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ABSTRACT

In 2001, use of the STRIDE data base for the purposes of analyzing drug prices and the impact of public policies on drug markets came under serious attack by the National Research Council (Manski et al., 2001; Horowitz, 2001). While some of the criticisms raised by the committee were valid, many of the concerns can be easily addressed through more careful use of the data. In this paper, we first disprove Horowitz's main argument that prices are different for observations collected by different agencies within a city. We then revisit other issues raised by the NRC and discuss how certain limitations can be easily overcome through the adoption of random coefficient models of drug prices and by paying serious attention to drug form and distribution levels. Although the sample remains a convenience sample, we demonstrate how construction of city-specific price and purity series that pay careful attention to the data and incorporate existing knowledge of drug markets (e.g. the expected purity hypothesis) are internally consistent and can be externally validated. The findings from this study have important implications regarding the utility of these data and the appropriateness of using them in economic analyses of supply, demand and harms.

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1. INTRODUCTION

During this period of rising government debt, significant attention is again being given to the substantial amount of tax payer dollars allocated to controlling illicit drug use. In FY 2008, the federal government spent nearly $13 billion trying to control the U.S. drug problem, of which $8.3 billion was spent on disrupting illicit drug markets (ONDCP, 2007). The enormous outlay continues despite criticisms that the federal government lacks a means for evaluating the effectiveness of their policies and the money being spent (National Research Council (NRC), 2001).

One of the primary data sources used for evaluating the impact of supply side strategies on drug markets is the Drug Enforcement Agency's (DEA's) System to Retrieve Information from Drug Evidence (STRIDE) database. The DEA has been collecting information on drug transactions made by federal agents, law enforcement and their informants as part of the STRIDE database since the late 1970s. The data include information on the nature of the transaction (a purchase or a seizure), where it took place, the total amount paid when the transaction involved a purchase, the type of illicit substance, the quantity involved, and for most drugs the purity of the drug. A major criticism of the data is that they represent a convenience sample and are generated by purposeful policing activities (NRC, 2001; Horowitz, 2001). As such, the price series generated from STRIDE are believed to be an artifact of the data acquisition procedure and not an accurate indicator of price variation within the geographic markets in which they are collected. Evidence supporting this position is provided by Horowitz (2001), who shows large differences in price estimates obtained from different agencies within the same city, calling to question the internal validity of the data.

The question of whether STRIDE is a valid data source is important to answer for policy makers and researchers alike. Price data are necessary for us to understand both the supply and demand for drugs and how markets operate, particularly given the illicit nature of this market. A large stream of research has already been developed using the STRIDE data, informing our understanding of drug markets and how they work. For example, the data have been used to examine quantity discounts and quality premia for illicit drugs (Caulkins and Padman, 1993; Caulkins, 1994 and 1997a), risk premia in black markets (Miron, 2003; Caulkins & Reuter, 1998), geographic variation in drug prices (Caulkins, 1995), the responsiveness of demand for illicit drugs (Williams et al., 2004; DeSimone and Farrelly, 2003; Grossman and Chaloupka, 1998; Saffer and Chaloupka, 1999) and harms from drug use (Dave, 2006; Dobkins and Nicosia, Forthcoming; Caulkins, 2001). In addition, policy makers use information to reconcile supply- and demand- side estimates of the total amount of specific illicit drugs produced and consumed. If the data are flawed, then knowledge we think we gained from these analyses must also be reconsidered. Moreover, we lose the only current source of data for which information is available on transaction price, quantity and potency. No other national data system collects this kind of information on drug prices.

In this paper we reconsider the issue of the validity of the STRIDE data for estimating drug price series. We test the internal validity of STRIDE and demonstrate that when substantive knowledge about drug markets is incorporated into the use of STRIDE data, the data do in fact generate consistent trends across agencies within the same market, thus refuting the main criticism of Horowitz (2001). Another contribution of this paper is that we develop a statistical model of drug price series that reflect substantive knowledge about drug markets. We use the Granger-Sims causality framework to demonstrate the external validity of these price

series by using them to predict emergency room mentions, an independent indicator of drug demand that is available for cities across the United States. Therefore, unlike Horowitz (2001) and the NRC (2001), we conclude that STRIDE is useful for estimating trends in the price of illicit drugs.

2. THE STRIDE DATA

For over 25 years, the Drug Enforcement Agency (DEA) has maintained detailed information on drug transactions made by federal, state and local agencies engaged in law enforcement activities targeting drug markets. The primary purposes of the database are to catalog and control the inventory of drug acquisitions made by DEA agents; to keep current with the types of drugs being distributed and the characteristics of those drugs; and to use these data as part of prosecutions of federal drug offenders. Only acquisitions that are sent to a DEA laboratory for analysis are included in the database, although the acquisition could be made by federal agents, local law enforcement, or informants. While most state and local police agencies do not submit information on their undercover acquisitions to DEA laboratories, there are a few exceptions—in particular, the Metropolitan Police of Washington, DC.

It is the extremely rich content of information contained in STRIDE that makes it particularly appealing to researchers and policy analysts. The STRIDE data indicate the date, location, nature of the acquisition by law enforcement (seizure or purchase), weight, purity, chemical nature of the drug, and, for purchases only, the price paid.

The main limitation of STRIDE is that the data contained within it are neither a random, probabilistic, or representative sample of all drug transactions occurring in any geographic area. Of course, it would be difficult to create such a sampling frame given the underground nature of

drug markets, but the concern is that the data are generated as a result of purposeful law enforcement activities that are both strategic and deterministic. The timing and location of encounters are often erratic and the number of observations from a given location can vary dramatically from year to year, particularly for smaller cities. Furthermore, there is concern that the data in the sample may be biased if law enforcement agents pay systematically different prices than typical buyers in the market (Caulkins, 1997b). It has been argued that law enforcement agents and their informants risk detection if they appear ignorant of reasonable pricing for specific quantities of drug. Even if law enforcement agents do pay more on average, as long as the bias is stable over time the data would still be useful for understanding movement in prices over time. Nonetheless, both the nature of how the sample is created as well as the biases possibly contained in it have important implications for how these data can be used (Caulkins et al., 2004).

3. THE HOROWITZ CRITIQUE

Horowitz' (2001) critique focuses on the issue of representativeness of STRIDE by examining observations within a single city with an uncharacteristically high number of observations, Washington, DC. In this city, there are a substantial number of observations generated by two specific agencies, the DEA and the Metropolitan Police of DC (MPDC), as well as a number of observations from other Federal and state (Virginia and Maryland) agencies and programs. The real distribution of prices paid is unknown, so Horowitz tests whether the distribution of prices generated by DEA and the MPDC agencies are similar, given the argument that if buyers from different agencies within the same city and time period pay significantly

different prices per pure gram, then that would raise serious doubts about the reliability of the data and its utility.

Although some price dispersion is expected for a black market good, the trend in prices across agencies should be the same if the variation is random. However, if nonrandom factors influence the distribution of prices in the market, such as familiarity between buyers and sellers, then it is possible that changes in these nonrandom factors over time could lead to observed price changes in that market in the absence of a real change in the distribution of prices. Specifically, Horowitz argues that law enforcement agents within the MPDC are more likely than DEA agents in Washington DC to be familiar with the local drug markets and build long term relationships with low-end dealers.

Horowitz estimates price models using data from 1990 through the second quarter of 1998. Using Least Absolute Deviation in order to minimize the impact of outliers, his model is the following:

$$\log \Pi_{ijt} = \beta_{0jt} + \beta_{1jt}[AMT1_{ijt}] + \beta_{2jt}[AMT2_{ijt}] + \beta_{3jt} \log P_{ijt} + \beta_{4jt} MD_{ijt} + \beta_{5jt} VA_{ijt} + U_{ijt} \quad \textbf{(1)}$$

where Π_{ijt} is the real (inflation-adjusted) price per gram for observation *i* by agency *j* in year *t*, *P* is purity, *MD* and *VA* are dummy variables for having the transaction take place in Maryland and Virginia, and the quantity (AMT) variables are the following (with *Q* being the measure of quantity of the transaction in grams):

$$AMT1 = [I(\log Q_{ijt} \leq -1.5)(\log Q_{ijt} + 1.5) - 1.5]$$
$$AMT2 = [(\log Q_{ijt} + 1.5) I(\log Q_{ijt} > -1.5)]$$

These quantity variables allow for a spline with the knot at *log(Q)* equal to -1.5, the equivalent of 0.22 grams. An additional spline knot for DEA observations is used for 1991 and 1992 at 2.7 grams. The additional spline knot is added in partial recognition of the fact that the

typical transaction amount for DEA agents is systematically larger than that of the MPDC and hence might reflect higher quantity discounts given the larger transaction purchases made.

