THE INTRODUCTION OF CRACK COCAINE AND THE RISE IN URBAN CRIME RATES

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ABSTRACT

Despite widespread popular accounts linking crack cocaine to inner-city decay, little systematic research has analyzed the effect of the introduction of crack on urban crime. We study this question using FBI crime rates for 27 metropolitan areas and two sources of information on the date at which crack first appeared in those cities. Using methods designed to control for confounding time trends and unobserved differences among metropolitan areas, we find that the introduction of crack has substantial effects on violent crime but essentially no effect on property crime. We explain these results by characterizing crack cocaine as a technological innovation in the market for cocaine intoxication and by positing that different types of crimes play different roles in the market for illegal drugs. In a market with incomplete property rights and inelastic demand, a technological innovation increases violence on the part of distributors but decreases property crime on the part of consumers. We also find evidence that the increase in urban crime during the 1980's occurred in two distinct phases: an early phase largely attributable to the spread of crack and a later phase largely unrelated to it.

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I. Introduction

Crack cocaine, a simple derivative of powdered cocaine hydrochloride, appears to have been first developed in the early 1980's [Kozel 1997]. It then spread through cities across the country over the course of the decade. By popular account, the arrival of crack cocaine has led to increases in central-city crime and accelerated trends toward general urban decay. Popular and ethnographic reports have linked crack to gang violence, high murder rates, urban unemployment, poverty, and family disruption [Shenon 1986, Chiles 1986, Wolff 1988, Anderson 1990, Johnson et al. 1990].

Despite widespread interest in the topic, however, little systematic research has analyzed the extent to which the introduction of crack led to increased crime in American cities. We take up this topic here for a number of reasons. First, it is important to determine the extent to which a single event, such as the introduction of crack, can influence an important measure of social welfare such as the urban crime rate. Second, the introduction of crack can be thought of as a shock to the cocaine market, and hence may provide some useful insights into the workings of that market. Finally, the introduction of crack is potentially capable of explaining why demographic forecasting models failed to predict the increase in crime during the 1980's.

We analyze FBI reported crime rates from 1979 to 1991 for 27 metropolitan areas across the country. We relate these crime data to information on the year in which crack was introduced into each of these cities. Our introduction dates are drawn from two independent sources. The first is a survey of police chiefs. In 1991, we mailed out a survey in which we asked a number of questions about how crack cocaine had affected each respondent's city. One question asked when the police department first became

aware of the existence of crack. Our second source is drawn from data on emergency room admissions collected by National Institute on Drug Abuse (NIDA). In the NIDA data, hospitals report the type of drug present in each drug-related emergency room admission. They also report the route by which the drug was administered. Because cocaine was rarely smoked prior to the introduction of crack [Chitwood 1985; Siegel 1985], we interpret a sharp increase in the fraction of cocaine-related admissions involving smoked cocaine as evidence of the arrival of crack.

Using the introduction dates from these two sources, we seek to determine how urban crime rates rose after the introduction of crack. We develop an analytical strategy designed to solve many of the problems inherent in a simple before-and-after approach, which is important because a before-and-after comparison could confound the effect of the introduction of crack with the effects of other economy-wide forces affecting the trend in central-city crime. For example, the real wages of low-skill workers fell steadily over our sample period, and wages affect the rate of property crimes committed by youths [Grogger 1997].

Moreover, a simple before-and-after approach would fail to isolate the effects of the introduction of crack unless the spread of crack across cities was effectively random with respect to characteristics of those cities. If, alternatively, some metropolitan areas were more susceptible to the introduction of crack due to area-specific factors—such as local labor markets, judicial rulings affecting the climate of law enforcement, or the pre-existing structure of illicit drug markets—then a simple before-and-after approach would confound the effects of the introduction of crack with the effects of those factors that influence the timing with which crack was introduced.

Our analytical strategy controls for economy-wide trends as well as area-specific confounding factors. We also account for potentially unobservable influences, since many of the factors that we need to control for are likely to be difficult to measure. Our approach relies on a simple observation: that crack markets are largely limited to the central city [Fagan and Chin 1990; Johnson, et al. 1990]. We thus estimate the effect of the introduction of crack on urban crime by comparing changes in central city crime rates to changes in suburban crime rates within metropolitan areas. In effect, we use the suburbs in a given area as a control for the central city. Not only does this approach account for economy-wide time trends and time-invariant characteristics of the metropolitan area, it also controls for area effects that vary with time.

