A Time-Series Analysis of Crime, Deterrence, and Drug Abuse in New York City

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Since Gary S. Becker's (1968) groundbreaking work on the economics of crime, economists have expanded upon both the theory and the empirical analysis of crime (e.g., Isaac Ehrlich, 1973; M. K. Block and J. M. Heineke, 1975; Ehrlich, 1975; Ann Dryden Witte, 1980). According to the standard theoretical framework, optimizing individuals engage in criminal activities depending upon the expected payoffs of the criminal activity, the return to legal labor-market activity, tastes, and the costs of criminal activity, such as those associated with apprehension, conviction, and punishment. Excellent reviews of the literature appear in Daniel Nagin (1978), Sharon Long and Witte (1981), Richard Freeman (1983), and Theodore G. Chiricos (1987). While some studies reported evidence that increases in criminal-justice sanctions reduce criminal activity (Ehrlich, 1975; Witte, 1980; Stephen K. Layson, 1985; Jeffrey Grogger, 1991; Steven D. Levitt, 1997), others found either a weak relationship, or none at all between the two (Samuel L. Myers, Jr., 1983; James Peery Cover and Paul D. Thistle, 1988; Christopher Cornwell and William N. Trumbull, 1994). Contradictory results can be explained, at least in part, by the empirical problems inherent in crime research, the most significant being the simultaneity between crime and criminal-justice sanctions.[1] Thus, after 30 years of empirical research there is no consensus on the impact of police and arrests on criminal activity.

The purpose of this study is to provide new, and potentially more refined, evidence on the crime-deterrence relationship using a unique data set, which consists of monthly observations in New York City for nearly 30 years. This is the only data set of its kind, based on high-frequency observations of five different crimes, the corresponding arrests, the size of the police force, and a poverty indicator, spanning decades of experience in one city.[2] Consequently, this is the first paper that employs high-frequency time series of individual crime categories to circumvent many problems found in studies that employ cross-sectional or low-frequency (e.g., annual) time-series data sets. We also use recent advances in time-series econometrics to test and correct for problems that may have contaminated the results of previous time-series analyses of crime. We find robust evidence for the deterrent effects of arrests and police on most categories of serious felony offenses.

Another unique feature of the study is the addition of drug-use proxies. In the 1980's and into 1990 the media focused much attention on drug abuse, crime control, and the criminal-justice system. It had been claimed that in-

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[1] Franklin Fisher and Daniel Nagin's (1978) article describing the problem is a classic in the field. Recent literature suggests several new approaches to the simultaneity problem: using careful empirical analyses of individual rather than aggregate data (Grogger, 1991; Helen Tauchen et al., 1994), and finding better exogenous instruments for identification (Levitt, 1996, 1997).

[2] Among the advantages of using just one city is the fact that there is one unit defining and collecting crime and deterrence data, which prevents inconsistencies across observations.

creases in violence and other crimes were due solely to the "drug epidemic." Many policy makers believed that the "crime problem" was strictly due to the "drug problem." In response to the crack epidemic and soaring crime rates, there was a large increase in resources devoted to drug control.[3] The inclusion of drug-use proxies allows us to compare the relative magnitude of the effects of local law-enforcement activities on crime with the magnitude of variations in drug usage on crime. Our results indicate that drug usage has only a small effect on some property crimes, and that local law-enforcement effects on crime are stronger and more significant.

I. The Model

The crime-supply equation, can be written as:

$$(1) \qquad CR = f(POL, ARR, POV, Q),$$

where CR stands for criminal activity, POL represents the size of the police force, ARR is crime arrests, POV represents legal-market opportunities, proxied by poverty, and Q is drug use. Excluding the drug-use variable, this equation is one variant of the model used in the economics of crime literature.[4] It has been so thoroughly discussed in the articles cited above, that we present only a brief description. The model includes police as a determinant of crime because police officers may have an additional general deterrent effect in addition to arrests for the specific crimes. POL and ARR are endogenous variables, where the size of the police force depends on criminal activity, the fiscal condition of the city, the extent of drug use, as well as other exogenous variables, such as electoral cycles (e.g., Levitt [1997]). Crime arrests are a function of the criminal activity and police force. The economic model of crime predicts that an increase in deterrence variables (police and arrests) should reduce criminal activity, and an increase in poverty should increase it.

There exists a voluminous literature on the relationship between drug use and crime written by criminologists. This literature does not, however, provide conclusive evidence on the interrelationship between drug use and crime. In their review of recent studies on the relationship between drug abuse and predatory crime, Jan M. Chaiken and Marcia R. Chaiken (1990) present surprisingly guarded conclusions stating that "··· there appears to be no simple general relation between high rates of drug use and high rates of crime." Lana D. Harrison (1992), in another literature review, comes to a similar conclusion: that the causal link between nondrug crime and drug usage has not yet been established, although the two appear to be correlated.

In this paper we add drug use to the analysis, a variable not usually included in economics of crime studies. Drug use, according to Paul Goldstein (1985), can affect criminal activity through three channels. The first is the "pharmacological" effect: drug use may increase aggression and therefore violent crime. The second is the "economic" effect: some users turn to crime to finance expenditures on drugs.[5] The third is the "systemic" effect: violence occurs in the drug market because the participants cannot rely on contracts and courts to resolve disputes.

The net effect of these factors on crime depends on their relative magnitudes and on the price elasticity of demand for illegal drugs.[6] For example, if the demand for drugs is price inelastic,[7] an increase in drug consumption, due to

[3] See David W. Rasmussen and Bruce L. Benson (1994) for a discussion of these trends.

[4] Theoretical justification of the inclusion of drug use in the crime equation can be found, among others, in Ehrlich (1973).

[5] According to Bruce D. Johnson et al. (1985), among heroin users in New York City during the early 1980's, approximately 33 percent of total income (cash plus in-kind) was derived from nondrug criminal activity and approximately 36 percent of total income was derived from drug sales. Other income was derived from earnings, public support, and support from family members and friends. Although some users may substitute drug crimes for non-drug crimes when the drug market expands, a study by Peter Reuter et al. (1990) found evidence of complementarity between drug income and income from both nondrug crimes and legal earnings for a cross section of individuals arrested for drug sales in Washington, DC in the mid-1980's.

[6] To the extent that the "systemic" effect captures the violence stemming from the sellers who fight over the producer surplus, the proxies of drug consumption do not accurately capture the "systemic" effect.

[7] Recent studies by Becker et al. (1991) on cigarettes, Henry Saffer and Frank Chaloupka (1995) on cocaine and heroin, Jan C. van Ours (1995) on opium, and Michael

a rightward shift of the supply curve of drugs, would be associated with a large decrease in price, and a decrease in drug spending.[8] If the economic effect dominates, then this will result in a decrease in crime. The reverse would be true if the demand for drugs is price elastic.[9]

II. Data

This study utilizes a unique data set, which was constructed using records of the Crime Analysis Unit of the New York City Police Department (NYPD), the Office of Management Analysis and Planning of the NYPD, the New York City Department of Health, and the New York City Department of Human Resources. The Crime Analysis Unit of the NYPD has collected consistent monthly data on crime commission and arrests since 1970. These data form the core of our data set. Almost all of the research on criminal activity has focused on the seven "index" crimes: murder, felonious assault, rape, robbery, burglary, grand larceny, and motor-vehicle theft. We examine all but rape and grand larceny. We exclude rape because reporting frequencies vary significantly over time.[10] We exclude grand larceny because the definition of this crime has changed over time. In 1986, New York increased the value of the damage from \$100 to \$250 to be included into the category of grand larceny.[11] This change, as well as the decrease in the real value of the minimum damage due to inflation, influences the reporting rates and the categorization of this crime.

We include two criminal-justice sanction variables: arrests for the specific crime, and the number of police officers. The monthly number of arrests by crime category was obtained from the Crime Analysis Unit of the NYPD. The number of police officers was obtained from the Office of Management Analysis and Planning of the NYPD. The data obtained from the NYPD span the period January 1970–December 1996. Data restrictions preclude the use of additional criminal-justice variables which have traditionally appeared in crime-supply functions: the probability of conviction and the average length of sentence.[12]

Our measure of drug use is the number of deaths in New York City which are due to drug poisoning. Data on the amount of drugs consumed are not available. Jeffrey A. Miron and Jeffrey Zwiebel (1991, 1995) and Miron (1998) used the death rate from the cirrhosis of the liver, the death rate from alcoholism, the drunkenness arrest rate, and the number of first admittances to mental hospitals for alcoholic psychosis as proxies for alcohol consumption during prohibition for similar reasons. The number of drug deaths was obtained from the New York City Health Department, and covers the period 1970–1996. Although the codes allow the coroner to specify the type of drug, the vast majority of cases were coded as drug-type unknown. Therefore, we cannot disaggregate drug deaths by type of drug. These data have the advantage of not requiring honest self-reporting, and of being closely tied to heavy use.[13]

Grossman and Frank Chaloupka (1998) on cocaine find price-elasticity estimates ranging from inelastic to elastic.