Horowitz estimates this model for both DEA and MPDC observations and conducts several tests of whether the observed markets are the same across agencies. These include: (1) asymptotic chi-squared tests for whether the coefficient estimates for each year are the same for DEA and MPDC observations; (2) asymptotic chi-square tests for the coefficient estimates on the quantity discount (β_2); and (3) asymptotic chi-square tests that the nine annual predicted prices for the MPDC and DEA models (evaluated at one gram and 75 percent purity) are the same.

In the chi-squared tests for crack cocaine, Horowitz finds that the coefficient estimates and predicted prices are statistically significantly different for the MPDC and DEA models. Furthermore, he finds that the price levels and trends are different. He concludes that both the MPDC and DEA sets of observations cannot both be representative of the true crack cocaine market, so we cannot know what the actual market distribution is. He shows similar results for heroin and thus concludes that the data should not be used to evaluate policy.

4. THE IMPORTANCE OF UNDERSTANDING SUPPLY CHAINS FOR DRUGS

There are two major problems in Horowitz' analysis. First, he ignores the fact that distribution levels in drug markets are characterized by differences in average purity and average quantity traded (Caulkins, 1994). The average purity of a drug traded at the wholesale distribution level is typically higher than the average purity of a drug traded at the retail level (e.g., a street dealer selling to an individual user), especially for powder cocaine and heroin. Drugs get diluted as they move down the distribution chain in the United States (Caulkins,

1997a). Tables 1 and 2 show that the DEA observations are not only more likely to involve transactions of 5 or more grams (a higher part of the supply chain) in the case of crack and heroin, but they also involve higher purity. The MPDC participates in purchases that are typically much smaller (closer to retail transactions) and on average have lower purity. Although Horowitz's models allow for the relationship between price and quantity to differ across specific quantity levels, they do not allow the relationship between price and the purity of the drug to change.

The second major problem with Horowitz' analysis is that, given the differences in quantity and purity between higher and lower distribution levels, any chosen quantity and purity at which to evaluate predicted price could not be in the central part of the range of values for both distribution levels. Horowitz uses one gram as the evaluation quantity for crack cocaine, which is high in the distribution for the MPDC sample (85^{th} percentile) and low in the distribution for the DEA sample (11^{th} percentile).

To demonstrate the importance of recognizing the differences in quantities and purity across different levels of the supply chain (i.e., different distribution levels) and in using out-of-range evaluation quantities, we replicate Horowitz' model and original findings and then demonstrate how incorporating knowledge of distribution levels changes his primary results. We begin by estimating a model identical to Horowitz for crack cocaine. We predict prices by evaluating them at a quantity of one gram at 75 percent purity in Washington, DC (following Horowitz). The predicted prices generated from this model yield identical price trends to those reported in Horowitz (see Figure 1). An asymptotic chi-squared test of the null hypothesis that the predicted prices from the DEA and MPDC models are equal ($\chi^2(9)=109.91$, $p=0$) is consistent with the result obtained by Horowitz and we also reject the null. Note that we cannot

produce the exact price series and test statistics as Horowitz (2001) because the sample changes over time due to observations being added to the sample as cases get closed.

-- Insert Figure 1 about here ---

Next we examine price series from the same agencies but break the data into two "distribution" levels. The specification of distribution levels is not a precise science. Although the term "retail" typically refers to transactions where the buyer is the end-user, there is no way of identifying end users from low-end sellers in the STRIDE data. Although some transaction sizes are relatively more common than others in the data, it is not clear which transaction sizes only identify end users. In previous work (Caulkins et al., 2004; Arkes et al., 2004), transactions involving up to one gram of crack cocaine were defined as retail-level transactions. Using this cut-off when examining data from these two agencies, however, we see from Table 1 that we would have very few observations in the DEA sample for some years in our retail sample, making estimation of a price series from the DEA series very imprecise. Instead, to increase the number of DEA observations included in the lower distribution level, we use 5 grams as our threshold for differentiating two basic markets. Although not ideal, this approach enables us to have observations from both agencies in both samples and makes the samples more homogenous relative to specific markets. It is still possible that quantity discounts differ within these markets given how broadly they have been defined. However, the goal here is not to precisely identify separate markets and the magnitude of the price discounts across them, but rather to demonstrate that ignoring their existence can generate misleading results.[1] In separating the model into two

[1] For the lower distribution level (less than or equal to 5 grams), we have the problem of over fitting with the DEA sample, as we only have 217 observations from the DEA and 50 explanatory variables in our Horowitz replication

distribution levels, we must make one additional modification to Horowitz's model. For the lower distribution level, there were several years with too few observations in Maryland and Virginia for identification so we had to exclude these year-state interaction terms; for the higher distribution levels, there were more observations in each year, but including them made little difference for the price series.

If we assume that these two distribution levels represent different points in a supply chain, then we need to consider evaluating prices at a quantity and purity that is representative of the typical transaction occurring within that distribution level. For the lower distribution level, we use one gram and 75 percent purity, just as Horowitz had. Even with the more homogeneous samples between DEA and MPDC, one gram is at the 45th percentile for the DEA observations and 93rd percentile for the MPDC observations. Thus, it is possible that the predicted prices from these two series will look fairly different because the typical transaction made by each of these agencies even within this cut-off are quite different. For the higher distribution level, we evaluate price at 75 percent purity and 25 grams, which is the 35th percentile for DEA observations and the 49th percentile for MPDC observations.[2]

Figure 2 presents the price charts for crack cocaine for the lower quantity distribution involving amounts less than or equal to 5 grams. The prices for the DEA and MPDC observations are much more similar in this case than they were when all the observations are pooled across distribution levels. While the predicted price remains higher for DEA

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model due to interactions between year and location identifiers for Maryland and Virginia. We tested for the joint significance of these interactions and found them to be insignificant. There are hardly any observations from Maryland or Virginia in the MDPC data, so all coefficient estimates on the interaction terms are dropped from that model automatically. In the sample of observations greater than 5 grams, the interaction terms are again jointly insignificant. Thus, to reduce the number of parameters that need to be estimated and the problem of over fitting, we drop the interaction terms from the models we estimate next.

[2] If we had chosen 30 grams, that would have been the 52nd percentile for DEA observations and the 66th percentile for MPDC observations.

observations than MPDC observations, the difference in the prices is no longer statistically significant ($\chi^2(9)=2.57$, p=0.97). In addition, the correlation between the two series is 0.68.

-- Insert Figure 2 about here --

The predicted prices each agency generated from the models at higher quantity distribution are even closer, as can be seen in Figure 3. Again, the difference in the prices are insignificant ($\chi^2(9)=7.95$, p=.54), and the series are highly correlated (corr=0.89). Further, as one would expect given the existence of quantity discounts, the predicted prices per gram at the higher quantity level are actually lower than the predicted prices per gram at the lower quantity level for both agencies (as can be seen by comparing Figure 2 and Figure 3).

-- Insert Figure 3 about here --

In Figures A1 and A2 in the Appendix, we show that the results by distribution level hold when we extend the data through the end of 2005. We find no significant differences in predicted prices generated from the two different agencies at either distribution level and the agency trends look even more similar in the later years for both levels. The correlations between the DEA and MPDC price series are 0.65 for the lower level and 0.81 for the higher distribution level.

Finally, we formally test whether we need to split the sample into different distribution levels. For both the DEA and MPDC samples, we include interaction terms of the indicator for the higher distribution level with each yearly quantity and purity variable. We then test for the joint significance of the interaction terms. The test statistics for the DEA and MPDC samples, respectively, are $F_{27, 712} = 2.36$ ($p<0.0001$) and $F_{27, 2608}=2.46$ ($p<0.0001$), indicating that it is important to split the sample by distribution level.