In the next section we discuss previous work on the link between crack and crime. We then describe our data, discussing in particular how we estimate the dates at which crack was introduced into each of the cities in our sample. The fourth section formalizes our analytical approach. The results, presented in section V, exhibit an unexpected pattern: whereas the introduction of crack led to substantial increases in most violent crimes, it had little if any effect on property crimes. In section VI we offer an explanation for this pattern that emphasizes the different roles played by violent and property crimes in markets for illicit drugs. Section VII concludes.

II. Previous Research

Most research on the link between crack and crime addresses different aspects of the problem than that which concerns us here. Several studies have been largely descriptive. Dembo et al. [1990], Inciardi [1990], and Inciardi and Pottieger [1994] analyze data from various Florida samples of persons with differing degrees of

involvement in crime or drugs. All find that crack users and dealers commit a substantial amount of crime, and Inciardi [1990] finds that persons with greater involvement in the crack trade tend to commit more crime.

Fagan and Chin [1990] study a sample of drug users from northern Manhattan. Their goal is to assess whether the link between crack and crime reflects the self-selection of crime-prone individuals into the crack trade or a causal effect of crack involvement on crime. Their evidence is mixed. On the one hand, crack sellers are drawn from populations which likely would have been violent even in the absence of crack. On the other, for most crack sellers, violence more often increased than decreased after they started using drugs.

The two studies closest to ours are those by Blumstein [1995] and Cork [1997]. Blumstein [1995] displays time-series plots of homicide data disaggregated by age and race. He notes that juvenile homicides show sharp upturns in the mid-1980s, particularly for blacks. He speculates that this increase in youth murders is related to the crack trade, although he provides no test of this hypothesis.

Cork [1997] attempts to quantify the link between youth homicide and crack, asking whether, on a city-by-city basis, the rise in youth murders post-dates the introduction of crack cocaine. Although the Cork paper is the most similar to ours of all previous studies, it differs from our research in several important respects. First, Cork focuses primarily on a narrow class of crime: youth homicide. Our study, in contrast, analyzes the effect of the introduction of crack on all crimes reported by the FBI. Second, the Cork analysis fails to account for other factors—observable or unobservable—which may have caused youth homicides to rise during the 1980s

independently of crack. Cork uses a maximum likelihood approach to identify the year in which youth homicides first began to rise, then compares that date to his estimate of the date at which crack first appeared. Implicitly, this approach attributes the rise in youth homicide entirely to the arrival of crack, without allowing for other contemporaneous and potentially confounding influences.

Finally, Cork uses a substantially different data source for estimating crack introduction dates: the federal Drug Enforcement Administration's (DEA) STRIDE data. According to Cork, these data provide city-specific counts of arrests for crack cocaine from 1980 to 1994. For each city, Cork uses a maximum likelihood approach to find the breakpoint in the crack arrest trend, that is, the year in which crack arrests first began to rise sharply. He then uses his estimated breakpoint as his introduction date. A weakness of Cork's data is that they include only DEA arrests, whereas the vast majority of drug arrests are made by local law enforcement authorities. Thus an increase in arrests may reflect changes in DEA enforcement priorities as much as they reflect the arrival of crack. A further problem with federal arrest data is that the arrest counts in some cities are quite small and they vary greatly from year to year. For example, the STRIDE data show only one arrest in Chicago during 1990 [Cork 1997, p. 18]. This causes Cork's maximum likelihood algorithm to fail to converge when a number of different years are tried as candidate breakpoints. In other words, many potential breakpoints are effectively excluded from consideration because Cork's approach breaks down numerically. We take two different approaches to dating the introduction of crack, which we discuss in the next section.

III. Data

To implement the statistical approach described above, we require: (i) the date that crack cocaine was introduced in each urban area; and (ii) crime rate data for both the central-city and suburban parts of each of a number of metropolitan areas. We have assembled this information for 27 Metropolitan Statistical Areas (MSA's) for the period 1979 to 1991.

A. Crack Cocaine Introduction Dates

1. Police Data

We measure crack cocaine introduction dates in two ways. First, in 1991 we surveyed various police departments about the effect that crack had on their city. The surveys were addressed to the chief of police in each city, and included a question about the date when they had first encountered crack. Out of 27 surveys mailed out, we received responses from 25 police departments. A few departments provided responses to both the original survey and to a follow-up questionnaire. In those cases we used the more complete response. Introduction dates from our police survey are listed in the first column of Table 1. The reported introduction dates range from 1981 in Atlanta to 1991 in Milwaukee. The modal introduction year is 1986.