[8] Rasmussen and Benson (1994) discuss changes in the cocaine market between 1979 and 1990. They conclude that during this period increases in cocaine supply have been stronger and more significant than increases in cocaine demand. This is because quantity increases have been coupled with price reductions. Among other reasons, they cite the specific example of the introduction of crack cocaine as a technological advancement which allowed for the large increase in supply. In our case, even though we do not have a clean and continuous price variable, the price measure we have is negatively correlated with the measure of the drug use.

[9] In addition, drug usage may have an indirect effect on crime. If increased drug usage causes increased levels of criminal-justice resources to be devoted to drug crimes (such as more police officers being devoted to drug busts), this may reduce the probability of arrest for those who commit nondrug crimes.

[10] See Jim Galvin (1985).

[11] Source: New York City Police Department Crime Analysis Unit personal communication.

[12] It is important to ascertain changes in the severity of punishment because of the possibility of indirect effects of drug usage on crime. That is, if higher drug usage causes greater numbers of drug criminals to be sent to prison, and if this results in prison crowding, then the effect of drug usage on nondrug crime may be due to reduced sanctions for nondrug crimes. There is no evidence for reductions in imprisonments for nondrug felons. According to the New York State Department of Corrections, during both the 1970's and the 1980's, prison commitments rose faster than arrests for nondrug crimes in New York. Thus, when drug usage was rising, the probability of imprisonment given arrest for nondrug felonies was also rising.

[13] At the beginning of the crack era, before many medical doctors were aware of the drug, some of the deaths may have been diagnosed as nondrug related. As the awareness increased, the probability of missing the drug usage as a

Because of the difficulty and importance of measuring drug usage, we examined two alternative measures of drug usage: the number of releases from all hospitals where the primary reason of admission was drug dependence and drug poisoning,[14] and felony drug arrests.[15] The results are discussed in the paper, but because they were similar to those obtained with drug deaths, they are not reported in detail.

It has been claimed that drug deaths may be inversely related to drug usage. When drug prices are high, usage would decrease, but adverse reactions by drug users would increase due to greater adulteration. To examine this possibility, we utilized data on the prices of heroin and cocaine from Drug Enforcement Agency purchases of drugs in New York City for 1977 through 1989. Because the data on price are very noisy and have gaps, they are not suitable for use in the regressions. Nevertheless, we computed a three-month moving average of prices to reduce the noise and then calculated its zero-order correlation with our three measures of drug use. The correlations ranged from -0.53 to -0.71.[16] That is, for both price measures and for all three drug-use measures, there was a negative and significant correlation between price and our usage proxies. Thus, there is no evidence that our usage indicator(s) is negatively related to actual usage.

Table 1 presents the mean values for the variables. All time series relate to New York City and cover the period from January 1970 until December 1996. Note that we use actual crimes committed rather than rates because of controversies over the population in New York City during this period. The graphs presented in Figures 1–5 display police, drug-related deaths, and the five crimes. They include the actual values of the variables, represented by the jagged line, along with the underlying trend component, represented as a smooth line. The trend component enables the reader to visualize the long-term swings of the variable, with most of the noise eliminated. The trend components were calculated using the Hodrick-Prescott filter.[17] The figures demonstrate the importance of covering a long time span, and thus observing sufficient variation in the variables.

TABLE 1—MEANS OF THE VARIABLES

VARIABLE	Monthly means, NYC January 1970–December 1996
DRUG USAGE	
Drug deaths	60
POLICE	
Number of officers	27,208
ARRESTS	
Murder arrest	99
Assault arrest	1,421
Robbery arrest	1,809
Burglary arrest	1,226
Motor-vehicle theft arrest	782
CRIMES	
Murder	138
Assault	2,657
Robbery	6,882
Burglary	11,975
Motor-vehicle theft	8,112
POVERTY	
AFDC cases	250,106

cause of death should have decreased. Thus, the drug-death data may underestimate the prevalence of the drug use around 1985, when crack was first introduced to the market.

[14] These data, which are obtained from New York State-Wide Planning and Research Cooperative System, cover the period 1980–1996.

[15] These data cover the entire 27-year period. This series does not have the disadvantage of the other two, but has another drawback. Drug arrests is a potential policy variable, where police decide on the level of drug arrests, depending on the relative severity of not only the drug problem but also the crime problem. In addition, one may expect that increased drug arrests cause a decrease in non-drug arrests, holding police constant. Despite these reservations, the three measures of drug usage appear to move together, as reported in the data section.

[16] The correlations were negative, but higher in absolute value between drug-use measures and prices for five-, seven-, and nine-month moving averages, ranging from -0.57 to -0.72.

[17] We used the Hodrick-Prescott filter (Robert J. Hodrick and Edward C. Prescott, 1997) to obtain the slowly evolving trend component. In this procedure, the trend component in the variable under investigation, Γ is obtained by solving the following convex minimization problem:

$$\min \sum_{t=1}^{T} (X_t - \Gamma_t)^2 + \lambda \sum_{t=3}^{T} (X_t - 2\Gamma_{t-1} + \Gamma_{t-2})^2,$$

where X is the variable of interest, and λ is the weight on squared second difference of growth component, which penalizes acceleration in the trend. Following previous examples (e.g., Keith Blackburn and Morten O. Ravn, 1992; Mocan, 1999), λ is set to be 1,600, but the decomposition was not sensitive to the variations in the value of λ.

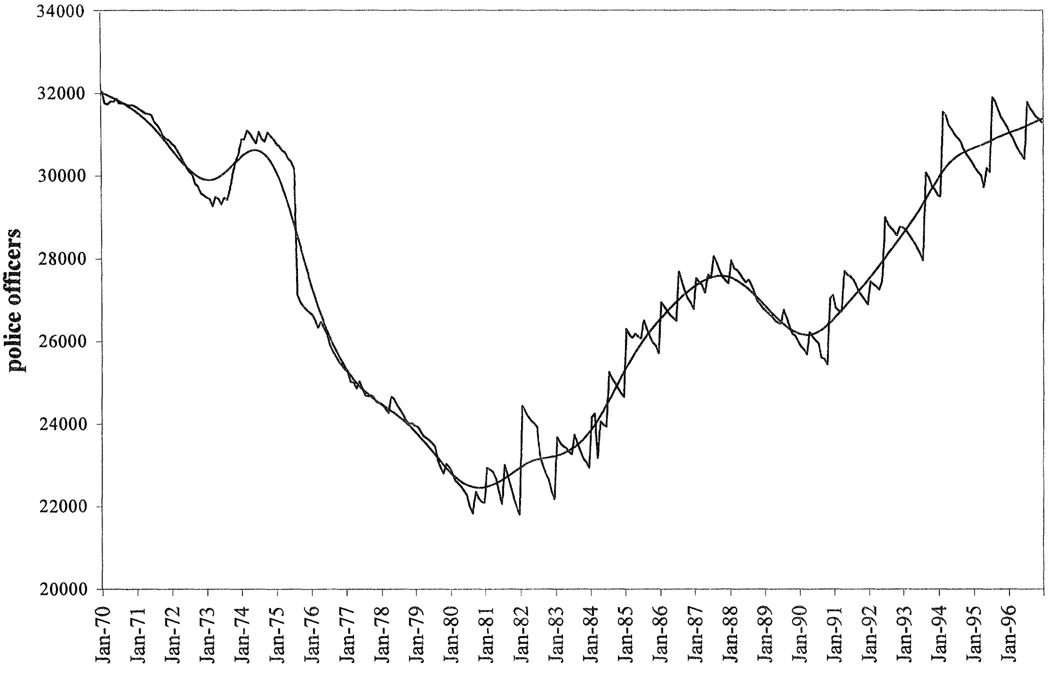

FIGURE 1. POLICE OFFICERS, NEW YORK CITY

Figure 1 presents the number of police officers in New York City. The variable is "total uniform strength," and consists of the number of sworn officers on the payroll. It excludes individuals who have left the police force but are receiving terminal paychecks. Similarly, it does not include civilians, or officers who have been hired but have not completed their six-month training course at the Police Academy.[18] The steep decline between the mid-1970's and early 1980's was an exogenous event due to the fiscal crisis in New York City. Due to layoff and attrition, the police force declined about one-third from a peak of about 32,000 in 1970 to a trough of under 22,000 in the early 1980's. The police force had been increased to about 27,500 in 1988, only half the way back to its former peak. After declining again between 1988 and 1991, the police force was increased to about 31,000 in 1996, almost reaching its 1970 level. The large variation in the size of the police force allows us to observe a range that is far greater than that experienced in most cities.

Deaths due to drugs (Figure 2), declined between 1970 and 1978. They rose after 1979, reaching a plateau in the first half of the 1980's. They began rising again around 1985, reaching a peak in 1988. In the peak year of 1988 there were an average of 101 drug deaths per month compared to 72 in the previous peak year of 1971—an increase of almost 40 percent. Comparing the trough, which occurred in 1978 (with about 21 deaths per month), to the peak of 1988 provides an increase of almost 400 percent. Drug deaths declined between 1988 and 1991, and started rising again after 1991 and leveling off at an average of 92 deaths per month in 1993–1994. Another decline began in 1995.

