequency, confirm this result. Saffer, Chaloupka, and Dave (2001) also suggest that a reallocation of resources from criminal justice to drug treatment may be more cost-effective.

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**Table 1**
**Drug Use Forecasting System**
**Sample Means**

| Variable | Definition | Mean |
|---|---|---|
| Recent Cocaine Use Urinalysis | Percent of arrestees in each MSA whose urine tested positive for cocaine use in the past 48 – 72 hours | 0.3976 (0.1374) |
| Logistic Recent Cocaine Use Urinalysis | Log of the odds of recent cocaine use urinalysis | -0.4587 (0.6312) |
| Recent Heroin Use Urinalysis | Percent of arrestees in each MSA whose urine tested positive for opiate use in the past 48 – 72 hours | 0.0827 (0.0585) |
| Logistic Recent Heroin Use Urinalysis | Log of the odds of recent heroin use urinalysis | -2.6622 (0.8136) |
| Recent Cocaine Use Self-Report | Percent of arrestees in each MSA who reported using cocaine in the past 72 hours | 0.2130 (0.0800) |
| Logistic Recent Cocaine Use Self-Report | Log of the odds of recent cocaine use self-report | -1.3833 (0.5286) |
| Recent Heroin Use Self-Report | Percent of arrestees in each MSA who reported using heroin in the past 72 hours | 0.0505 (0.0476) |
| Logistic Recent Heroin Use Self-Report | Log of the odds of recent heroin use self-report | -3.4140 (1.1522) |
| Past Month Cocaine Use | Percent of arrestees in each MSA who reported using cocaine in the past 30 days | 0.2803 (0.0902) |
| Logistic Past Month Cocaine Use | Log of the odds of past month cocaine use | -0.9920 (0.4763) |
| Past Month Heroin Use | Percent of arrestees in each MSA who reported using heroin in the past 30 days | 0.0641 (0.0548) |
| Logistic Past Month Heroin Use | Log of the odds of past month heroin use | -3.0819 (1.0485) |
| Frequency Past Month Cocaine Use | Mean number of days in each MSA that cocaine was used in the past 30 days, conditional on users | 23.2946 (4.5912) |
| Log Frequency Past Month Cocaine Use | Log of frequency past month cocaine use | 3.1281 (0.2040) |
| Frequency Past Month Heroin Use | Mean number of days in each MSA that heroin was used in the past 30 days, conditional on users | 17.0798 (4.3605) |
| Log Frequency Past Month Heroin Use | Log of frequency past month heroin use | 2.7862 (0.3798) |
| Cocaine Price | Price of one pure gram of cocaine, divided by the annual national consumer price index | 80.47 (27.81) |
| Heroin Price | Price of one pure gram of heroin, divided by the annual national consumer price index | 490.18 (373.78) |
| Male | Percent of arrestees in each MSA who are male | 0.7586 (0.1174) |
| Black | Percent of arrestees in each MSA who are black | 0.5152 (0.2592) |
| Other Race | Percent of arrestees in each MSA who are of a race other than white or black | 0.0248 (0.0529) |
| Hispanic | Percent of arrestees in each MSA who are Hispanic | 0.1628 (0.1792) |
| Age 16-24 | Percent of arrestees in each MSA who are between the ages of 16 through 24 | 0.3338 (0.0571) |
| Age 25-54 | Percent of arrestees in each MSA who are between the ages of 25 through 54 | 0.6495 (0.0567) |
| High School Graduate | Percent of arrestees in each MSA who are high school graduates or above | 0.5946 |