To summarize the findings from our replication of Horowitz's work, we find that the price differences observed between DEA and MPDC observations are primarily due to differences between these agencies in the level of the supply chain targeted by the policing activities. Differences in average prices as well as price trends disappear once observations are analyzed on a market-level basis.

5. ADDITIONAL ISSUES TO CONSIDER WHEN USING STRIDE HEROIN DATA

The model above demonstrates that recognition of a supply chain has important implications on the consistency of price trends generated from the STRIDE data. Horowitz also examined heroin observations, considering three price series in Washington DC in light of what he believed to be sufficient data observations from MPDC, DEA, and the Domestic Monitoring Program (DMP). Ignoring differences in distribution levels of the supply chain, Horowitz finds that different predicted price trends exist by agency/program when evaluated at a common weight (0.75 grams) and purity (20 percent). It is easy to explain the differences in predicted trends between the DEA and MPDC in light of the significantly different quantities involved in typical transactions. Looking at Table 2, DEA observations generally involve higher quantities than the MPDC (and the DMP) observations, with 88% of DEA observations in the higher distribution level ($g > 1$) but 87-88% of MPDC's and DMP's observations at the retail level ($g \leq 1$). In fact, Table 2 shows there are not enough small DEA observations or large MPDC observations to conduct any analysis by market level for both series; the two agencies do not make enough purchases on overlapping quantities.

Although the MPDC and DMP series both have a large number of observations less than or equal to one gram between 1997 and 2004, it would still be inappropriate to compare these

two series in light of the heterogeneous types of heroin represented in the DMP sample. The DMP observations, unlike other observations in the STRIDE data, are generated by random purchases made by law enforcement agents or their informants with the sole purpose of monitoring the quality, type and amount of heroin available on the street in particular cities, as opposed to collecting data for prosecutions. Each quarter they go out on the streets and see how much heroin and what type of heroin they can get for $100. These are not part of strategic activities, but rather reflect random buys out on the street, conducted purely for the purposes of monitoring heroin supply. Although that may make the DMP series sound ideal for analytical use, the problem is that different types of heroin are purchased under this program, and the type varies substantially within and across cities and over time.[3] The type of heroin is indicated through secondary drug codes available in the STRIDE database, but is not usually investigated. Thus, the only way to use DMP observations in a meaningful way is to disaggregate them into the actual type of heroin purchased, which dramatically reduces the sample size for Washington DC. Thus, one should not compare prices from DMP to those of the other agencies but the reason is that these do not represent a homogenous product.

6. IMPROVING MODELS FOR ESTIMATING PRICES FROM STRIDE

6.1 Constructing an Appropriate Model for Drug Prices

It is important to realize that the flaws in Horowitz's previous work were not statistically based but rather the result of disregarding knowledge of how drug markets operate. Despite this oversight, Horowitz generally recognized other important aspects of these markets that need to be considered when using these data. In particular, the paper emphasized considering

[3] There are at least three physically distinguishable types of heroin available in the United States: white heroin, black tar heroin and brown heroin.

homogenous drug products and examining trends in localized markets to reduce noise. However, as demonstrated here, errors can still occur in light of the general lack of knowledge about these data caused by the unavailability of a codebook (e.g. the fact that DMP observations mix heterogeneous forms of heroin). We aim to advance the methods for using these data by producing a model for predicting price and purity trends from the STRIDE data that properly considers several important aspects of the data and drug markets. We demonstrate that our model generates price series that are not only internally valid but also externally valid.

There are four primary aspects of drug markets that are important to consider when developing price and purity models for illicit drugs. First, drugs are an experience good, and hence purity is not known with certainty at the point the buyer makes the transaction. Second, the effects of quantity and purity on price can be different at different levels, so distribution levels matter. Third, local trends are likely to generally reflect national trends in the long run, although short term differences are possible. Fourth, quantity discounts and average purity levels can differ across cities (i.e. drug markets are local).

To make sure that price series generated from the STRIDE data reflect these four considerations, we make several adjustments to Horowitz's empirical model that result in obtaining price series that are both internally and externally valid. First, to address the fact that drugs are experience goods, we estimate price as a function of expected pure amount not actual pure amount. Though a buyer is unlikely to know the purity of a single purchase he/she makes, the buyer will have expectations about the purity based on prior experience. Prior analyses of the STRIDE database found evidence of measurement error in observed price and improvements in model fit when predicting price with expected rather than observed purity (Caulkins, 1994). Therefore, we retain transactions with zero or very low purity that do not have much lower prices

than other observations of a more typical purity because we presume they represent a rip-off and are a realistic reflection of what actually happens in the marketplace.

The second modification to the empirical model is the separation of models at different distribution levels. As shown earlier, separate models at different distribution levels are needed because of differences in how quantity and purity affect price at different quantity levels. We sought to define market levels with roughly equal numbers of observations in each level but with round number boundaries for the years for which we have data (1981-2005). In all cases except powder cocaine, three levels were identified for each drug, with each level in most cases containing between 25 and 50 percent of the total number of observations for that drug. In the case of powder cocaine, there were enough data to identify a fourth distribution level. Given that these market levels' boundaries were largely data driven, one should assign little meaning to the labels assigned to each.

The final modification to the empirical model is the adoption of hierarchical modeling (HM), which enables unique relationships to exist between quantity, purity and price within each city while still using information from observations in all cities to estimate general trends overall. Although drug markets are geographically small and limited in terms of how they function and their ability to price discriminate, they must all follow a few basic "rules" that are the same across all cities. Price will be a function of both expected purity and quantity, and the market would not allow huge deviations from a general range to exist for more then a short period of time (when sufficient information flows to correct the differences in markets).

In the models we present here, we apply hierarchical modeling to data from 29 cities and 9 regions across the United States. Models of purity are estimated first using hierarchical linear modeling, the results of which are used to formulate estimates of expected purity for each

purchase observation in each city and time period. The model for purity for transaction *i* from city *j* at time *k* is:

$$Purity_{ijk} = \gamma_0 + \gamma_1 time_{ijk} + \gamma_2 AMT_{ijk} + u_{0j} + u_{1j} time_{ijk} + u_{2j} AMT_{ijk} + \varepsilon_{ijk} \quad (2)$$

where time is measured using dummy variables representing a year-quarter (i.e., 100 quarters over 25 years) or just a year, and AMT_{ijk} is the raw weight of the observation. The γ_0 through γ_2 coefficients represent the fixed effects for the intercept, amount, and time, respectively, and the corresponding city-specific random effects, u_{0j}-u_{2j}, are assumed to follow normal distributions. Errors ε_{ijk} are assumed to independently follow a normal distribution with mean 0 and variance σ^2. Expected purity was estimated for each observation from this model. About one-half of a percent of heroin cases had predicted purity below 0 percent. For these, we changed the predicted purity to equal 0.5 percent.

To model drug prices, we use a hierarchical generalized linear model (Wolfinger & O'Connell 1993; Breslow & Clayton 1993) in which price is assumed to follow a gamma distribution with mean μ and variance function $\phi\mu^2$, where

$$\begin{aligned} \mu &= E(price_{ijk} \mid \nu) \\ &= \exp\{\beta_0 + \beta_1 time_j + \beta_2 (\ln(AMT_{ijk}) + \ln(\hat{purity}_{ijk}) \\ &+ \nu_{0j} + \nu_{1j} time_j + \nu_{2j} (\ln(AMT_{ijk}) + \ln(\hat{purity}_{ijk}))\} \end{aligned} \quad (3)$$

where β represents the fixed effects for intercept, time and the logarithm of the amount plus the logarithm of the expected purity, ϕ is a dispersion parameter and the ν terms are the corresponding city random effects that are assumed to be normally distributed with mean vector **0** and variance/covariance matrix **D**. The sum of the natural logarithm of quantity (AMT) and the natural logarithm of expected purity is a way of specifying the price in terms of the natural logarithm of expected pure grams – i.e., multiplying the weight by expected purity generates an

estimate of the weight in expected pure grams. Specifying amount and expected purity into one variable (expected pure grams) also serves to provide identification for the model, which is necessary because all of the explanatory variables in the purity model of equation (2) are in the price model of equation (3).