The pattern of drug deaths presented in Figure 2 is consistent with other drug-use proxies. The simple correlation between drug deaths and drug arrests is 0.65 (1970–1996). It is 0.70 between drug deaths and hospital releases (1980–1996), and 0.85 between drug arrests and hospital

[18] The NYPD and the transit and housing police forces merged in 1995. We have subtracted the size of the transit and housing police from the totals since April of 1995.

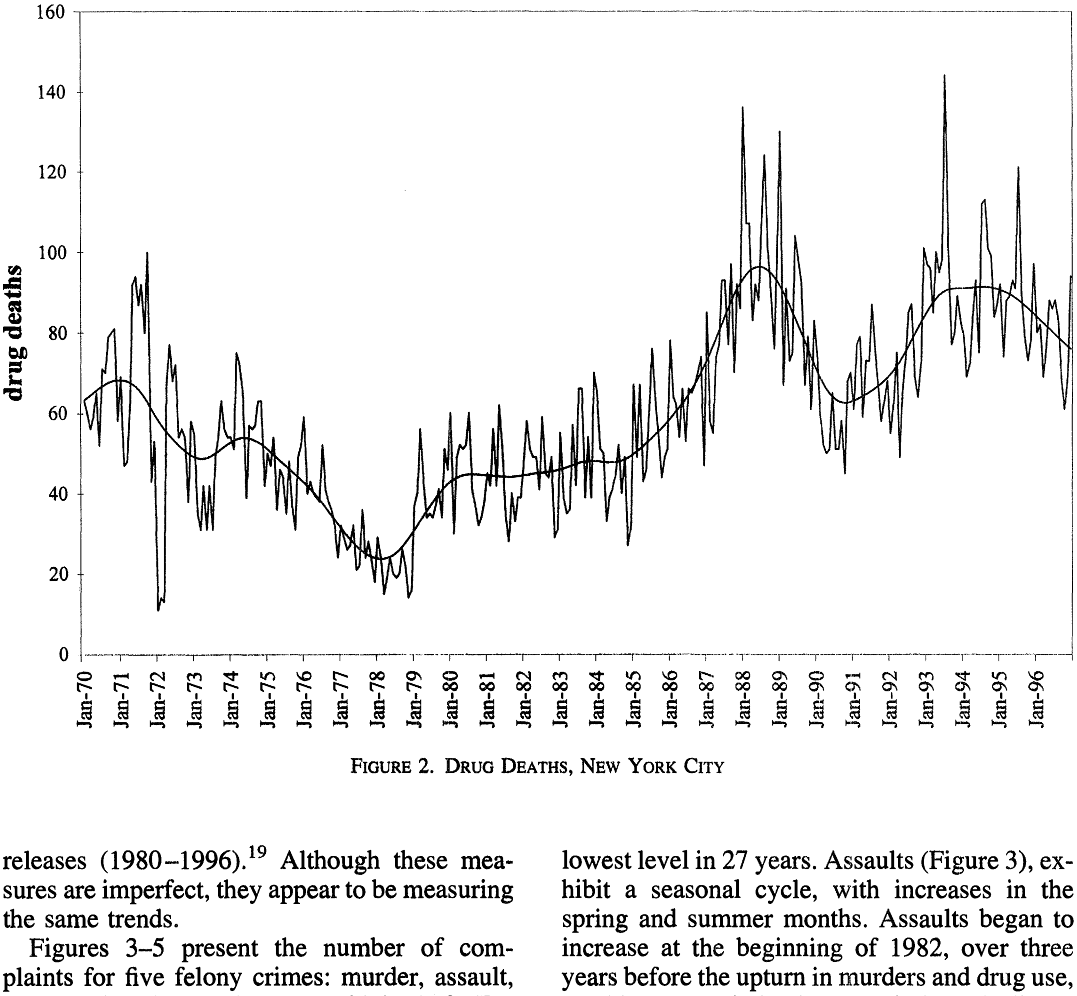

FIGURE 2. DRUG DEATHS, NEW YORK CITY

releases (1980–1996).[19] Although these measures are imperfect, they appear to be measuring the same trends.

Figures 3–5 present the number of complaints for five felony crimes: murder, assault, robbery, burglary and motor-vehicle theft. Examining trends in these data allow us to place the "crime epidemic" of the 1980's into perspective and allows a visual comparison of crime trends to trends in the police force and drug usage. The monthly number of murders (Figure 3) turned up in mid-1985. The total number of murders in 1990 was 2,262, an increase of 24 percent from the previous peak in 1981. Murders increased about 63 percent from the mid-1980's until 1990. Starting in 1991, the year in which police force began its second expansion, murders declined steadily, until the average monthly murders in 1996 was 82, the lowest level in 27 years. Assaults (Figure 3), exhibit a seasonal cycle, with increases in the spring and summer months. Assaults began to increase at the beginning of 1982, over three years before the upturn in murders and drug use, reaching a peak in 1989 and then declining afterwards. Assaults in 1989 were 67 percent higher than their previous peak in 1979 and were 71 percent higher than the most recent trough in 1983. By 1996, assaults had fallen 25 percent from the 1989 peak.

Robberies (Figure 4) exhibit a cyclical pattern. The latest upswing took place in mid-1987, and the latest downturn was in 1991. The number of robberies in 1990 was about 7 percent below the previous peak in 1981. Burglaries, also displayed in Figure 4, declined almost 40 percent between the first and the second half of the 1980's. Burglaries remained fairly constant between 1985 and 1989 and then declined. The 1996 level in burglaries was about 29 percent of the previous peak in 1980. Motor-vehicle thefts (Figure 5), which exhibit cyclical behavior

[19] The correlations between seasonally adjusted series were 0.68, 0.72, and 0.98, respectively.

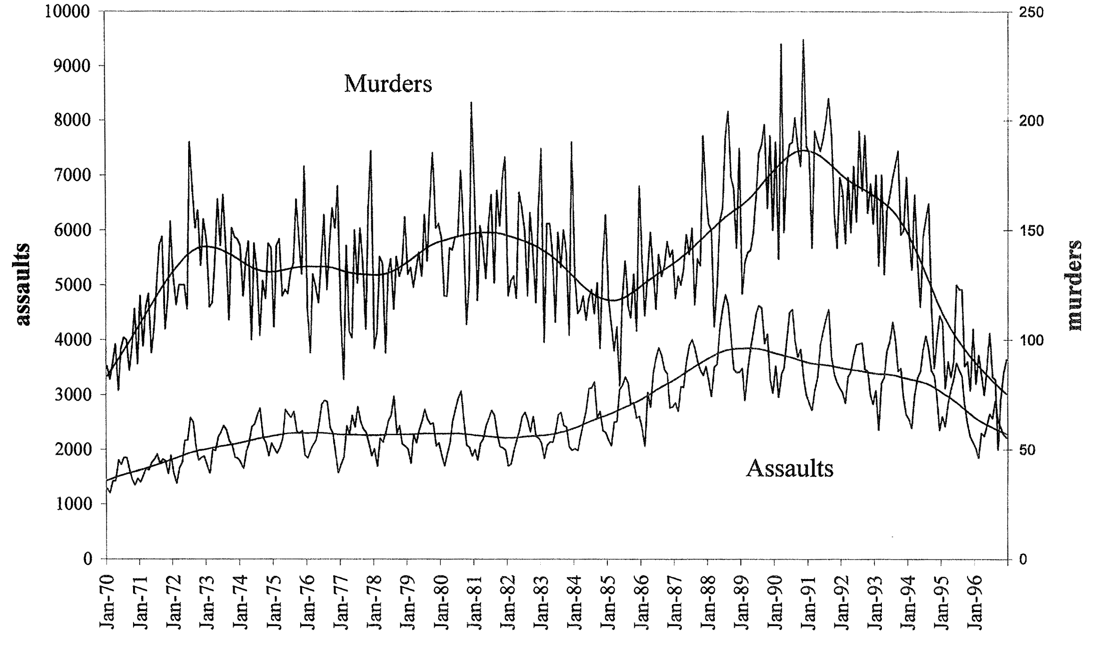

FIGURE 3. MURDERS/FELONY ASSAULTS, NEW YORK CITY

similar to robberies and burglaries, increased dramatically after 1985. The level in 1990 was 37 percent higher than the previous peak in 1982 and about 85 percent higher than its most recent trough in 1985. Similar to other crimes, motor-vehicle theft started to decline after 1990. As Figures 3, 4, and 5 demonstrate, in 1996 murders, robberies, burglaries, and motor-vehicle theft were at their lowest levels since 1970.

A cursory look at the data shows that there was a large increase in drug consumption in the 1980's as proxied by drug deaths, and that some crime categories increased significantly during the same decade, although the timing is not perfectly coincidental. In addition, the upsurge in crime occurred during a period in which the police force was growing. Thus, a cursory inspection of the graphs might support the notion that the increases in crime were caused by increases in drug consumption and that local law-enforcement efforts were not effective in combating crime. Any visual relationship between crime, police, and drug use is only speculative. To isolate the impacts of deterrence and drug use, we present a multivariate statistical analysis.

III. The Simultaneity Problem

The main problem with cross-sectional data is identification. If crime, police, arrests, and drug use are all determined simultaneously, it is difficult to find enough exogenous variables to be meaningfully excluded from some of the equations to allow identification. Using a time series of high frequency allows us to circumvent most of the simultaneity issues, as well as allowing an exploration of some of the dynamics of criminal behavior.