| | | |
|---|---|---|
| | | (0.0685) |
| Full-Time Employment | Percent of arrestees in each MSA whose main source of income in the past 30 days was from full-time employment | 0.3901<br>(0.0998) |
| Married | Percent of arrestees in each MSA who are married | 0.1597<br>(0.0522) |
| Drug Charge | Percent of arrestees in each MSA whose most serious offense charge was drug related | 0.1734<br>(0.0757) |
| MSA Income | Per capita personal income in each MSA, divided by the annual national consumer price index | 16.8784<br>(2.6015) |
| MSA Unemployment | Unemployment rate in each MSA | 0.0544<br>(0.0208) |
| DUF Arrest Rate | Total number of arrestees in DUF divided by total number of arrests in each MSA | 0.0113<br>(0.0090) |
| Log DUF Arrest Rate | Natural logarithm of DUF Arrest Rate | -4.7746<br>(0.8132) |
| Drug Possession Arrest Rate | Percent of arrests in each MSA resulting from any drug sale or trafficking | 0.0777<br>(0.0367) |
| Drug Violation Arrest Rate | Total number of arrests in each MSA due to any drug violation divided by MSA population | 0.0056<br>(0.0025) |
| Drug Sale Arrest Rate | Total number of arrests in each MSA due to any drug sale or trafficking divided by MSA population | 0.0014<br>(0.0012) |
| Cocaine Sale Arrest Rate | Total number of arrests in each MSA due to cocaine sale or trafficking divided by MSA population | 0.0008<br>(0.0010) |
| Marijuana Sale Arrest Rate | Total number of arrests in each MSA due to marijuana sale or trafficking divided by MSA population | 0.0003<br>(0.0002) |
| Population | Total MSA population | 2978176<br>(2369104) |
| Observations | | 332 |

Notes: Standard deviations are in parentheses. Number of observations listed represents the maximum number. For some variables, the actual sample size is slightly less due to missing information.

**Table 2**
**Logistic Cocaine & Heroin Use**
**Baseline Models**

| Dependent Variable | Logistic Recent Cocaine Use | | | | Logistic Recent Heroin Use | | | |
|---|---|---|---|---|---|---|---|---|
| Specification | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Own Price (Cocaine / Heroin) | -0.00425*** (-4.27) ε = -0.204 | -0.00452*** (-5.68) ε = -0.217 | -0.00399*** (-5.01) ε = -0.192 | -0.00231*** (-3.36) ε = -0.111 | -0.00030** (-2.11) ε = -0.134 | -0.00022*** (-2.66) ε = -0.098 | -0.00025*** (-2.81) ε = -0.112 | -0.00011* (-1.61) ε = -0.049 |
| Male | 0.34056 (1.35) | Yes*** | Yes*** | Yes*** | 1.18552*** (2.95) | Yes*** | Yes*** | Yes*** |
| Black | 1.38365*** (8.46) | | | | -1.48631*** (-5.85) | | | |
| Other Race | -1.53597** (-2.17) | | | | -2.92378*** (-2.92) | | | |
| Hispanic | 1.17571*** (5.11) | | | | 0.28981 (0.82) | | | |
| Age 16-24 | 6.63717* (1.82) | | | | 6.81469 (1.15) | | | |
| Age 25-54 | 9.86560*** (2.67) | | | | 3.89146 (0.65) | | | |
| High School Graduate | -0.47737 (-1.01) | | | | 0.88981 (1.08) | | | |
| Full-Time Employment | -0.47854 (-1.42) | | | | -4.26460*** (-7.50) | | | |
| Married | -2.25552*** (-2.88) | | | | -0.82250 (-0.65) | | | |
| MSA Income | -0.02060* (-1.95) | | | | 0.03856** (2.38) | | | |
| MSA Unemployment | -0.45419 (-0.41) | | | | 1.66783 (0.34) | | | |
| Drug Charge | 0.37793 (1.20) | | | | 0.88997* (1.90) | | | |
| Drug Possession Arrest Rate | -1.96280** (-2.23) | Yes | No | Yes | -5.67362*** (-4.11) | Yes | No | Yes |
| DUF Arrest Rate | -0.07976** (-2.10) | Yes | No | Yes | -0.19246*** (-3.35) | Yes*** | No | Yes** |
| Year Effects | Yes*** | Yes*** | Yes*** | Yes*** | Yes** | Yes*** | Yes*** | Yes*** |
| MSA Effects | No | Yes*** | Yes*** | Yes*** | No | Yes*** | Yes*** | Yes*** |
| MSA-Linear Trend | No | No | No | Yes*** | No | No | No | Yes*** |
| R-Squared | 0.698 | 0.889 | 0.868 | 0.940 | 0.536 | 0.887 | 0.868 | 0.932 |
| Observations | 300 | 300 | 322 | 300 | 281 | 281 | 301 | 281 |

Notes: All estimates are from weighted regressions. Dependent variable is log(A/1-A) where A is the percentage of arrestees in each MSA testing positive for cocaine or heroin use. T-ratios are in parentheses. *** significant at 1 percent ** significant at 5 percent * significant at 10 percent. Elasticities are reported where the own-price coefficient is significant at 10 percent or less in a one-tailed test.