2. Emergency Room Admissions Data

We also inferred crack introduction dates from the data on hospital emergency room admissions that are published by NIDA as part of the Drug Awareness Warning Network (DAWN). DAWN reports the number of drug-related emergency room admissions in a given metropolitan area by the type of drug involved in the event. Among cocaine-related ER events, it also reports how the drug had been administered.

Because powdered cocaine cannot be smoked, and free-base cocaine concocted with volatile solvents—the only other form of the drug that can be smoked—was relatively rare [Chitwood 1985, Siegel 1985], we interpret a discrete jump in the fraction of cocaine-related ER events attributed to smoked cocaine as evidence that crack had been introduced.

In many cases the year in which the break occurred was obvious from inspecting the data. Other cases were more ambiguous. We adopted an arm's length approach to interpreting all cases by asking the members of a class of 17 first-year Ph.D. students to inspect time-series plots of the emergency room data and to date the year in which the trend break occurs. We use their modal response as the introduction date. As shown in column (2) of Table 1, introduction date estimates based on emergency room admissions range from 1983 in Atlanta and Kansas City to 1987 in Buffalo, Dallas, New Orleans, and St. Louis. This measure also yields a modal introduction date of 1986.

3. Data from Congressional Testimony

For a few of the largest cities, additional information is available from a number of Congressional hearings held between 1985 and 1990. Based on the testimony of police chiefs or commanders from the respective cities, Congressional hearings place the introduction dates at 1985 for New York; late 1985 or early 1986 for Detroit; 1986 for Dallas; and 1988 for Chicago [Holliday 1986; Gilliam 1986; Vines 1990; Ramsey 1990]. This information accords nearly perfectly with the information from our survey of police departments. One might expect a close match, given that the sources were largely the same. Nevertheless, it is reassuring that the information we were provided in 1991, when the crack problem had become endemic in many cities, was the same as that provided to

Congressional committees in the mid-1980's, when the epidemic was, by all accounts, an urgent matter for the various police departments.

4. Dealing with the Discrepancies between Introduction Dates

In seven of the twenty cases for which data are available from both sources, the police survey and DAWN provide the same introduction date. In six other cases, the discrepancy is only one year; in the remaining cases, the discrepancy ranges from two to five years. In the cases where the dates differ, it is difficult to rationalize choosing either one of the introduction dates as uniformly superior to the other. In cities with pre-existing drug problems, police may have had early information on the arrival of a new drug. In cities where police attention was focused elsewhere, crack may have been observed in hospital emergency rooms before the police were aware of its presence. We therefore adopt an approach by which we combine the information from both sources rather than choosing one source over the other.

Based on the introduction dates, we break down the 1979-1991 time period for each metropolitan area into as many as three time segments. We label the period (strictly) prior to the earlier of the two introduction dates as "before crack" and the period (weakly) after the latter introduction date as "after crack". When the two sources disagree, we label the intervening period as "uncertain". All metropolitan areas have before-crack and after-crack segments. The thirteen metropolitan areas with differing reports have the intermediate uncertain segment as well. Seven metropolitan areas have estimates from only one of the sources, and therefore have no period of uncertainty.

B. Crime Rates

The number of reported offenses for the "index" crime categories--murder, rape, robbery, aggravated assault, burglary, larceny-theft, and auto-theft--are published for U.S. MSA's by the FBI in its annual Uniform Crime Reports, broken down by central-cities and suburbs. We analyze annual crime rates, coded as crimes per 100,000 residents.

Figure 1 displays a time-series plot of the average crime rate from our 27 sample MSA's. Also plotted is the nationwide crime rate from 1975 to 1991. Because urban areas have more crime, the crime rate for the sample MSA's is higher than that for the U.S. as a whole. Aside from the level differences, however, both series exhibit similar trends, peaking first in the early 1980's, falling for a few years, then rising again for the duration of the sample period. It is the post-1983 increase in crime rates that was missed by the demographic forecasting models, and that we attempt to explain below.