Consider equation (2), which is the empirical counterpart of equation (1)

$$(2)\quad CR_{it} = c_i + \Sigma\alpha_{ij}CR_{t-j} + \Sigma\beta_{ik}Q_{t-k} + \Sigma\gamma_{im}POL_{t-m} + \Sigma\delta_{ip}ARR_{t-p} + \Sigma\xi_{iq}POV_{t-q} + \Sigma\psi_{in}SEAS_n + \varepsilon_{it},$$

where CR_i stands for ith crime ($i = 1$: Robbery, $i = 2$: Burglary, etc.), and j, k, m, p, and q are the lag lengths of crime, drug deaths, the number of police officers, arrests, and poverty. $SEAS$ stands for monthly dummies to control

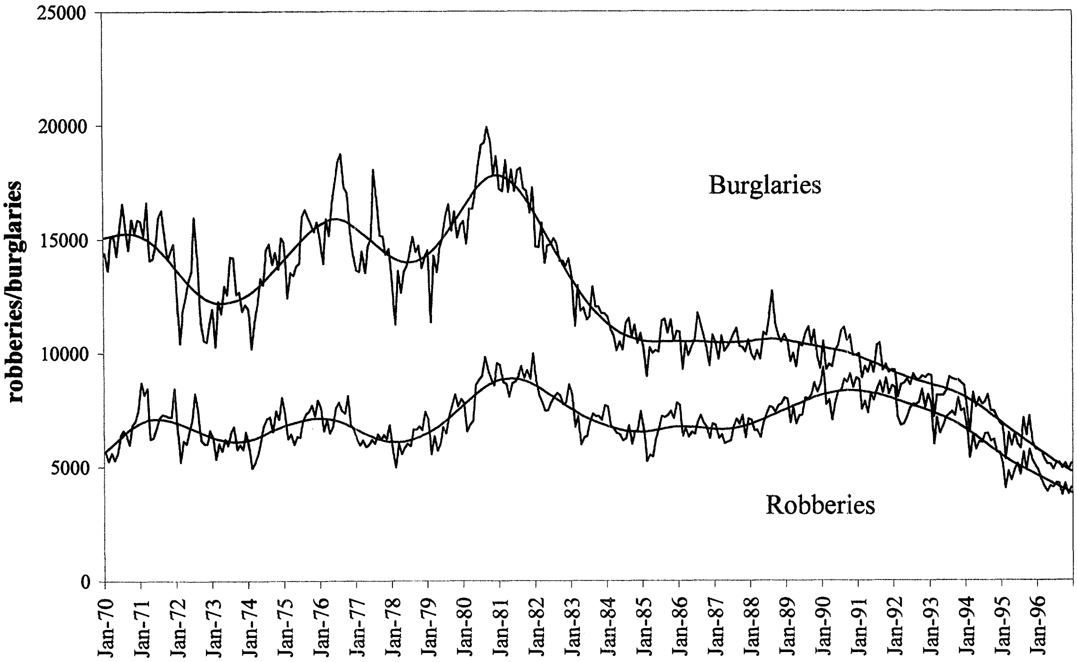

FIGURE 4. ROBBERIES/BURGLARIES, NEW YORK CITY

for the impact of seasonality. In equation (2) $j \geq 1$, $k \geq 1$, $m \geq 0$, $p \geq 1$, $q \geq 0$. Put differently, it is postulated that the number of crimes committed in month t depends upon the past dynamics of the same criminal activity, the past values of drug use, the current and past values of the number of police officers, the past values of arrests, and the current and past values of the rate of poverty. Poverty is approximated by the number of cases of Aid to Families with Dependent Children (AFDC).

Using monthly data allows us to eliminate the simultaneity issue between police and crime. Our police variable, "total uniform strength," includes only officers who have completed their six-month course at the Police Academy. Thus, it takes a minimum of six months between a policy change and the deployment of officers on the street (Todd S. Purdum, 1990). According to the Applicant Processing Department of the NYPD, the six-month period is a minimum, and will only occur if the Department planned on the new recruits. An unplanned policy change requires that certain tests beyond the written examination be given to applicants before they enter the Academy. In such a case, a nine-month lag is a more appropriate minimum time frame.[20] Note that neither the six-month nor the nine-month lag in testing and training includes the lag between the increase in crime and the policy decision to increase the size of the force. Thus, the actual lag may be even longer.

We also performed an empirical test to confirm whether the institutional evidence, cited above, was supported by our data. We ran a regression of police on its 18 lags, and the contemporaneous values and 18 lags of AFCD recipients, drug deaths, and total crime (the sum of all five crimes).[21] We could not reject the hypothesis that 0–6 lags of crime have no influence on police (χ^2 statistic was 8.83 with seven degrees of freedom, with a p-value of 0.26). On the other hand, we strongly rejected the hypothesis that the remaining lags of crime (7 through 18) do not have an impact on current

[20] Personal communication with Captain William Schmidt of the Applicant Processing Department on September 15, 1998.

[21] Consistent with the models estimated in the paper, all variables were in differences and a co-integration term was included.

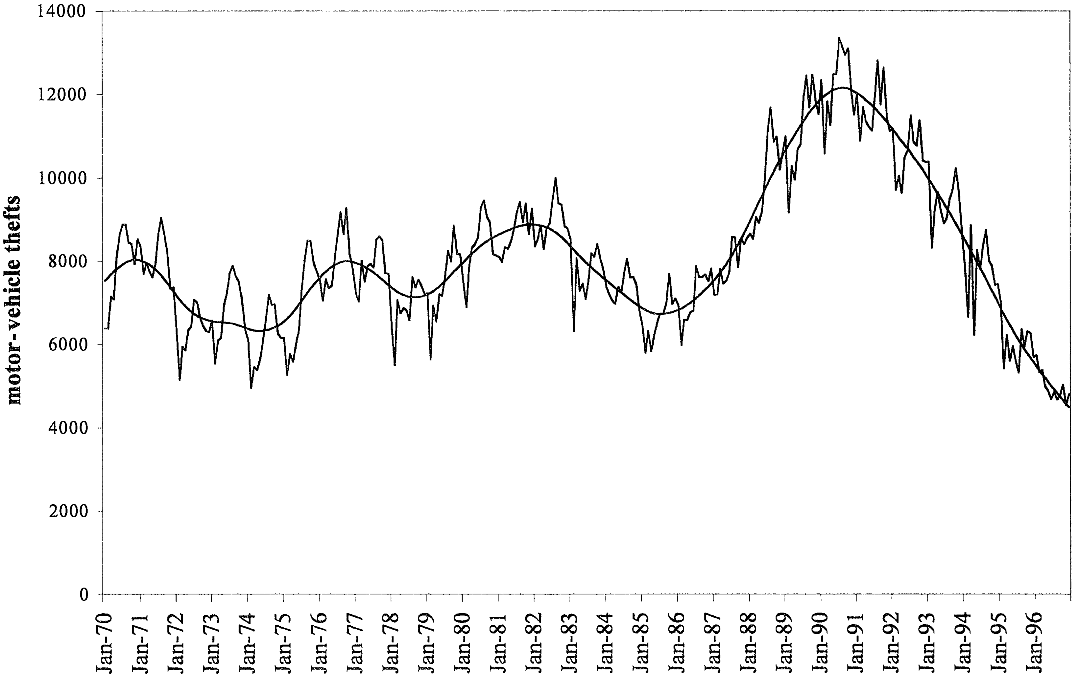

FIGURE 5. MOTOR-VEHICLE THEFTS, NEW YORK CITY

police with a χ^2 statistic of 29.72 and a p-value of 0.003. We obtained the same results when we ran the model with 24 lags of all variables. χ^2 for 0–6 lags of crime was 9.12 with a p-value of 0.24, and it was 46.99 with a p-value of 0.0002. Thus, we confirm, empirically, that the police force reacts to crime with a lag of at least six months.

Because current arrests are likely to be influenced by current criminal activity, a simultaneity bias is created if contemporaneous values of arrests are included in the crime equation. Exclusion of contemporaneous values of arrests helps identify the crime equation and avoid simultaneity bias. Using monthly observations provides a rationale for lagging crime arrests by one month. It is plausible that increased arrests do not immediately affect criminal behavior. It takes time for criminals and potential criminals to perceive that such a change has occurred. To the extent that it takes at least a month for criminals to process that information and to change their behavior, crime should depend on lagged arrests.

Current arrests could affect current crime through the incapacitation effect. To gauge the magnitude of such an effect, we explored national-level data. According to the U.S. Department of Justice study (Brian A. Reaves and Jacob Peres, 1994), in the 75 largest counties of the United States, well over half (63 percent) of those arrested on a state felony charge were released prior to case disposition in 1992.[22] The pretrial release rate varies by charge. Only 24 percent of those arrested for murders were released compared to 68 percent of those arrested for felony assault. For those who were released, 52 percent were released within a day, and 77 percent were released within a week. In addition, most felony defendants waited longer than a month for their case to go to trial. In 1992, only 14 percent of felony defendants were adjudicated within one month, the median time to adjudication was 83 days, and 10 percent of all felony cases had not been adjudicated within one year. Thus, most of the felony defendants

[22] The rate was 66 percent in 1988, the first year such data were available.

were released shortly after arrest and did not go to trial within the month. This suggests that the judicial system does not generate immediate incapacitation for most felony offenders. Along the same lines, Levitt (1998) found that deterrence is a more important factor than incapacitation to impact criminal activity.