**Table 3**
**Logistic Cocaine & Heroin Use**
**Restricted Samples**

| Dependent Variable | Logistic Recent Cocaine Use | | | | | |
|---|---|---|---|---|---|---|
| Sample | Drug Offenders | | Non-Drug Offenders | | Non-Drug Misdemeanor Offenders | |
| Specification | 1 | 2 | 3 | 4 | 5 | 6 |
| Cocaine Price | -0.00330*** (-2.50) ε = -0.122 | -0.00452*** (-3.97) ε = -0.167 | -0.00548*** (-5.93) ε = -0.276 | -0.00404*** (-4.90) ε = -0.204 | -0.00606*** (-6.22) ε = -0.302 | -0.00406*** (-4.01) ε = -0.202 |
| Individual / MSA Covariates | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** |
| Year Effects | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** |
| MSA Effects | No | Yes*** | No | Yes*** | No | Yes*** |
| R-Squared | 0.512 | 0.795 | 0.695 | 0.862 | 0.741 | 0.853 |
| Observations | 321 | 321 | 322 | 322 | 320 | 321 |
| Recent Cocaine Use - Urinalysis | 0.538 | | 0.368 | | 0.375 | |
| Recent Cocaine Use - Self Report | 0.314 | | 0.191 | | 0.204 | |
| Past Month Cocaine Use - Self Report | 0.394 | | 0.255 | | 0.263 | |
| Frequency Past Month Cocaine Use - Self Report | 24.1 | | 23.1 | | 23.0 | |

| Dependent Variable | Logistic Recent Heroin Use | | | | | |
|---|---|---|---|---|---|---|
| Sample | Drug Offenders | | Non-Drug Offenders | | Non-Drug Misdemeanor Offenders | |
| Specification | 1 | 2 | 3 | 4 | 5 | 6 |
| Heroin Price | -0.00034** (-1.66) ε = -0.147 | -0.00017* (-1.34) ε = -0.073 | -0.00043*** (-2.94) ε = -0.194 | -0.00030*** (-3.25) ε = -0.135 | -0.00053*** (-3.77) ε = -0.237 | -0.00018*** (-2.05) ε = -0.081 |
| Individual / MSA Covariates | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** |
| Year Effects | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** |
| MSA Effects | No | Yes*** | No | Yes*** | No | Yes*** |
| R-Squared | 0.271 | 0.805 | 0.492 | 0.847 | 0.578 | 0.848 |
| Observations | 295 | 295 | 301 | 301 | 288 | 288 |
| Recent Heroin Use - Urinalysis | 0.113 | | 0.075 | | 0.078 | |
| Recent Heroin Use - Self-Report | 0.074 | | 0.045 | | 0.044 | |
| Past Month Heroin Use - Self Report | 0.090 | | 0.058 | | 0.057 | |
| Frequency Past Month Heroin Use - Self-Report | 18.0 | | 16.9 | | 16.6 | |

Notes: All estimates are from weighted regressions. Dependent variable is log(A/1-A) where A is the percentage of arrestees in each MSA testing positive for cocaine or heroin use. T-ratios are in parentheses. *** significant at 1 percent ** significant at 5 percent * significant at 10 percent. Elasticities are reported where the own-price coefficient is significant at 10 percent or less in a one-tailed test. Individual/MSA covariates include: male, black, other race, Hispanic, age 16-24, age 25-54, high school graduate, full-time employment, married, MSA income, and MSA unemployment.

**Table 4**
**Logistic Cocaine & Heroin Use**
**Lagged & Leading Prices**

| Dependent Variable | Logistic Recent Cocaine Use | | | | |
|---|---|---|---|---|---|
| Specification | 1 | 2 | 3 | 4 | 5 |
| Cocaine Price | -0.00454***<br>(-3.95)<br>ε = -0.220 | -0.00362***<br>(-4.47)<br>ε = -0.175 | -0.00190***<br>(-2.85)<br>ε = -0.092 | -0.00371***<br>(-4.35)<br>ε = -0.180 | -0.00359***<br>(-4.23)<br>ε = -0.174 |
| 1 Year Lagged Cocaine Price | -0.00232**<br>(-2.03)<br>ε = -0.116 | -0.00301***<br>(-3.85)<br>ε = -0.151 | -0.00092*<br>(-1.37)<br>ε = -0.046 | -0.00322***<br>(-3.69)<br>ε = -0.162 | -0.00287***<br>(-3.29)<br>ε = -0.144 |
| 2 Year Lagged Cocaine Price | -0.00001<br>(-0.01) | -0.00255***<br>(-3.51)<br>ε = -0.136 | -0.00016<br>(-0.25) | No | -0.00207***<br>(-2.59)<br>ε = -0.111 |
| 1 Year Leading Cocaine Price | No | No | No | Yes | Yes |
| Long Run Elasticity | -0.333 | -0.445 | -0.137 | -0.336 | -0.414 |
| Individual / MSA Covariates | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** |
| Year Effects | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** |
| MSA Effects | No | Yes*** | Yes*** | Yes*** | Yes*** |
| MSA-Linear Trend | No | No | Yes*** | No | No |
| R-Squared | 0.679 | 0.879 | 0.929 | 0.878 | 0.880 |