6.2 Properly Cleaning STRIDE Data

It is important to keep in mind that the STRIDE data set is an administrative data system used to track inventory of acquisitions; it was not designed for analytical purposes. Some values in the data are likely to reflect input errors or inaccurate reporting, not actual drug prices and purities.

This last point has important implications for how one cleans the data before analyses are even conducted. For example, while working on a project for the Office of National Drug Control Policy using STRIDE, we were told by a former DEA lab technician that it is extremely difficult to detect the actual purity of a drug when the quantity involved is smaller than 0.1 grams. The task is even more difficult depending on the type and form of the drug being examined. When actual purity cannot be detected, a zero value may be used or purity may be entered as missing. Thus, to better differentiate true zero purity observations from those that simply reflect an inability to detect a substance, it is common practice to discard observations smaller than 0.1 grams.

In addition to problems determining actual purity in small transaction amounts, it is the case that gross outliers exist in both the price and purity data. Purity values in excess of 100 percent do exist in the data and are the result of data entry errors. Gross outliers in price are also common, although it can be difficult to determine what the appropriate bounds are for discarding

these observations. Following methods similar to those used in the past (Abt, 2001), we specify a fairly broad range in which to reasonably expect real prices to fall and then use an extreme residual outlier analysis to identify and discard additional observations that appear extreme and have a large effect on the regression results. In terms of gross outliers, we discard observations that have a real price per gram (in 2005 dollars) that are outside the $5 to $1500 range for crack and powder cocaine and outside the $5 to $2500 range for heroin. We then estimate the model once with just random intercepts; delete extreme residuals by cutting from the sample the observations that have the top one percent of residuals on the positive side; and re-estimate the model with the full set of random effects across cities.

6.3 Results: Predicted price series from STRIDE and internal validity

The models provide a predicted price for each of the 29 cities and 9 regions for each year. In Figures 4 through 7, we present price series for each drug for the Washington, DC metropolitan area, with the corresponding predicted prices in Tables A1-A4 in the Appendix. We show the series for crack cocaine, powder cocaine, and heroin, with three or four distribution levels for each drug.

In Figures 5, 6, and 7, we evaluate prices at 100-percent purity and a quantity that is close to the median for each distribution level. This set-up produces a "price-per-pure-gram." In Figure 4, however, we evaluate the price at the same quantity levels, but at 75 percent purity and just for 1990-2005 in order to generate series that are more comparable to results presented in Figures 2 and 3. It should be remembered though that the evaluation amount still differs in these predicted prices using the HM modeling and that results from all agencies reporting data are included (not just DEA and MPDC), so direct comparisons need to be made with this in mind.

Overall the price trends generated in Figures 4 through 7 for each of these drugs demonstrate a general decrease in the price of each drug since the early- to mid-1980s. Furthermore, they demonstrate that the price per gram varies considerably across the distribution levels for all drugs, and that quantity discounts appear to be quite significant.

If we look more closely at the trend in prices presented in Figure 4 for crack cocaine and compare the results involving amounts greater than 15 grams (and evaluated at 38 grams) to those presented in Figure 3 (which show results for the two agencies for amounts greater than 5 grams and evaluated at 25 grams), we see trends that are generally consistent between 1990 and 1998. The level of prices predicted for Washington DC from the HM model are slightly higher despite being evaluated at a higher quantity level, but this might reflect the fact that transactions for DC from other agencies are being included and a longer time period is evaluated (which influences the model through the grand mean and city-specific effects). Despite a relatively small difference in levels (both hover around $50 per gram), the trends are generally consistent across the two figures. If you compare the results for up to 1 gram (evaluated at 0.3 grams) in Figure 4 to those in Figure 2 (evaluated at 1 gram), the HM series in Figure 4 looks a bit noisier and stays at a level closer to $150. That difference in terms of noise of the series is likely driven by the exclusion in our lowest distribution of higher level amounts. The trend for the second distribution level in Figure 4 (amounts involving 1 to 15 grams) is significantly smoother and closely parallels that for the MPDC, albeit at a lower level (because it is being evaluated at a higher quantity of 5 grams).

The main point from these comparisons is that merging the data collected by all agencies and estimating series for all cities using an HM framework generates a price series that is generally consistent with what we observe when estimating series for a single agency in a single

city, providing additional evidence of the internal consistency of the data when used properly. When prices are evaluated at 100% purity (as shown in Figure 5 through 7) the trend line moves up (i.e. it costs more per gram because of the higher potency, as theory would predict), but the trends remain consistent with that observed at lower purities. But the trends do differ in at least one important way across distribution levels for the same drug evaluated at the same purity. The retail level trend (i.e. the trend for the lowest quantity amount) is always noisier than that for higher quantity amounts. There are at least two potential explanations for this: (1) rip offs are far more likely to occur among buyers and sellers at the retail level, where exchanges are more frequently made between people who are unfamiliar with each other, and (2) law enforcement rarely focuses their attention and resources on small retail transactions, so these series may be more sensitive to data composition issues (agencies involved, location of the transaction, etc) than transaction at higher levels.

7. EXTERNAL VALIDITY OF PRICE SERIES GENERATED USING STRIDE PRICE AND PURITY DATA

While we previously showed that it is possible to generate internally valid price series from the data, it is equally important to demonstrate that the trends in price series convey real information. This can be done by directly modeling prices obtained from our constructed price series for specific locations with data from external sources tracking other relevant aspects of the drug problem that should be highly predicted by prices. Here we develop a model that tests whether the predicted city-specific retail-level prices are reflective of changes in demand, as indicated by movements in the number of drug-involved emergency department episodes which

are available at a local level. In particular, we employ a Granger-Sims causality test (Granger, 1969) to assess whether changes in the price of a drug predicts the future number of emergency-room mentions for that drug.

Data on emergency room mentions come from the 1994-2002 Drug Abuse Warning Network (DAWN). The Drug Abuse Warning Network (DAWN) data provides information on the number of instances of cases in which a given drug is involved in emergency department (ED) visits or deaths. DAWN is organized so that it provides estimates on the total number of drug-abuse-related ED visits and deaths and the total number of mentions of drugs in 21 cities, quarterly, over the 1994-2002 period. Up to four drugs can be mentioned for a given ED visit, and up to six drugs can be mentioned for a death. We analyze the rate of drug mentions in the population for each city.

To estimate this model, we take the predicted heron prices from the price models, described above, for the DAWN cities. To use a city-quarter observation in our model for ED visits, we use the condition that there had to be 5 observations in the one-quarter-lagged city-quarter cell to be used in the model.[4] We do this so that the price series for these cities closely reflected the actual STRIDE data for a given city rather than information borrowed from different city-quarters. We limit the sample to the 16 DAWN cities that had this sufficient number of observations for at least 18 of the 36 quarters in the 1994-2002 DAWN period. No cities met these criteria for powder cocaine and only three cities met the criteria for crack cocaine.[5] Thus we focus on external validation on the heroin price series.

[4] We use lagged because we are examining whether lagged price affects drug mentions.
[5] The cities that we use for the heroin analysis are: Atlanta, Boston, Chicago, Denver, Detroit, Miami, New Orleans, New York, Newark, Philadelphia, Phoenix, San Diego, San Francisco, Seattle, St. Louis, and Washington, DC.

To estimate heroin prices, our sample from STRIDE consists of observations that are between 0.1 and 1 gram and that have the drug code "9200.005."[6] From the price models, the predicted prices are evaluated at roughly the median quantity and purity levels for the period for which DAWN data are available (1994-2002). The evaluation quantity and purity are 0.4 grams and 35%.