To estimate the impact of immediate incapacitation on crime, we applied the following algorithm. First, we obtained information about the offense rates of criminals who were arrested and imprisoned. Mark A. Peterson et al. (1980) calculated that criminals commit the following crimes with the following mean annual frequencies: murders, 0.27; robberies, 4.61; assaults, 4.47; burglaries, 15.29; and motor-vehicle thefts, 5.25. To compute the number of crimes that would have been committed in the absence of incapacitation, an assumption needs to be made about the time distribution of crimes. If criminals space crimes evenly throughout the year, then no crimes except burglary will occur more than once per calendar month. Since burglaries occur every 24 days (15.29 per year), only burglars who are arrested in the first six days of the month (20 percent of those arrested), would have gone on to commit another burglary in the same calendar month. According to the Bureau of Justice Statistics (Reaves and Perez, 1994), 49 percent of the burglars are incapacitated postarrest. Thus, for each burglary arrest, 0.098 burglaries (0.2×0.49) will be averted in the same calendar month due to incapacitation. The average number of burglary arrests per month is 1,226 in New York City between 1970 and 1996 (see Table 1). This suggests that a 10-percent increase in burglary arrests in a given month would generate an incapacitation-related decrease in burglaries in the same month by 12, which is 0.1 percent of the average number of burglaries. Thus, under the assumption of even spacing, incapacitation effects would be zero for all crimes other than burglary and would be quite small for burglaries.

To get an upper-bound estimate of the incapacitation effect, we use a Poisson distribution, and assume that crimes are random and independent events. On average, offenders who are incarcerated are assumed to be arrested in the middle of the month. We use the same crime frequencies we cite above, and convert these to 15-day rates of commission in the same calendar month.[23] In addition, we apply the detention rates for each crime (Reaves and Perez, 1994) as follows: murder, 76 percent; robbery, 50 percent; assault, 32 percent; burglary, 49 percent; and motor-vehicle theft, 33 percent. Applying the Poisson distribution, assuming that release occurs immediately for those not detained, and allowing for multiple crimes per month for each person arrested, the average number of the same crimes averted in the same calendar month due to the incapacitation effect is 0.008 for murder, 0.09 for robbery, 0.06 for assault, 0.31 for burglary, and 0.07 for motor-vehicle theft. For each crime category, allowing arrests to increase 10 percent in a month would result in a same-month reduction in crimes due to incapacitation of: 0.08 for murders, 16 for robberies, 8 for assaults, 38 for burglaries, and 6 for motor-vehicle thefts. As a percent of the average number of monthly crimes, these convert to 0.06 percent for murders, 0.24 percent for robberies, 0.32 percent for assaults, 0.31 percent for burglaries, and 0.07 percent for motor-vehicle thefts. This translates into the following incapacitation elasticities of crime: -0.006 for murders, -0.024 for robberies, -0.032 for assaults, -0.031 for burglaries, and -0.007 for motor-vehicle thefts. Thus, even using the upper-bound estimates, the immediate incapacitation effect is small, with same-month incapacitation elasticities ranging from 0 to -0.03.[24]

It is also possible that first-month deterrence effects could be large for released arrestees, if they faced harsh penalties for a subsequent arrest while awaiting trial. Surprisingly, the offenders who are released prior to trial and who are rearrested for a second felony during the pretrial period face a probability of rerelease of 61 percent, almost identical to the initial release rate of 63 percent. Thus, marginal sanctions do not increase immediately following arrest and release.

Although immediate incapacitation and deterrence effects were estimated to be small, we also estimated the crime equations with the inclusion of the contemporaneous value of the

[23] Fifteen days will be the average length of time in jail for the average person arrested in the middle of the month.

[24] These elasticities reflect only same-crime effects, and do not include effects due to cross-crime incapacitation.

arrests to allow for potential instantaneous effects. Our results were not sensitive to the inclusion of the contemporaneous arrests. This suggests that neither simultaneity bias (due to the inclusion of current arrests) nor model misspecification (due to the exclusion of current arrests) is a major factor in the estimation. We also used two-stage least squares (TSLS) to estimate the effect of arrests on crime. Instrumentation and the results from alternative specifications are explained below. Simultaneity in equation (2) could still emerge if the errors were serially correlated. This is also tested in the results section.

A similar issue arises with current values of drug use. To eliminate potential simultaneity between current drug use and current crime, we lagged drug use one period. However, to the extent that drug use has an immediate impact on crime, we have created a misspecification. As with arrests, in one specification we estimated the crime equation with the inclusion of the contemporaneous value of drug use, and obtained similar results. We also attacked this problem with a TSLS approach. The results are explained in Section V.

IV. Time-Series Properties of the Variables

It is well known that the usual techniques of regression analysis can result in highly misleading conclusions when variables contain stochastic trends (Clive W. J. Granger and Paul Newbold, 1974; Charles R. Nelson and Heejoon Kang, 1984; J. H. Stock and Mark W. Watson, 1988). In particular, if the dependent variable and at least one independent variable contain stochastic trends, and if they are not co-integrated, the regression results are spurious (Granger and Newbold, 1974; P. C. B. Phillips, 1986). To identify the correct specification of equation (2), an investigation of the presence of stochastic trends in the variables is needed. First, standard augmented Dickey-Fuller tests were applied. They indicated the presence of unit roots in the variables under investigation.

Given the evidence provided by David F. Hendry and Adrian J. Neale (1991) that regime shifts can mimic unit roots in autoregressive time series, it is important to investigate whether the variables are indeed governed by stochastic trends or whether breaks in their underlying trends are responsible for the appearance of the unit root. Following Eric Zivot and Donald W. K. Andrews (1992), who extended Pierre Perron's (1989) test where the breakpoint is estimated, rather than fixed, and Baldev Raj and Daniel J. Slottje (1994) and Mocan (1999), who applied the test to several inequality measures, we applied unit-root tests that allow for segmented trends with level and slope shifts at endogenously determined break points. In no case could we reject the hypothesis of a unit root. This means that the proper specification of equation (2) should involve regressing the first difference of crime variables on the first difference of police, drug use, arrests, and AFDC cases, and should not include a time trend as a regressor.

Although the variables are governed by stochastic trends, if there exists a linear combination of them which is stationary with zero mean, then they are co-integrated. In this case, there exists a common factor in all, and the variables do not diverge from one another in the long run. Co-integration tests suggested that there is evidence of co-integration between crime, arrest, drug use, and the police force in all cases. Therefore, the estimated regressions include an error-correction term.[25]

John H. Cochrane (1991) points out that there exist stationary and unit-root processes for which the result of any inference is arbitrarily close in finite samples. Similar points have been raised and the resilience of the unit-root tests against trend-stationary alternatives has been questioned by others (e.g., Christopher A. Sims and Harald Uhlig, 1991; David N. DeJong et al., 1992; Glenn D. Rudebusch, 1993). Nelson and C. J. Murray (1997) state that recent papers brought the literature to a full circle on the issue of unit root in U.S. real GDP, and they analyze the robustness of recent findings with respect to finite sample implications of data-based model specifications and the effects of test size. Thus, given the current controversy on the issue of unit roots, and given that it is not possible to determine the exact structure of the underlying data generating mechanism with a finite sample, the evidence of a unit root, and therefore the

[25] The results of these tests are available upon request.

need to employ the data in first-difference form, can be considered an approximation of the exact structure.

V. Results

The regression results are presented in Table 2. The optimal lag-length for each variable was determined by Akaike Information Criterion (H. Akaike, 1973), and reported next to the crime category. The natural logarithms of the variables were taken before differencing. Estimations were carried out using a heteroskedasticity and serial correlation robust covariance matrix with serial correlation up to lag twelve. Lagrange-multiplier tests were used to determine whether the residuals of the estimated models are white noise. The test statistics reported in Table 2, which are distributed as χ^2 with 12 degrees of freedom, confirmed the hypothesis of no serial correlation in errors up to lag 12.[26,27] In the interest of space, Table 2 does not report the estimated coefficients of the seasonal dummies or the error-correction term.

All five crime categories are influenced by the number of police officers with short lags. For example, changes in the contemporaneous value and two past values of the police-force growth (lags = 0–2) influence the current rate of growth of murders; and the growth rate of assaults are affected by the growth rate of the contemporaneous and immediate past of police.

It is interesting to note that arrests have different lag structures between violent and nonviolent crimes. Arrests have short-lived impacts for assault and murder: assaults are influenced by assault arrests up to four months ago, and murders are influenced by three lags of murder arrests. Robberies, burglaries, and motor-vehicle thefts, on the other hand, present a longer dependence on arrests. Robberies and motor-vehicle thefts are influenced by arrests that took place up to 12 and 14 months ago, respectively. Burglaries exhibit the longest dependence on arrests with 21 lags. With the exception of robberies, drug use also has a short-duration impact on crime.