| Dependent Variable | Logistic Recent Heroin Use | | | | |
|---|---|---|---|---|---|
| Specification | 1 | 2 | 3 | 4 | 5 |
| Heroin Price | -0.00027*<br>(-1.58)<br>ε = -0.121 | -0.00017**<br>(-1.89)<br>ε = -0.076 | -0.00012**<br>(-1.75)<br>ε = -0.054 | -0.00020**<br>(-2.24)<br>ε = -0.090 | -0.00016**<br>(-1.83)<br>ε = -0.072 |
| 1 Year Lagged Heroin Price | -0.00031**<br>(-2.06)<br>ε = -0.164 | -0.00030***<br>(-3.92)<br>ε = -0.159 | -0.00029***<br>(-4.67)<br>ε = -0.154 | -0.00028***<br>(-3.47)<br>ε = -0.149 | -0.00024***<br>(-3.02)<br>ε = -0.127 |
| 2 Year Lagged Heroin Price | -0.00015<br>(-1.14) | -0.00007<br>(-0.94) | -0.00008*<br>(-1.39)<br>ε = -0.046 | No | -0.00009<br>(-1.22) |
| 1 Year Leading Heroin Price | No | No | No | Yes | Yes |
| Long Run Elasticity | -0.261 | -0.211 | -0.220 | -0.216 | -0.180 |
| Individual / MSA Covariates | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** |
| Year Effects | Yes** | Yes*** | Yes*** | Yes*** | Yes*** |
| MSA Effects | No | Yes*** | Yes*** | Yes*** | Yes*** |
| MSA-Linear Trend | No | No | Yes*** | No | No |
| R-Squared | 0.460 | 0.879 | 0.942 | 0.887 | 0.892 |

Notes: All estimates are from weighted regressions. Dependent variable is log(A/1-A) where A is the percentage of arrestees in each MSA testing positive for cocaine or heroin use. T-ratios are in parentheses. *** significant at 1 percent ** significant at 5 percent * significant at 10 percent. Elasticities are reported where the own-price coefficient is significant at 10 percent or less in a one-tailed test. Individual/MSA covariates include: male, black, other race, Hispanic, age 16-24, age 25-54, high school graduate, full-time employment, married, MSA income, and MSA unemployment.