7.1 Estimating the Effect of Price or Purity on Emergency-Room Mentions of Heroin

With the predicted price of heroin, we estimate Poisson regression models to determine whether the STRIDE price estimates are meaningful. We assume that the mean number of emergency room visits in city *c* and quarter *t* is λ_{ct}, where:

$$\ln(\lambda_{ct}) = \beta_c + \sum_{l=1}^{L} \{\beta_l P_{c,t-1} + \alpha_l Y_{c,t-1}\} + \ln(n_{ct}) .$$

Here $Y_{c,t-l}$ and $P_{c,t-l}$ are the observed number of emergency room mentions and the price for heroin in city *c* in *l* quarters lagged from quarter *t* (*e.g., l=1* implies time *t-1*) up to *L* lags, and n_{ct} represents the population of city c at time t. Thus, for a one-period-lagged model, we are examining whether last period's price affects the current period's rate of drug mentions in emergency rooms while controlling for last period's rate of drug mentions and emergency room mentions.

Table 3 shows the results of these regressions. The first column of Table 3 provides the coefficient estimates for the one-quarter-lagged model, which includes the lagged price and the lagged rate of heroin drug mentions. The second column shows the coefficients from a two-quarter-lagged model with both the prices and lagged rate of heroin mentions from both one-

[6] The latter criterion makes sure we do not include black tar heroin in our heroin observations, given a buyer can physically distinguish black tar heroin from white heroin.

quarter and two-quarters lagged. The model in the third column is the same one-quarter-lagged model of the first column but is fit to the same set of observations as is the two-quarter-lagged model in order to facilitate comparison of the one-lagged and two-lagged models using the Bayesian Information Criterion (BIC). The number of observations is lower for the two-quarter-lagged model because there is the additional requirement that there had to be at least 5 valid STRIDE observations for the city not just for the lagged quarter, but also for the twice-lagged quarter.

In model (1), the one-quarter lagged heroin prices have a negative and significant effect on emergency room mentions of heroin. A $10 increase in the price of a pure gram leads to a 1.7-percent decrease in heroin mentions in emergency rooms ($p<0.01$). In the two-quarter-lagged model (2), the one-quarter-lagged price turns out to be small and insignificant, but the two-quarter-lagged price is negative and significant, indicating again that a higher price for heroin leads to fewer heroin-related emergency-room visits. In model (3), again using the one-quarter-lagged model, but with just the sample size from model (2), the coefficient estimate on price is no longer significant. The BIC is lower in the two-quarter-lagged model than in the one-quarter-lagged model (column 3), suggesting that this is a better model than the one-quarter-lagged model. Though there is a difference in the significance of the one-quarter lagged heroin price in models (1) and (3), this is attributable to the loss of 78 observations when including two-quarter lags in the model and we use column (1) as the definitive results for the model containing a one-quarter lag.

The results from the first two models support the conclusion that higher prices predict lower demand for heroin, as indicated by the number of accidents and events related to heroin. The fact that price series generated from STRIDE data are not just statistically correlated with an

independent city-specific data series tracking a different aspect of the drug problem but also have predictive power supports the conclusion that real information is being provided in these data. Such a conclusion goes a step further than findings from other studies that have just shown a correlation between price series generated from STRIDE and other measures of the drug problem (Dobkins & Nicosia, Forthcoming, Dave 2006, Williams et al, 2004, DeSimone & Farrelly, 2003; Caulkins 2001). Unlike those previous studies which simply show a strong correlation, we empirically test the predictive power of prices using the Granger-Sims causality framework and show that they do in fact predict a change in consumption, controlling for other factors.

8. CONCLUSIONS

The purpose of this paper is to challenge critiques of the STRIDE data and to establish city-specific drug prices in a manner that generates internally and externally consistent price series. Horowitz (2001) claimed that STRIDE was internally inconsistent because prices within Washington, DC collected by different law enforcement agencies (DEA and MPDC) were different. We demonstrate that these differences are largely the product of the two agencies being involved in transactions at two different levels of the distribution chain. In particular, DEA collected data on large transactions typically at the wholesale and mid-level range, while MPDC collected data at the retail level. When we split the samples by distribution levels, then differences in the predicted prices between the two agencies' observations disappeared.

We then tested the external validity of a price series that more seriously addressed the issue of differential distribution levels and considered the local nature of drug markets. Price series generated from this model were again empirically consistent with simpler models

employing a subset of the data and focusing on just one city. Finally, we tested the external validity of our price series by assessing the correlation and predictive power of our constructed prices with an external data source: city-specific heroin-related emergency room episodes. We find that, consistent with economic theory, higher heroin prices lead to a decrease in such incidents, thus indicating that demand is lower when price is higher. More importantly, we show that the price series is statistically correlated with external measures of the drug problem in a manner one would expect, supporting the notion that real information is conveyed through temporal movements of these price data.

The findings suggest that STRIDE, despite having numerous shortcomings, may still be useful to researchers and policy makers interested in examining factors related to changes in illicit drug prices over time or using information on changes in prices to understand movements in demand or supply. The findings also show, however, that estimates of the average price level from these data at a given point in time are extremely sensitive and uncertain. When estimating average price levels, the nonrepresentativeness of the data as well as analytic decisions regarding how to use the data dramatically impact the average price level generated from models using the data. Hence, our analyses do not support the use of STRIDE for studies evaluating issues related to the average level of drug prices in a particular point in time. For example, using these data to determine the total expenditure on drugs in a given year or to back out total quantity consumed from an expenditure equation at a given point in time is not recommended. However, once proper methods are used to properly clean the data and to take into account important aspects of drug markets, the short-term and long-term movements in average prices for specific cities evidenced in STRIDE can be used to examine changes in demand or supply over time.

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Figure 1. Predicted price trends for for crack cocaine for DEA and MPDC observations in the Washington metropolitan area, evaluated at 1 gram at 75% purity, 1990-1998Q2 (replication of Horowitz) (N=775 DEA, 2672 MPDC)

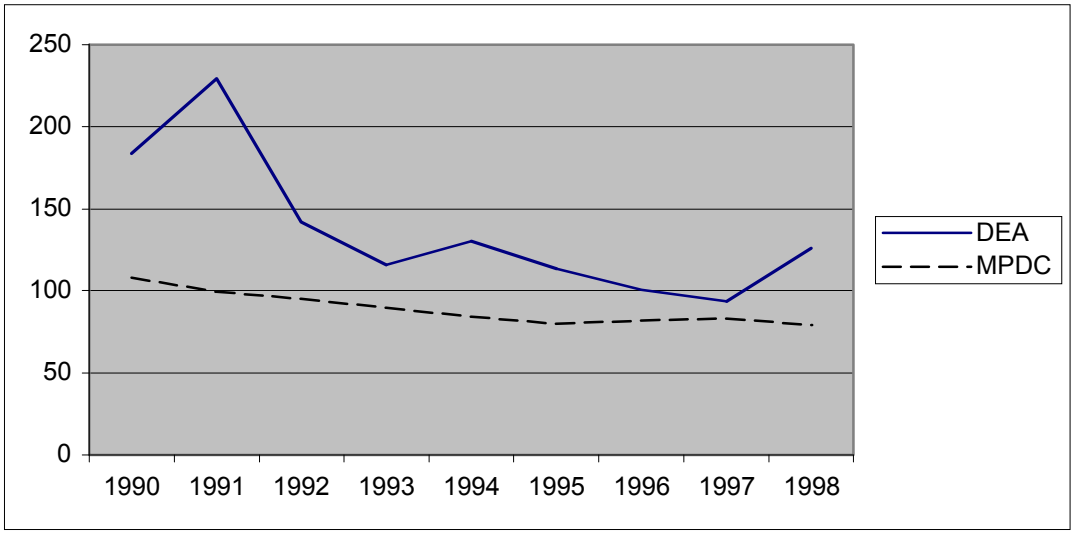


Figure 2. Predicted price trends for Washington metropolitan area crack cocaine for DEA and MPDC observations less than or equal to 5 grams, evaluated at 1 gram and 75% purity, 1990-1998Q2. (N=217 DEA, 2386 MPDC)