In Table 2, the first segment for each crime category presents the estimated coefficients in the corresponding equation. Because the explanatory variables generally enter with more than one lag, the sum of the estimated coefficients is calculated, which represents the long-run impact of the explanatory variables on the crime variable. $\Sigma\alpha$ stands for the sum of the lagged crime growth coefficients; $\Sigma\beta$ is the sum of the coefficients of drug-use growth. $\Sigma\gamma$, $\Sigma\delta$, and $\Sigma\xi$ represent the sum of the coefficients of the growth in the number of police officers, the number of arrests, and the AFDC cases, respectively.

$\Sigma\delta$ for murders is -0.336, indicating that a 10-percent increase in the growth rate of arrests generates a 3.4-percent decrease in the growth rate of murders. Although the second lag of police growth (γ_2) is negative and highly significant, the sum of the police coefficients is not statistically different from zero. Hence, the results suggest that arrests constitute deterrence for murders. For assaults, there is no compelling evidence of a deterrence effect, although the contemporaneous value of police is significantly negative. The growth in poverty, approximated by the rate of growth in the AFDC cases, has a positive and significant impact on both murders and assaults.

Law enforcement has a significant deterrent effect on robberies, burglaries, and motor-vehicle theft. For example, for robberies, the sum of the current and lagged arrest growth ($\Sigma\delta$) is -0.940, and for motor-vehicle theft it is -0.395. An increase in the growth rate of police officers is associated with a reduction in the growth rate of burglaries and robberies, although the relationship is only significant at the 11-percent level in the latter.

Murder and assault growth rates are not related to changes in the growth rate of drug use. This result, which is somewhat surprising, is consistent with the one reported by Corman et al. (1991). Using an intervention analysis, they failed to document a structural upturn in the time-series behavior of murders in New York City around 1985. One explanation for this result is that the increase in the supply of drugs that constituted the crack-cocaine epidemic reduced the producer surplus fought over,

[26] The critical value at the 10-percent level is 18.54. All test statistics are below that number.

[27] Very similar results are obtained when the data are aggregated to quarterly, biannual, and annual frequencies, although statistical significance is largely diminished in biannual and annual data.

TABLE 2—REGRESSION RESULTS

	Models with drug deaths (January 1970–December 1996)		Models with drug deaths (January 1970–December 1996)
Murder	(α) Lagged crime: 1–7	Assault	(α) Lagged crime: 1–9
	(β) Lagged drug use: 1–2		(β) Lagged drug use: 1–2
	(γ) Lagged police: 0–2		(γ) Lagged police: 0–1
	(δ) Lagged arrest: 1–3		(δ) Lagged arrest: 1–4
	(ξ) Lagged AFDC: 0–2		(ξ) Lagged AFDC: 0–1
	$c = 0.115^{***}$ (3.504)		$c = -0.121^{***}$ (−3.731)
	$\alpha_1 = -0.659^{***}$ (−7.220)		$\alpha_1 = -0.405^{***}$ (−4.823)
	$\alpha_2 = -0.494^{***}$ (−4.601)		$\alpha_2 = -0.280^{***}$ (−2.688)
	$\alpha_3 = -0.339^{***}$ (−3.297)		$\alpha_3 = -0.176$ (−1.567)
	$\alpha_4 = -0.314^{***}$ (−3.527)		$\alpha_4 = -0.208^{**}$ (−2.061)
	$\alpha_5 = -0.262^{**}$ (−2.396)		$\alpha_5 = -0.184^{**}$ (−2.118)
	$\alpha_6 = -0.141$ (−1.455)		$\alpha_6 = -0.143^{*}$ (−1.699)
	$\alpha_7 = -0.078$ (−1.086)		$\alpha_7 = 0.001$ (0.008)
	$\beta_1 = 0.012$ (0.331)		$\alpha_8 = -0.038$ (−0.488)
	$\beta_2 = -0.020$ (−0.640)		$\alpha_9 = 0.088$ (1.373)
	$\gamma_0 = 0.349$ (0.650)		$\beta_1 = -0.012$ (−0.925)
	$\gamma_1 = -0.587$ (−1.107)		$\beta_2 = -0.013$ (−1.189)
	$\gamma_2 = -1.148^{***}$ (−2.996)		$\gamma_0 = -0.286^{*}$ (−1.681)
	$\delta_1 = -0.127^{*}$ (−1.779)		$\gamma_1 = -0.002$ (−0.013)
	$\delta_2 = -0.131$ (−1.489)		$\delta_1 = -0.056$ (−0.841)
	$\delta_3 = -0.078$ (−1.009)		$\delta_2 = -0.009$ (−0.136)
	$\xi_0 = 1.515$ (1.008)		$\delta_3 = -0.052$ (−0.736)
	$\xi_1 = 0.869$ (0.523)		$\delta_4 = 0.045$ (0.589)
	$\xi_2 = 0.732$ (0.583)		$\xi_0 = 0.043$ (0.088)
			$\xi_1 = 1.346^{*}$ (1.786)
	$\Sigma\alpha_i = -2.287^{***}$ (−3.876)		$\Sigma\alpha_i = -1.345^{**}$ (−2.337)
	$\Sigma\beta_i = -0.008$ (−0.139)		$\Sigma\beta_i = -0.025$ (−1.234)
	$\Sigma\gamma_i = -1.385$ (−1.471)		$\Sigma\gamma_i = -0.288$ (−1.297)
	$\Sigma\delta_i = -0.336^{*}$ (−1.697)		$\Sigma\delta_i = -0.072$ (−0.351)
	$\Sigma\xi_i = 3.116^{*}$ (1.913)		$\Sigma\xi_i = 1.389^{*}$ (1.676)
	Adjusted $R^2 = 0.481$		Adjusted $R^2 = 0.685$
	$\chi^2(12)$ for ($\rho_1 = \cdots = \rho_{12} = 0$): 7.06		$\chi^2(12)$ for ($\rho_1 = \cdots = \rho_{12} = 0$): 7.92
Robbery	(α) Lagged crime: 1–5	Burglary	(α) Lagged crime: 1–9
	(β) Lagged drug use: 1–13		(β) Lagged drug use: 1–3
	(γ) Lagged police: 0–3		(γ) Lagged police: 0
	(δ) Lagged arrest: 1–12		(δ) Lagged arrest: 1–21
	(ξ) Lagged AFDC: 0–2		(ξ) Lagged AFDC: 0–2
	$c = 0.066^{***}$ (4.562)		$c = -0.012$ (−0.680)
	$\alpha_1 = -0.090$ (−1.198)		$\alpha_1 = -0.238^{***}$ (−3.599)
	$\alpha_2 = -0.099$ (−1.341)		$\alpha_2 = -0.106$ (−1.558)
	$\alpha_3 = -0.059$ (−0.815)		$\alpha_3 = 0.020$ (0.359)
	$\alpha_4 = 0.025$ (0.415)		$\alpha_4 = -0.119^{**}$ (−2.038)
	$\alpha_5 = -0.086$ (−1.539)		$\alpha_5 = 0.109^{*}$ (1.869)
	$\beta_1 = 0.014$ (1.269)		$\alpha_6 = 0.105$ (1.320)
	$\beta_2 = 0.024^{*}$ (1.823)		$\alpha_7 = -0.021$ (−0.291)
	$\beta_3 = 0.032^{***}$ (2.825)		$\alpha_8 = 0.110$ (1.410)
	$\beta_4 = 0.018$ (1.102)		$\alpha_9 = 0.142^{**}$ (2.565)
	$\beta_5 = -0.012$ (−0.747)		$\beta_1 = 0.013^{*}$ (1.931)
	$\beta_6 = 0.002$ (0.084)		$\beta_2 = 0.019^{*}$ (1.812)
	$\beta_7 = 0.035^{**}$ (2.510)		$\beta_3 = 0.025^{***}$ (2.797)
	$\beta_8 = 0.037^{**}$ (2.424)		$\gamma_0 = -0.419^{***}$ (−2.995)
	$\beta_9 = 0.010$ (0.924)		$\delta_1 = -0.094^{***}$ (−2.846)
	$\beta_{10} = 0.037^{***}$ (3.397)		$\delta_2 = -0.100^{***}$ (−2.673)
	$\beta_{11} = 0.033^{***}$ (2.966)		$\delta_3 = -0.095^{**}$ (−2.381)