**Table 5**
**Logistic Cocaine and Heroin Use**
**With Lagged Enforcement Measures**

| Specification | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| Dependent Variable | Logistic Recent Cocaine Use | | | | | | | |
| Cocaine Price | -0.00393***<br>(-4.56)<br>ε = -0.191 | -0.00381***<br>(-4.51)<br>ε = -0.185 | -0.00340***<br>(-3.68)<br>ε = -0.165 | -0.00340***<br>(-3.81)<br>ε = -0.165 | -0.00244***<br>(-2.97)<br>ε = -0.118 | -0.00236***<br>(-2.91)<br>ε = -0.114 | -0.00228***<br>(-2.55)<br>ε = -0.111 | -0.00208**<br>(-2.33)<br>ε = -0.101 |
| Individual / MSA Covariates | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** |
| Lagged Enforcement | Group 1*** | Group 2*** | Group3*** | Group 4*** | Group 1*** | Group 2*** | Group3*** | Group 4*** |
| Year Effects | Yes*** | Yes*** | Yes*** | Yes*** | Yes** | Yes** | Yes** | Yes** |
| MSA Effects | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** |
| MSA-Linear Trend | No | No | No | No | Yes*** | Yes*** | Yes*** | Yes*** |
| R-Squared | 0.889 | 0.892 | 0.897 | 0.901 | 0.936 | 0.939 | 0.937 | 0.940 |
| Dependent Variable | Logistic Recent Heroin Use | | | | | | | |
| Heroin Price | -0.00029***<br>(-2.92)<br>ε = -0.130 | -0.00025***<br>(-2.49)<br>ε = -0.112 | -0.00029***<br>(-2.76)<br>ε = -0.130 | -0.00026***<br>(-2.44)<br>ε = -0.117 | -0.00021**<br>(-2.26)<br>ε = -0.094 | -0.00020**<br>(-2.08)<br>ε = -0.090 | -0.00018**<br>(-1.67)<br>ε = -0.081 | -0.00017*<br>(-1.51)<br>ε = -0.076 |
| Individual / MSA Covariates | Yes*** | Yes*** | Yes*** | Yes*** | Yes** | Yes* | Yes | Yes |
| Lagged Enforcement | Group 1*** | Group 2*** | Group3*** | Group 4*** | Group 1** | Group 2* | Group3** | Group 4 |
| Year Effects | Yes*** | Yes*** | Yes*** | Yes*** | Yes | Yes | Yes | Yes |
| MSA Effects | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** |
| MSA-Linear Trend | No | No | No | No | Yes*** | Yes*** | Yes*** | Yes*** |
| R-Squared | 0.899 | 0.900 | 0.901 | 0.903 | 0.935 | 0.935 | 0.934 | 0.932 |

Notes: All estimates are from weighted regressions. Dependent variable is log(A/1-A) where A is the percentage of arrestees in each MSA testing positive for cocaine or heroin use. T-ratios are in parentheses. *** significant at 1 percent ** significant at 5 percent * significant at 10 percent. Group 1 enforcement variables are: lagged one year drug violation arrest rate and drug sale arrest rate. Group 2 enforcement variables are: lagged one year drug violation arrest rate and cocaine/heroin sale arrest rate. Group 3 enforcement variables are: lagged one year drug violation arrest rate and marijuana sale arrest rate. Group 4 enforcement variables are: one and two year lagged drug violation arrest rate and cocaine/heroin sale arrest rate. Elasticities are reported where the own-price coefficient is significant at 10 percent or less in a one-tailed test. Individual/MSA covariates include: male, black, other race, Hispanic, age 16-24, age 25-54, high school graduate, full-time employment, married, MSA income, and MSA unemployment.

**Table 6**
**Logistic Cocaine and Heroin Use**
**Cross Prices**

| Dependent Variable | Logistic Recent Cocaine Use | | | | Logistic Recent Heroin Use | | | |
|---|---|---|---|---|---|---|---|---|
| Specification | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Cocaine Price | -0.00635***<br>(-5.52)<br>ε = -0.305 | -0.00540***<br>(-4.23)<br>ε = -0.259 | -0.00479***<br>(-5.19)<br>ε = -0.230 | -0.00413***<br>(-4.61)<br>ε = -0.198 | -0.00202<br>(-0.99) | -0.00129<br>(-0.57) | 0.00137<br>(1.12) | 0.00164<br>(1.37) |
| Heroin Price | 0.00001<br>(0.17) | 0.00003<br>(0.41) | -0.00012**<br>(-2.24)<br>ε = -0.035 | -0.00009*<br>(-1.75)<br>ε = -0.026 | -0.00037***<br>(-2.27)<br>ε = -0.165 | -0.00026*<br>(-1.50)<br>ε = -0.116 | -0.00026***<br>(-2.95)<br>ε = -0.116 | -0.00021***<br>(-2.35)<br>ε = -0.094 |
| 1 Year Lagged Cocaine Price | – | -0.00264**<br>(-2.10)<br>ε = -0.131 | – | -0.00337***<br>(-3.89)<br>ε = -0.167 | – | -0.00065<br>(-0.28) | – | 0.00057<br>(0.47) |
| 1 Year Lagged Heroin Price | – | 0.00002<br>(0.27) | – | -0.00013***<br>(-2.84)<br>ε = -0.044 | – | -0.00032**<br>(-2.26)<br>ε = -0.164 | – | -0.00033***<br>(-4.35)<br>ε = -0.169 |
| Individual / MSA Covariates | Yes*** | Yes*** | Yes*** | Yes | Yes*** | Yes*** | Yes*** | Yes |
| Year Effects | Yes*** | Yes*** | Yes*** | Yes*** | Yes* | Yes* | Yes*** | Yes*** |
| MSA Effects | No | No | Yes*** | Yes*** | No | No | Yes*** | Yes*** |
| R-Squared | 0.671 | 0.680 | 0.870 | 0.881 | 0.452 | 0.459 | 0.868 | 0.878 |