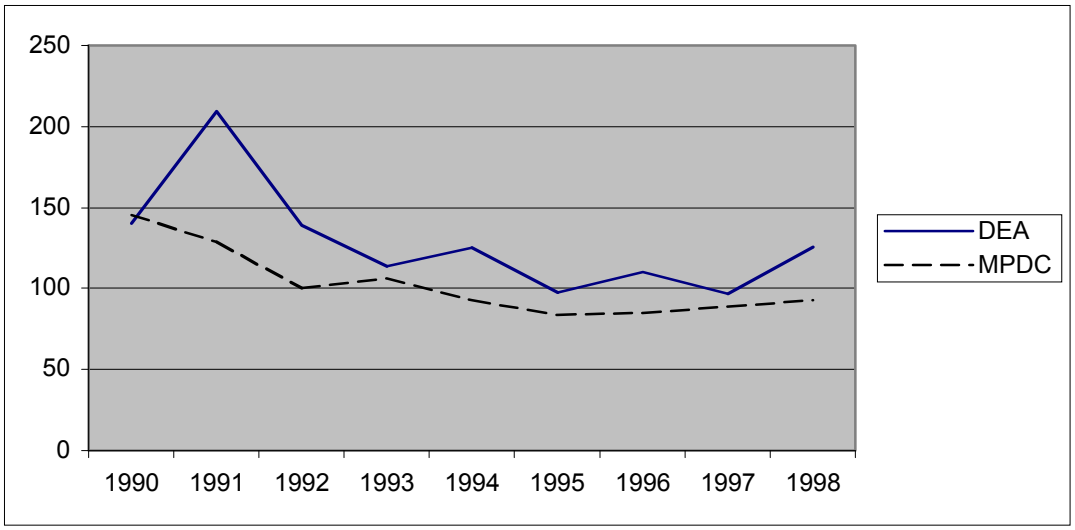


Figure 3. Predicted price trends for Washington metropolitan area crack cocaine for DEA and MPDC observations greater than 5 grams, evaluated at 25 grams and 75% purity, 1990-1998Q2. (N=558 DEA, 286 MPDC)

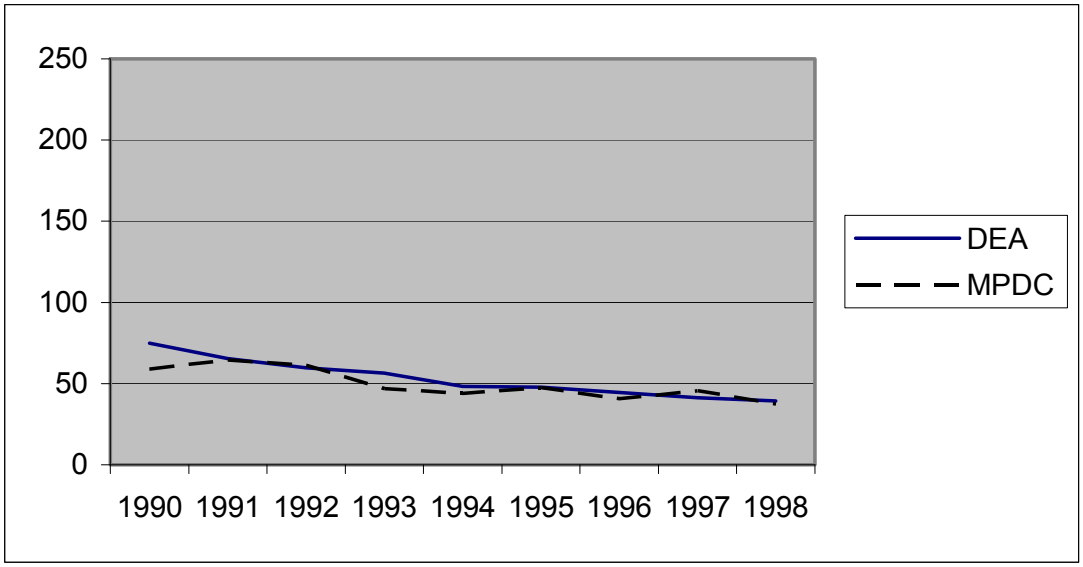
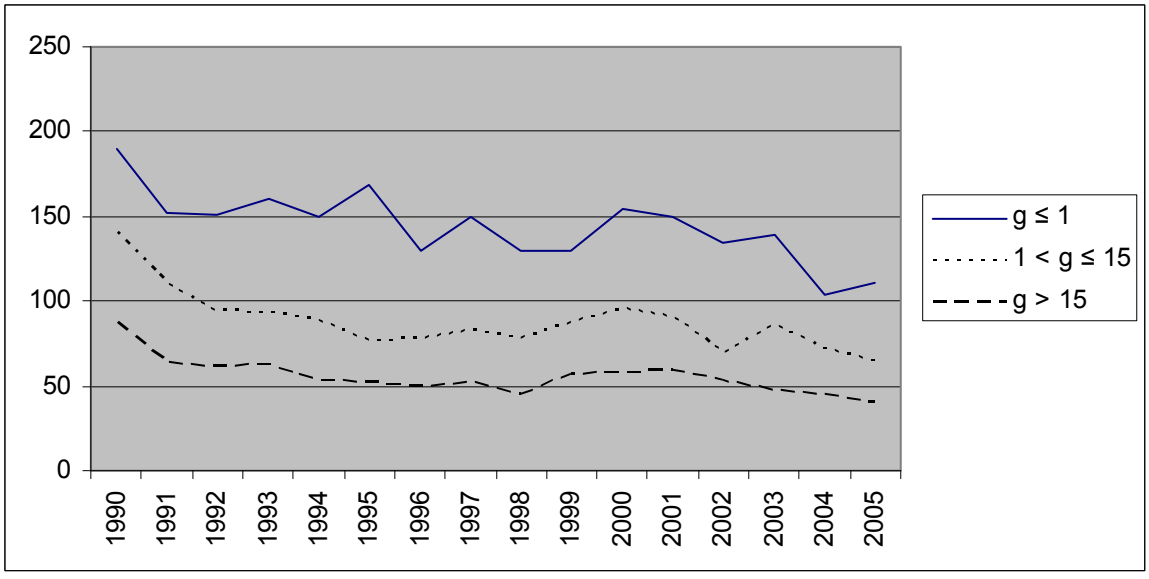
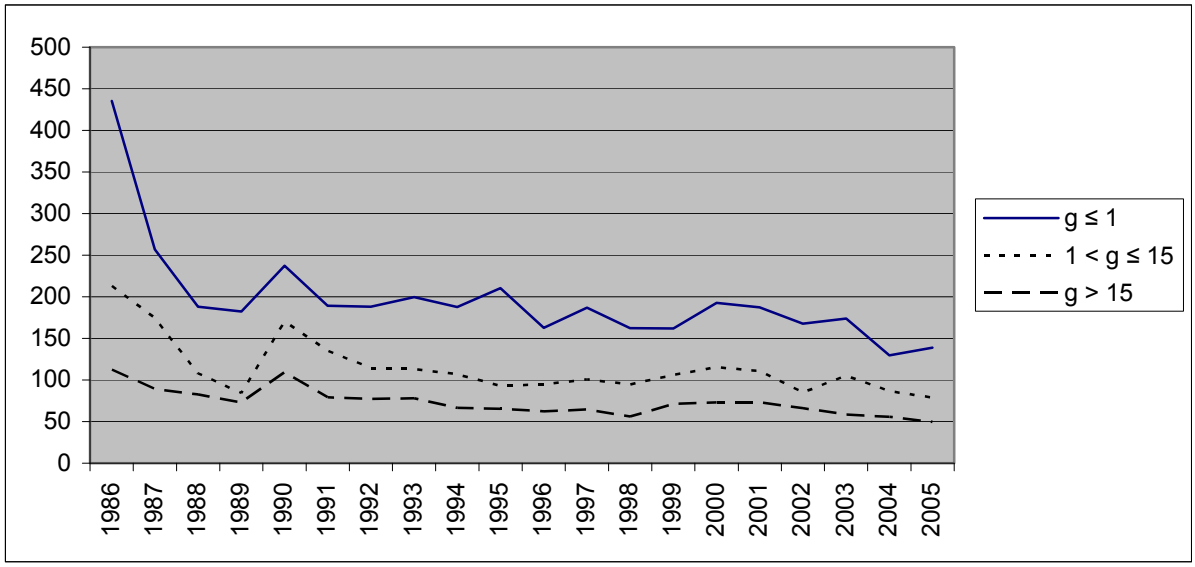


Figure 4. Predicted price-per-gram for crack cocaine in the Washington metropolitan area for three distribution levels, 1990-2005, evaluated at 75% purity.