TABLE 2—*CONTINUED*

	Models with drug deaths (January 1970–December 1996)	Models with drug deaths (January 1970–December 1996)
	$\beta_{12} = 0.019$ (1.414)	$\delta_4 = -0.047$ (-1.102)
	$\beta_{13} = 0.033$*** (4.128)	$\delta_5 = -0.124$** (-2.575)
	$\gamma_0 = -0.281$* (-1.811)	$\delta_6 = -0.158$*** (-2.904)
	$\gamma_1 = 0.174$ (0.693)	$\delta_7 = -0.066$ (-1.536)
	$\gamma_2 = -0.509$*** (-2.771)	$\delta_8 = -0.120$*** (-2.822)
	$\gamma_3 = 0.091$ (0.510)	$\delta_9 = 0.010$ (0.228)
	$\delta_1 = -0.152$*** (-3.469)	$\delta_{10} = 0.022$ (0.620)
	$\delta_2 = -0.099$ (-1.572)	$\delta_{11} = 0.078$** (2.178)
	$\delta_3 = -0.160$*** (-2.985)	$\delta_{12} = 0.089$** (2.420)
	$\delta_4 = -0.077$ (-1.527)	$\delta_{13} = 0.135$*** (3.325)
	$\delta_5 = -0.051$ (-1.058)	$\delta_{14} = 0.052$ (1.348)
	$\delta_6 = -0.083$* (-1.910)	$\delta_{15} = 0.032$ (0.854)
	$\delta_7 = -0.024$ (-0.620)	$\delta_{16} = 0.062$** (1.962)
	$\delta_8 = -0.059$* (-1.709)	$\delta_{17} = 0.114$*** (3.475)
	$\delta_9 = -0.046$ (-0.974)	$\delta_{18} = 0.064$* (1.826)
	$\delta_{10} = -0.069$* (-1.863)	$\delta_{19} = -0.089$** (-2.446)
	$\delta_{11} = -0.097$*** (-2.586)	$\delta_{20} = -0.076$** (-2.206)
	$\delta_{12} = -0.023$ (-0.558)	$\delta_{21} = -0.041$ (-1.347)
	$\xi_0 = 1.515$*** (2.877)	$\xi_0 = 0.742$ (1.427)
	$\xi_1 = -0.365$ (-0.716)	$\xi_1 = -0.729$ (-1.401)
	$\xi_2 = -0.579$ (-1.231)	$\xi_2 = 0.262$ (0.479)
	$\Sigma\alpha_i = -0.310$* (-1.720)	$\Sigma\alpha_i = 0.001$ (0.006)
	$\Sigma\beta_i = 0.283$** (2.432)	$\Sigma\beta_i = 0.057$*** (3.212)
	$\Sigma\gamma_i = -0.526$ (-1.618)	$\Sigma\gamma_i = -0.419$*** (-2.995)
	$\Sigma\delta_i = -0.940$*** (-3.247)	$\Sigma\delta_i = -0.355$ (-0.983)
	$\Sigma\xi_i = 0.571$ (0.727)	$\Sigma\xi_i = 0.276$ (0.400)
	Adjusted $R^2 = 0.663$	Adjusted $R^2 = 0.656$
	$\chi^2(12)$ for $(\rho_1 = \cdots = \rho_{12} = 0)$: 17.88	$\chi^2(12)$ for $(\rho_1 = \cdots = \rho_{12} = 0)$: 18.06
Motor-vehicle theft	(α) Lagged crime: 1–2	Motor-vehicle theft concluded
	(β) Lagged drug use: 1–8	
	(γ) Lagged police: 0–2	
	(δ) Lagged arrest: 1–14	
	(ξ) Lagged AFDC: 0–1	
	$c = -0.040$*** (-2.988)	$\delta_7 = -0.067$* (-1.913)
	$\alpha_1 = -0.230$*** (-2.749)	$\delta_8 = -0.069$** (-2.205)
	$\alpha_2 = 0.095$* (1.823)	$\delta_9 = -0.034$ (-1.038)
	$\beta_1 = 0.007$ (0.708)	$\delta_{10} = -0.001$ (-0.034)
	$\beta_2 = -0.013$ (-1.395)	$\delta_{11} = -0.013$ (-0.386)
	$\beta_3 = -0.009$ (-0.975)	$\delta_{12} = -0.029$ (-0.736)
	$\beta_4 = -0.005$ (-0.515)	$\delta_{13} = 0.102$*** (3.887)
	$\beta_5 = -0.024$*** (-2.619)	$\delta_{14} = 0.026$ (0.928)
	$\beta_6 = -0.032$*** (-3.268)	$\xi_0 = 1.646$** (2.373)
	$\beta_7 = 0.006$ (0.512)	$\xi_1 = -1.130$ (-1.626)
	$\beta_8 = 0.011$ (1.087)	
	$\gamma_0 = -0.222$ (-1.270)	
	$\gamma_1 = 0.256$ (0.871)	$\Sigma\alpha_i = -0.134$ (-1.148)
	$\gamma_2 = -0.486$** (-2.162)	$\Sigma\beta_i = -0.059$ (-1.483)
	$\delta_1 = -0.073$** (-2.385)	$\Sigma\gamma_i = -0.452$ (-1.371)
	$\delta_2 = -0.128$*** (-3.756)	$\Sigma\delta_i = -0.395$* (-1.882)
	$\delta_3 = -0.071$** (-2.429)	$\Sigma\xi_i = 0.516$ (0.674)
	$\delta_4 = -0.012$ (-0.311)	
	$\delta_5 = -0.017$ (-0.630)	Adjusted $R^2 = 0.635$
	$\delta_6 = -0.010$ (-0.344)	$\chi^2(12)$ for $(\rho_1 = \cdots = \rho_{12} = 0)$: 10.99

Notes: The values in parentheses are the corresponding t-ratios.
* Statistically significant at the 10-percent level or better.
** Statistically significant at the 5-percent level or better.
*** Statistically significant at the 1-percent level or better.

TABLE 3—SENSITIVITY ANALYSIS

Murder	Police	Arrests	AFDC	Drug use
Benchmark	−1.385	−0.336*	3.116*	−0.008
	(−1.471)	(−1.697)	(1.913)	(−0.139)
3 lags	−1.467	−0.331*	3.252*	0.012
	(−1.351)	(−1.679)	(1.797)	(0.211)
4 lags	−1.224	−0.420*	3.569*	0.015
	(−0.884)	(−1.793)	(1.927)	(0.223)
5 lags	−1.124	−0.653**	3.819*	0.007
	(−0.843)	(−2.249)	(1.959)	(0.069)
6 lags	−1.379	−0.669*	3.696*	−0.036
	(−0.966)	(−1.772)	(1.851)	(−0.310)
Assault	**Police**	**Arrests**	**AFDC**	**Drug use**
Benchmark	−0.288	−0.072	1.389*	−0.025
	(−1.297)	(−0.351)	(1.676)	(−1.234)
3 lags	−0.757*	−0.130	1.335	0.002
	(−1.803)	(−0.891)	(1.284)	(0.062)
4 lags	−0.636	−0.058	1.503	−0.024
	(−1.249)	(−0.263)	(1.395)	(−0.652)
5 lags	−0.452	−0.327	1.897*	−0.041
	(−0.726)	(−1.235)	(1.91)	(−0.850)
6 lags	−0.431	−0.497*	2.175**	−0.060
	(−0.668)	(−1.709)	(2.125)	(−1.199)
Robbery	**Police**	**Arrests**	**AFDC**	**Drug use**
Benchmark	−0.526	−0.940***	0.571	0.283**
	(−1.618)	(−3.247)	(0.727)	(2.432)
3 lags	−0.437	−0.426***	1.819**	0.054**
	(−1.260)	(−3.629)	(2.274)	(2.405)
4 lags	−0.881***	−0.469***	1.325	0.078***
	(−2.785)	(−3.427)	(1.446)	(2.616)
5 lags	−0.855**	−0.499***	1.590	0.021
	(−2.238)	(−2.881)	(1.470)	(0.572)
6 lags	−0.731*	−0.594***	1.998*	−0.020
	(−1.664)	(−2.935)	(1.661)	(−0.326)
9 lags	−0.928*	−0.603***	2.095	0.038
	(−1.703)	(−2.922)	(1.435)	(0.426)
12 lags	−1.068*	−0.827***	0.410	0.205**
	(−1.927)	(−3.298)	(0.356)	(2.017)
15 lags	−1.569**	−0.719**	−0.116	0.356***
	(−2.173)	(−2.540)	(−0.088)	(3.267)

Table 3—*Continued*

Burglary	Police	Arrests	AFDC	Drug use
Benchmark	−0.419***	−0.355	0.276	0.057***
	(−2.995)	(−0.983)	(0.400)	(3.212)
3 lags	−0.078	−0.199***	0.253	0.049**
	(−0.200)	(−2.872)	(0.332)	(2.553)
4 lags	−0.585	−0.197**	−0.112	0.050***
	(−1.610)	(−2.125)	(−0.143)	(2.959)
5 lags	−0.408	−0.256**	0.025	0.002
	(−1.083)	(−2.431)	(0.034)	(0.057)
6 lags	−0.647	−0.494***	0.268	−0.051
	(−1.599)	(−3.507)	(0.368)	(−0.847)
9 lags	−0.772	−0.698***	0.297	0.037
	(−1.293)	(−3.947)	(0.352)	(0.650)
12 lags	−0.987	−0.769***	0.545	0.169**
	(−1.236)	(−3.294)	(0.677)	(2.171)
15 lags	−0.952	−0.630*	0.619	0.331***
	(−1.194)	(−1.787)	(0.710)	(3.805)
24 lags	−0.472	−0.227	0.264	0.281*
	(−0.636)	(−0.543)	(0.318)	(1.854)

Motor-vehicle theft	Police	Arrests	AFDC	Drug use
Benchmark	−0.452	−0.395*	0.516	−0.059
	(−1.371)	(−1.882)	(0.674)	(−1.483)
3 lags	−0.570	−0.217***	0.036	0.015
	(−1.256)	(−3.141)	(0.036)	(0.841)
4 lags	−0.645	−0.230***	−0.244	0.020
	(−1.415)	(−2.932)	(−0.245)	(1.031)
5 lags	−0.673	−0.268***	−0.239	−0.005
	(−1.278)	(−2.914)	(−0.237)	(−0.198)
6 lags	−0.694	−0.262***	0.063	−0.093**
	(−1.183)	(−3.329)	(0.057)	(−2.465)
9 lags	−0.680	−0.459***	0.811	−0.074
	(−1.172)	(−3.335)	(0.661)	(−1.378)
12 lags	−0.770	−0.559**	0.650	−0.041
	(−1.115)	(−2.485)	(0.527)	(−0.555)
15 lags	−0.967	−0.247	−0.374	0.101
	(−1.475)	(−1.243)	(−0.364)	(1.028)

Notes: Lag lengths of explanatory variables in benchmark models are identical to those in Table 2. The entries are the sums of the estimated coefficients. The values in parentheses are the corresponding t-ratios.