Notes: All estimates are from weighted regressions. Dependent variable is log(A/1-A) where A is the percentage of arrestees in each MSA testing positive for cocaine or heroin use. T-ratios are in parentheses. *** significant at 1 percent ** significant at 5 percent * significant at 10 percent. Group 1 enforcement variables are: lagged one year drug violation arrest rate and drug sale arrest rate. Group 2 enforcement variables are: lagged one year drug violation arrest rate and cocaine/heroin sale arrest rate. Group 3 enforcement variables are: lagged one year drug violation arrest rate and marijuana sale arrest rate. Group 4 enforcement variables are: one and two year lagged drug violation arrest rate and cocaine/heroin sale arrest rate. Elasticities are reported where the own-price coefficient is significant at 10 percent or less in a one-tailed test. Individual/MSA covariates include: male, black, other race, Hispanic, age 16-24, age 25-54, high school graduate, full-time employment, married, MSA income, and MSA unemployment.

**Table 7**
**Cocaine and Heroin Use**
**Urinalysis vs. Self-Report**

| Dependent Variable | Logistic Recent Cocaine Use | | | | Logistic Recent Heroin Use | | | |
|---|---|---|---|---|---|---|---|---|
| | Urinalysis | Self-Report | Urinalysis | Self-Report | Urinalysis | Self-Report | Urinalysis | Self-Report |
| Specification | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Cocaine Price | -0.00529***<br>(-5.22)<br>ME = -0.0013<br>ε = -0.248 | -0.00564***<br>(-5.15)<br>ME = -0.0009<br>ε = -0.353 | -0.00365***<br>(-4.22)<br>ME = -0.0009<br>ε = -0.171 | -0.00378***<br>(-3.96)<br>ME = -0.0006<br>ε = -0.236 | -0.00044***<br>(-2.62)<br>ME = -.00003<br>ε = -0.196 | -0.00061***<br>(-2.65)<br>ME = -.00003<br>ε = -0.282 | -0.00019**<br>(-2.09)<br>ME = -.00001<br>ε = -0.085 | -0.00042**<br>(-2.21)<br>ME = -.00002<br>ε = -0.194 |
| Individual / MSA Covariates | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** |
| Year Effects | Yes*** | Yes | Yes*** | Yes*** | Yes | Yes*** | Yes*** | Yes** |
| MSA Effects | No | No | Yes*** | Yes*** | No | No | Yes*** | Yes*** |
| R-Squared | 0.656 | 0.550 | 0.869 | 0.810 | 0.463 | 0.515 | 0.879 | 0.766 |

| Dependent Variable | Log Recent Cocaine Use | | | | Log Recent Heroin Use | | | |
|---|---|---|---|---|---|---|---|---|
| | Urinalysis | Self-Report | Urinalysis | Self-Report | Urinalysis | Self-Report | Urinalysis | Self-Report |
| Specification | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Log Cocaine Price | -0.26795***<br>(-4.90) | -0.51824***<br>(-4.64) | -0.13492***<br>(-2.86) | -0.26424**<br>(-2.28) | -0.12202*<br>(-1.45) | -0.34596***<br>(-2.68) | -0.02882<br>(-0.59) | -0.30700***<br>(-2.78) |
| Individual / MSA Covariates | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** |
| Year Effects | Yes*** | Yes | Yes*** | Yes*** | Yes | Yes* | Yes** | Yes** |
| MSA Effects | No | No | Yes*** | Yes*** | No | No | Yes*** | Yes*** |
| R-Squared | 0.641 | 0.529 | 0.857 | 0.728 | 0.444 | 0.521 | 0.876 | 0.772 |

Notes: All estimates are from weighted regressions. Dependent variable is log(A/1-A) where A is the percentage of arrestees in each MSA testing positive for cocaine use or heroin use (urinalysis) or the percentage of arrestees in each MSA reporting positive cocaine or heroin use in the past 72 hours (self-report). T-ratios are in parentheses. *** significant at 1 percent ** significant at 5 percent * significant at 10 percent. Group 1 enforcement variables are: lagged one-year drug violation arrest rate and drug sale arrest rate. Group 2 enforcement variables are: lagged one-year drug violation arrest rate, cocaine/heroin sale arrest rate, and marijuana sale arrest rate. Group 3 enforcement variables are: lagged one- and two-year drug violation arrest rate and drug sale arrest rate. Group 4 enforcement variables are: lagged one- and two-year drug violation arrest rate, cocaine/heroin sale arrest rate, and marijuana sale arrest rate. Elasticities are reported where the own-price coefficient is significant at 10 percent or less in a one-tailed test. Individual/MSA covariates include: male, black, other race, Hispanic, age 16-24, age 25-54, high school graduate, full-time employment, married, MSA income, and MSA unemployment.