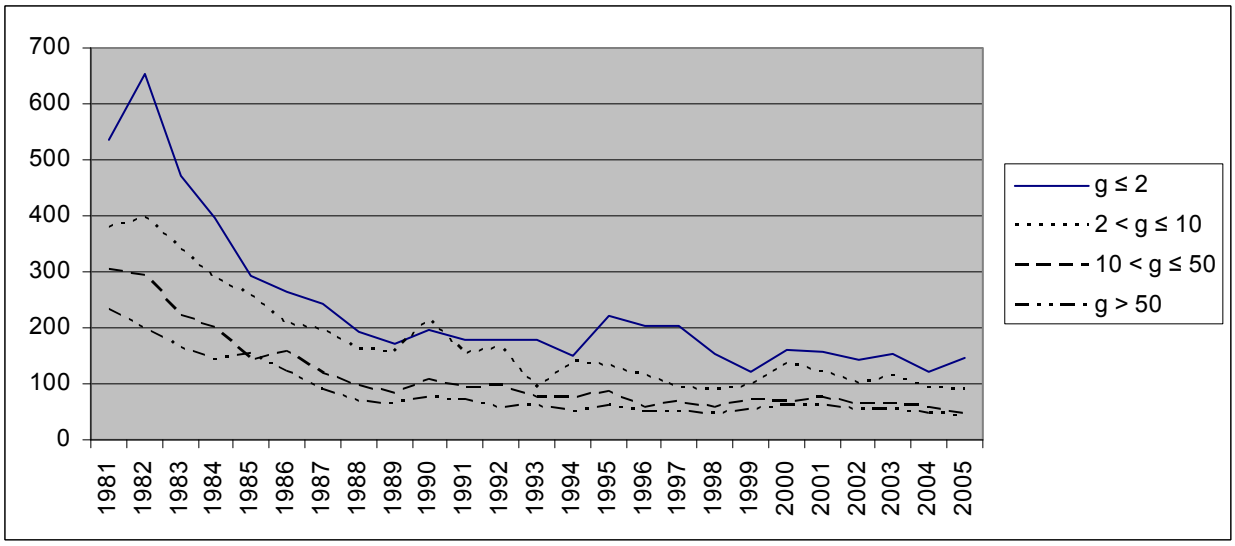
Note: The prices for the three distribution levels are evaluated at 0.3, 5, and 38 grams, which are roughly the median quantities for each distribution level.

Figure 5. Predicted price-per-pure-gram for crack cocaine in the Washington metropolitan area for three distribution levels, 1986-2005, evaluated at 100% purity.



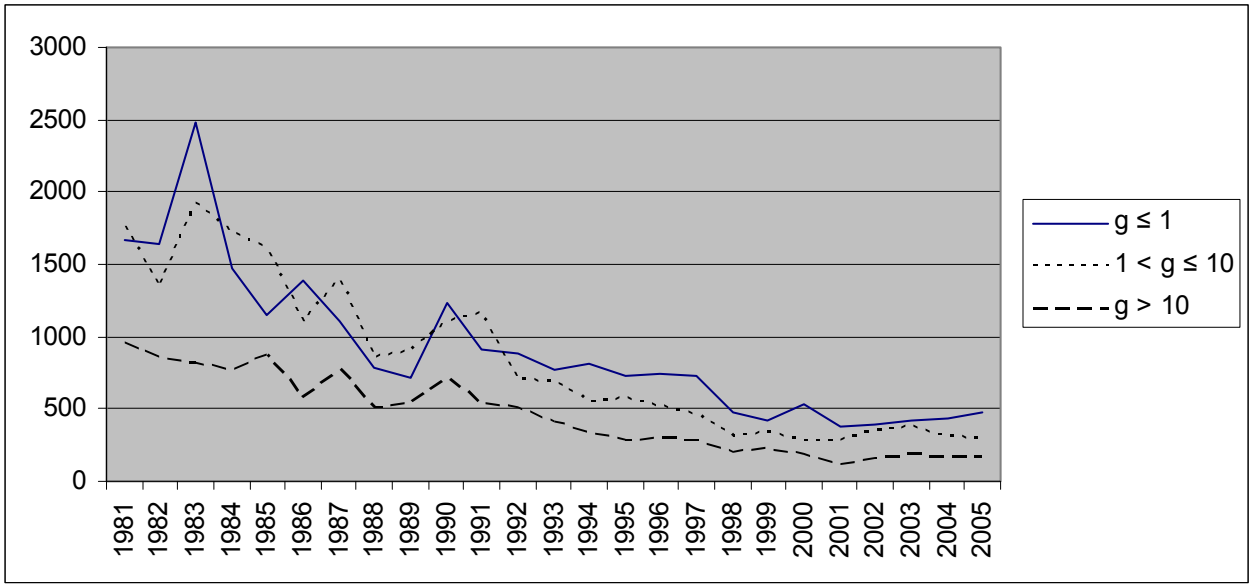
Note: The prices for the three distribution levels are evaluated at 0.3, 5, and 38 grams, which are roughly the median quantities for each distribution level.

Figure 6. Predicted price-per-pure-gram for powder cocaine in the Washington metropolitan area for four distribution levels, 1981-2005, evaluated at 100% purity.



Note: The prices for the four distribution levels are evaluated at 0.75, 5, 27, and 108 grams, which are roughly the median quantities for each distribution level.

Figure 7. Predicted price-per-pure-gram for heroin in the Washington metropolitan area for three distribution levels, 1981-2005, evaluated at 100% purity.



Note: The prices for the three distribution levels are evaluated at 0.4, 2.5, and 27.5 grams, which are roughly the median quantities for each distribution level.

Table 1. Crack cocaine observations by different quantity levels for DEA and MPDC data for the years evaluated by Horowitz.

	DEA				MPDC			
Year	g ≤ 1	1<g≤5	g>5	All	g ≤ 1	1<g≤5	g>5	All
1990	6	16	60	82	620	4	19	643
1991	6	24	107	137	846	11	33	890
1992	13	15	58	86	383	21	55	459
1993	9	3	48	60	194	10	46	250
1994	8	31	84	123	45	9	40	94
1995	22	14	48	84	62	10	18	90
1996	10	22	60	92	35	10	15	60
1997	5	4	58	67	55	26	49	130
1998(Q1&Q2)	3	6	35	44	36	9	11	56
Total for Horowitz's years	82	135	558	775	2276	110	286	2672
Distribution across levels	10.6%	17.4%	72.0%	100%	85.2%	4.1%	10.7%	100%
Average Purity	72.7%	73.0%	67.2%	68.8%	78.6%	68.0%	64.8%	76.7%

Table 2. Heroin observations by different quantity levels for DEA, MPDC, and DEA data for the years evaluated by Horowitz.

	DEA			MPDC			DMP		
	g ≤ 1	g > 1	All	g ≤ 1	g > 1	All	g ≤ 1	g > 1	All
1993	1	15	16	9	1	10	41	0	41
1994	0	3	3	9	2	11	41	0	41
1995	3	9	12	8	2	10	31	0	31
1996	2	4	6	14	24	38	39	0	39
1997	2	32	34	30	14	44	20	11	31
1998 (Q1 and Q2)	2	27	29	15	0	15	16	5	24
Total for Horowitz years	10	90	100	85	43	128	188	16	204
Distribution across levels	10.0%	90.0%	100.0 %	66.4%	33.6%	100.0 %	92.2%	7.8%	100.0 %
Average Purity	27.3%	59.2%	55.6%	26.3%	33.4%	28.8%	22.2%	18.4%	21.9%

Table 3. Effects of price and purity on the number of emergency room mentions of cocaine.