* Statistically significant at the 10-percent level or better.

** Statistically significant at the 5-percent level or better.

*** Statistically significant at the 1-percent level or better.

offsetting other effects of drugs on violent crime. Another explanation is that drug-related violence stems mostly from the interaction between sellers. This may not be strongly related to our drug-use measure, which is a proxy of drug consumption. Increases in the growth of drug use, however, are associated with increases in the growth rate of robberies and burglaries.[28]

To investigate the sensitivity of the results to variations in the lag specifications we re-estimated the models with ad hoc lag lengths. More precisely, we estimated the models for murders and assaults where the explanatory variables enter with 3, 4, 5, and 6 lags. Because robberies and motor-vehicle thefts include lags up to 13 and 14 in their original specifications, we estimated them with lag lengths of 3, 4, 5, 6, 9, 12, and 15. Finally, because arrests enter with 21 lags in the burglary equation, we estimated burglaries with

[28] The results were very similar when hospital releases and drug arrests were used as proxies for drug use.

3, 4, 5, 6, 9, 12, 15, and 24 lags. The results are reported in Table 3.

In Table 3, for ease of comparison, the first row under each crime category reproduces the lag specification and the results obtained from the benchmark models, presented in Table 2. Below the benchmark specification we report the sums of the estimated coefficients and their statistical significance for a variety of lag specifications, described above.

The results are robust. The signs of the police and arrests are always negative in all crimes for all lag specifications. Furthermore, arrests are significant in murders, robberies, burglaries, and motor-vehicle thefts. The sum of the police coefficients, which was not significant in the benchmark model for robberies, turns out to be significant in six out of seven ad hoc specifications. The poverty indicator, AFDC cases, has a positive impact on murders and assaults. The relations between drug use and robberies and burglaries are also consistent with the ones obtained from the benchmark model, although the models with 5, 6, and 9 lags do not yield statistically significant coefficients.

As discussed in Section III, we estimated equation (2) with the inclusion of the contemporaneous values of arrests and drug use. This specification, of course, suffers from the standard simultaneity problem, but it provides a useful comparison to the results displayed in Table 2. The results obtained from the inclusion of current values of arrest and drug use were very similar to the ones reported in Table 2. (These results, which are not reported in the interest of space, are available upon request.) This indicates that neither a potential simultaneity bias due to the inclusion of the contemporaneous values, nor a specification bias due to their exclusion, has a significant impact on the results.

We also estimated the models with TSLS in a number of different ways. First, we instrumented the current value of drug-use growth with the current value of the growth in drug arrests by the NYPD, and the current value of criminal arrest growth with the sixth or twelfth lag of police growth. Second, we dropped the police force from the model, instrumented the current value of criminal arrest growth with the current value of police growth, and instrumented the current value of drug-use growth with the current value of the growth in drug arrests by the NYPD.

Third, if the contemporaneous feedback between crime and drug use is stronger than that of crime and arrests, it is meaningful to estimate a crime model where arrests are lagged by one month, and drug use enters with lag zero. We estimated these models with TSLS where contemporaneous drug use is instrumented by drug arrests. Finally, based on Levitt's (1998) discussion of incapacitation and deterrent effects, we used current values of changes in growth rates of murders, assaults, burglaries, robberies, and burglaries to instrument changes in the growth rates of assault arrests, murder arrests, robbery arrests, burglary arrests, and motor-vehicle theft arrests, respectively. Levitt (1998) argues that incapacitation implies that an increase in the arrest rate for one crime will reduce all crimes, and deterrence predicts that an increase in the arrest rate for a particular crime will generate an increase in other crimes as criminals substitute away from the first crime. This argument suggests that one type of crime can be used to instrument a different type of arrest. For example, an increase in robbery arrests would have an impact on burglaries as well, suggesting that the contemporaneous value of burglaries could act as an instrument for robbery arrests.[29] In all these TSLS models the directions of the relationships remained the same, although the statistical significance of the relationships were reduced considerably. This is not surprising given that the variables are employed in first differences, and therefore the instruments are not highly correlated with the endogenous variables.

To put the results into perspective and to clarify the relative importance of deterrence and drug use on criminal activity, we used the sum of the coefficients reported in Table 2, and calculated the responsiveness of each crime to a 1-percent increase in arrests, police, and drug use. The calculated elasticities are reported in Table 4. We included values of elasticities only when the baseline equation or

[29] As we mentioned earlier, in the same paper, Levitt finds no significant incapacitation effect (Levitt, 1998).

TABLE 4—ARREST, POLICE, AND DRUG-USE ELASTICITIES OF CRIME

	Murder	Robbery	Burglary	Motor-vehicle theft
Arrests	−0.34	−0.94	−0.36	−0.40
	−0.31	−0.71	−0.39	−0.37
Police		−0.53	−0.42	
		−0.52	−0.41	
Drug use		0.28	0.06	
		0.18	0.04	

Notes: The first row in each cell reports the elasticity calculated using a zero-growth steady-state scenario for arrests and crime. The elasticities reported in the second row are calculated using the average of the year-to-year growth rates for arrests and crimes in the sample as the starting point.

several of the sensitivity analysis equations indicated significance. The first row in each cell reports the elasticity calculated using a zero-growth steady-state scenario for arrests and crime. The elasticities reported in the second row are calculated using the average of the year-to-year growth rates for arrests, police, drug use, and crimes in the sample as the starting point. Table 4 demonstrates, for example, that a 10-percent increase in murder arrests generates a 3.1- to 3.4- percent reduction in murders. Three main conclusions can be reached from examining this table. First, law-enforcement variables consistently deter felonies. Second, law-enforcement elasticities are smaller than one in absolute value, ranging from −0.3 to −0.9. Third, law-enforcement elasticities are always greater than drug-use elasticities, and drug-use elasticities are usually quite small in magnitude.

VI. Summary and Discussion

The purpose of this paper is to provide new evidence on the relationship among crime, deterrence, and drug use. As a potential solution to some of the difficult empirical problems encountered in previous research, we use high-frequency time-series data from New York City that span 1970 to 1996. Analyzing data that cover almost three decades enables us to observe significant variation in five different crimes and their determinants.

The results provide strong support for the deterrence hypothesis. Murders, robberies, burglaries, and motor-vehicle thefts decline in response to increases in arrests; an increase in the size of the police force generates a decrease in robberies and burglaries. We find no significant relationships between our drug-use measures and the violent crimes of felonious assault and murder, or between drug use and motor-vehicle thefts. On the other hand, we find a positive relationship between drug use and robberies and burglaries. We also find that an increase in the growth rate of poverty, proxied by the number of AFDC cases, generates an increase in the growth rate of murders and assaults. These results are robust with respect to variations in model specifications.

The policy implications of our results are straightforward. To combat serious felony crimes, local law-enforcement decision makers can increase the size of the police force, and they can allocate police in a way that maximizes deterrence of serious felonies. It is noteworthy that in New York City between 1970 and 1980, the police force decreased by about one-third, but felony arrests increased about 5 percent. This was accomplished because arrests for misdemeanors, the less serious crimes, decreased almost 40 percent; and arrests for violations, the least serious level of offenses, decreased over 80 percent. Thus, police were able to reallocate their increasingly scarce resources to combat the most serious crimes.

Our results suggest that increased law enforcement is a more effective method of crime prevention in comparison to efforts targeted at drug use. This is because, although we have statistical evidence that drug usage affects robbery and burglary, the relationship is weaker in comparison to the one between arrests and crime. For example, a 10-percent decrease in drug use, proxied by drug deaths, generates a 1.8- to 2.8-percent decrease in robberies, while a 10-percent increase in robbery arrests brings about a 7.1- to 9.4-percent decrease in robberies. Furthermore, there is no consensus that any criminal-justice program, drug-prevention program, or rehabilitation program has resulted in decreases in drug use of any magnitude. No policy could guarantee a reduction in drug use by a given magnitude, whereas an increase in law enforcement is relatively straightforward to implement.

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