**Table 8**
**Logistic Cocaine and Heroin Use**
**Arellano – Bond Estimation**

| Dependent Variable | Logistic Recent Cocaine Use | | | | | |
|---|---|---|---|---|---|---|
| Specification | 1 | 2 | 3 | 4 | 5 | 6 |
| Lagged 1 Year Logistic Cocaine Use | 0.35406***<br>(4.09) | 0.35316***<br>(7.25) | 0.34696***<br>(7.01) | 0.4550***<br>(7.37) | 0.44388***<br>(8.62) | 0.44623***<br>(8.41) |
| Cocaine Price | -0.00413***<br>(-3.41)<br>SR ε = -0.198<br>LR ε = -0.306 | -0.00433***<br>(-5.65)<br>SR ε = -0.207<br>LR ε = -0.320 | -0.00477***<br>(-5.69)<br>SR ε = -0.228<br>LR ε = -0.349 | -0.00186**<br>(-1.97)<br>SR ε = -0.089<br>LR ε = -0.163 | -0.00244***<br>(-2.66)<br>SR ε = -0.117<br>LR ε = -0.210 | -0.00252***<br>(-2.32)<br>SR ε = -0.121<br>LR ε = -0.219 |
| Year Effects | No | No | No | Yes | Yes | Yes |
| Cocaine Price Treatment | Exogenous | Predetermined | Endogenous | Exogenous | Predetermined | Endogenous |
| Sargan Overidentification Test | 0.060 | 0.090 | 0.057 | 0.266 | 0.172 | 0.121 |
| AR(1) Test | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| AR(2) Test | 0.186 | 0.187 | 0.165 | 0.436 | 0.334 | 0.324 |

| Dependent Variable | Logistic Recent Heroin Use | | | | | |
|---|---|---|---|---|---|---|
| Specification | 1 | 2 | 3 | 4 | 5 | 6 |
| Lagged 1 Year Logistic Cocaine Use | 0.21623**<br>(2.39) | 0.35717***<br>(5.19) | 0.31955***<br>(4.52) | 0.30121***<br>(3.39) | 0.40393***<br>(5.69) | 0.36940***<br>(4.97) |
| Cocaine Price | -0.00015*<br>(-1.60)<br>SR ε = -0.065<br>LR ε = -0.083 | -0.00023***<br>(-2.63)<br>SR ε = -0.100<br>LR ε = -0.156 | -0.00026***<br>(-2.78)<br>SR ε = -0.113<br>LR ε = -0.166 | -0.00014*<br>(-1.35)<br>SR ε = -0.061<br>LR ε = -0.087 | -0.00022**<br>(-2.29)<br>SR ε = -0.096<br>LR ε = -0.161 | -0.00025***<br>(-2.33)<br>SR ε = -0.109<br>LR ε = -0.173 |
| Year Effects | No | No | No | Yes | Yes | Yes |
| Cocaine Price Treatment | Exogenous | Predetermined | Endogenous | Exogenous | Predetermined | Endogenous |
| Sargan Overidentification Test | 0.000 | 0.152 | 0.105 | 0.000 | 0.209 | 0.135 |
| AR(1) Test | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| AR(2) Test | 0.141 | 0.141 | 0.124 | 0.220 | 0.187 | 0.170 |

Notes: Dependent variable is log(A/1-A) where A is the percentage of arrestees in each MSA testing positive for cocaine or heroin use. Z-values are in parentheses. *** significant at 1 percent ** significant at 5 percent * significant at 10 percent. Elasticities are reported where the own-price coefficient is significant at 10 percent or less in a one-tailed test. Individual/MSA covariates include: male, black, other race, Hispanic, age 16-24, age 25-54, high school graduate, full-time employment, married, MSA income, and MSA unemployment.