	(1)	(2)	(3)
	Lag for one quarter:	Lags for two quarters:	Lag for one quarter with same sample as that for lags with two quarters:
One-quarter lagged heroin price	-0.0017*** (0.0005)	0.00008 (0.00013)	-0.0007 (0.0006)
Two-quarter lagged heroin price		-0.00107** (0.00013)	
One-quarter lagged rate of heroin mentions	2395.4*** (215.0)	1905.3*** (50.4)	2233.4*** (246.4)
Two-quarter lagged rate of heroin mentions		412.2*** (53.7)	
BIC	12,441	10,059	10,173
# observations	460	382	382

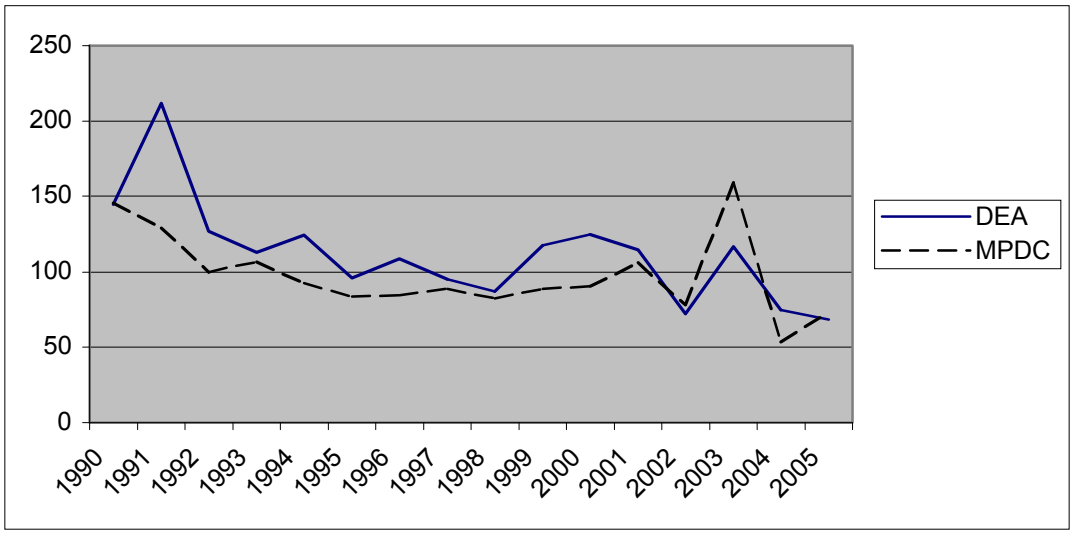
***p < 0.01; **p < 0.05

Standard errors are in parentheses.

BIC results show one lag suffices for predicting the model.

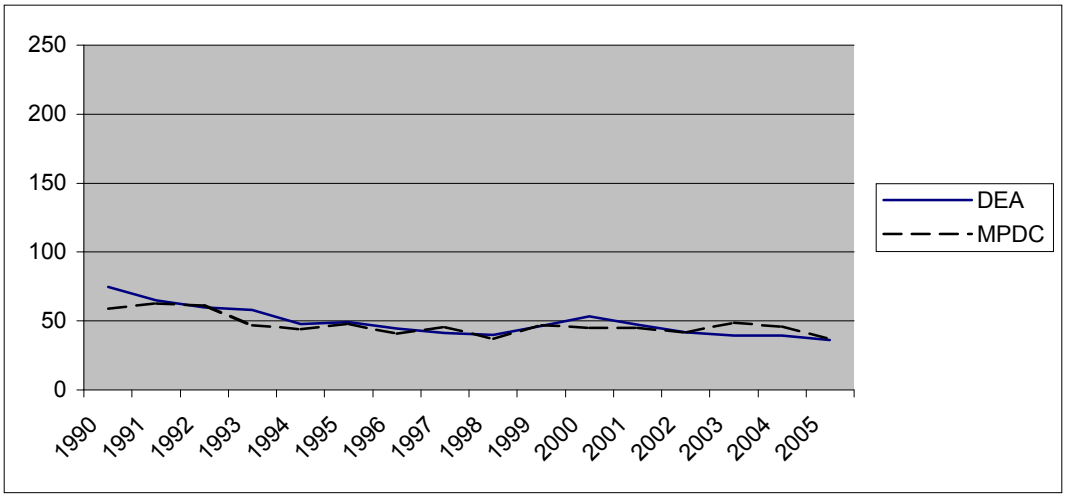
APPENDIX

Figure A1. Predicted price trends for DEA and MPDC observations less than or equal to 5 grams, evaluated at 1 gram and 75% purity, 1990-2005. (N=402 DEA, 3336 MPDC)



$\chi^2(16)$==10.78 (p=0.82) ; Correlation=0.65

Figure A2. Predicted price trends for DEA and MPDC observations greater than 5 grams, evaluated at 25 grams and 75% purity, 1990-2005. (N=959 DEA, 485 MPDC)



$\chi^2(16)$=0.68 (p=1.00); Correlation=0.81

Table A1. Predicted prices per gram for crack cocaine for the Washington, DC metropolitan area for three distribution levels, 1986-2005, evaluated at 75% purity.

	$g \leq 1$	$1 < g \leq 15$	$g > 15$
1990	190	140	87
1991	152	111	63
1992	151	94	62
1993	160	93	62
1994	150	88	53
1995	169	77	52
1996	130	78	50
1997	150	83	52
1998	130	78	45
1999	130	88	57
2000	154	95	58
2001	150	91	58
2002	134	70	53
2003	139	87	47
2004	104	71	44
2005	111	65	40

Table A2. Predicted prices for one pure gram of crack cocaine for the Washington, DC metropolitan area for three distribution levels, 1986-2005, evaluated at 100% purity.

	$g \leq 1$	$1 < g \leq 15$	$g > 15$
1986	435	213	112
1987	257	174	89
1988	188	108	83
1989	182	84	73
1990	237	170	109
1991	189	135	79
1992	188	114	77
1993	200	113	78
1994	188	107	67
1995	210	93	65
1996	163	95	62
1997	187	101	65
1998	162	95	56
1999	162	106	71
2000	193	115	73
2001	187	111	73
2002	168	85	66
2003	174	105	59
2004	130	87	56
2005	139	79	50

Note: The prices for the three distribution levels are evaluated at 0.3, 5, and 38 grams, which are roughly the median quantities for each distribution level.

Table A3. Predicted prices for one pure gram of powder cocaine for the Washington, DC metropolitan area for three distribution levels, 1981-2005, evaluated at 100% purity.

	$g \leq 2$	$2 < g \leq 10$	$10 < g \leq 50$	$g > 50$
1981	536	379	303	231
1982	653	398	292	201
1983	473	340	223	165
1984	395	288	199	143
1985	292	258	144	152
1986	266	206	156	121
1987	243	196	117	88
1988	194	159	97	68
1989	172	155	83	65
1990	197	213	109	76
1991	179	154	94	70
1992	178	165	98	56
1993	178	91	73	60
1994	150	139	75	52
1995	223	131	87	61
1996	205	113	58	51
1997	204	93	67	50
1998	155	91	58	48
1999	122	98	72	52
2000	161	137	68	61
2001	156	121	74	60
2002	144	101	64	53
2003	154	114	63	52
2004	122	94	56	48
2005	146	89	47	42

Note: The prices for the four distribution levels are evaluated at 0.75, 5, 27, and 108 grams, which are roughly the median quantities for each distribution level.

Table A4. Predicted prices for one pure gram of heroin for the Washington, DC metropolitan area for three distribution levels, 1981-2005, evaluated at 75% purity.

	$g \leq 1$	$1 < g \leq 10$	$g > 10$
1981	1672	1762	951
1982	1634	1346	856
1983	2478	1917	813
1984	1472	1728	766
1985	1146	1616	867
1986	1381	1114	577
1987	1106	1402	773
1988	781	858	507
1989	720	891	536
1990	1233	1109	717
1991	913	1157	529
1992	880	700	504
1993	770	682	402
1994	813	548	340
1995	727	571	282
1996	741	520	297
1997	730	466	286
1998	475	305	198
1999	424	333	218
2000	527	286	177
2001	380	275	118
2002	386	355	152
2003	414	373	183
2004	430	309	172
2005	471	298	167

Note: The prices for the three distribution levels are evaluated at 0.4, 2.5, and 27.5 grams, which are roughly the median quantities for each distribution level.