Descriptive statistics by crime category are presented in Table 2.[1] Although there is considerable variation in crime rates by MSA, central cities are, not surprisingly, more crime-ridden than the suburbs. For instance, the mean robbery rate in the central cities is more than 5½ times greater than that in the suburbs; the mean murder rate in central cities is 5 times greater than that in the suburbs; the mean rape rate is nearly 4 times greater in central cities than in the suburbs; and the mean aggravated assault rate is about 3 times as great in the central cities. The disparity between mean central-city and suburban property

[1] With 27 MSA's and a 13-year sample period, one would expect a sample size of 351. The actual sample sizes are lower due to missing data. FBI data are unavailable for Buffalo in 1981, Miami in 1988, and Tampa in 1988 and 1990. Rape data for Chicago were not published after 1985. For this reason, we exclude Chicago from the rape tabulations altogether.

crimes rates (burglary, larceny-theft, and auto-theft) is less dramatic, though the central-city and suburban crime rates still differ by a factor of two or three.

Table 3 presents the crime data in a manner that sheds some light on the possible effects of the introduction of crack cocaine. For each of the seven index crime rates, we average the data separately for central cities and suburbs, each before and after the introduction of crack. Within each of the seven panels of Table 3, central-city data are presented in the first column and suburban data are presented in the second. The third column gives the difference in crime rates between the central cities and the suburbs. The first row of the table presents data from the before-crack period; the second presents the after-crack data. The third row reports the mean change before and after the introduction of crack. The entry in the third row, third column of each panel gives the difference between the cities and the suburbs in the before-and-after change in crime rates. Under our maintained assumption that crack had no effect on suburban crime rates, this is the so-called difference-in-difference estimator [Ashenfelter 1978] of the effect of the introduction of crack cocaine on central-city crime rates.[2]

For most of the index crimes, these estimates suggest that the introduction of crack had sizeable and significant positive effects. The difference-in-difference estimate of the effect on murder indicates that the introduction of crack caused murder rates to rise by 4.4 per 100,000 population, an amount equal to 18.7 percent of the before-crack murder rate in the central cities. The only statistically insignificant effects are for rape and burglary, although the robbery effect has a t-statistic of only 1.83.

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[2] If this assumption fails and the introduction of crack caused suburban crime to rise, then we understate the effect of the introduction of crack on urban crime.

From Table 3 one can also see how valuable it is to use the suburbs as controls for the central cities. The simple before-and-after estimate of the effect of the introduction of crack is given by the mean change over time in central-city crime rates, reported in the third row of the first column in each panel. With the exception of burglary, which actually fell over the sample period in both the central cites and suburbs, the simple before-and-after estimates are larger than the difference-in-difference estimates. For some crimes, such as murder and larceny-theft, the difference is small. For others, however, the difference between the two estimators is sizeable. The before-and-after estimate of the effect of crack on aggravated assault is 379.9; the difference-in-difference estimate is 308.1, 19 percent smaller. For auto thefts, the before-and-after estimate is 647.2, whereas the difference-in-difference estimate is 473.6, 30 percent smaller. For these two crimes, failing to account for economy-wide trends, as summarized by the changes in suburban crime rates, would lead to substantially larger estimates of the effects of the introduction of crack.

Suggestive as the difference-in-difference estimates may be, however, they implicitly impose the assumption that economy-wide trends in crime are the same between the central cities and suburbs. Since there is no *a priori* reason to assume that such trends would be the same, it would be desirable to present estimates based on a procedure that relaxes this potentially restrictive assumption. We now present and discuss such a procedure.

IV. Estimation

As noted in the introduction, consistently estimating the effects of the introduction of crack on urban crime rates requires a procedure that allows for both (i) economy-wide

trends in crime that are independent of the introduction of crack; and (ii) area- and year-specific unobservable factors that capture differences in susceptibility to crack between metropolitan areas and within metropolitan areas over time. The following estimator satisfies these conditions and allows for differential economy-wide crime trends between urban and suburban areas.

The model consists of two equations, one for the central cities (equation 1) and one for the suburbs (equation 2):

$$(1) \quad Y_{it}^{c} = I_{it}\gamma^{c} + U_{it}\beta^{c} + \mu_{it} + \delta_{t}^{c} + \varepsilon_{it}^{c} \qquad i=1,...,N;\ t=1,...,T$$

$$(2) \quad Y_{it}^{s} = \mu_{it} + \delta_{t}^{s} + \varepsilon_{it}^{s}$$

The dependent variable Y_{it}^{c} denotes the crime rate in the central city of MSA i in year t. The variable Y_{it}^{s} denotes the crime rate in the suburbs of MSA i in year t. The variable I_{it} is the dummy variable that captures the introduction of crack cocaine. For the central city of the ith MSA, it is equal to one during and after the latter of the two introduction dates given in Table 1, and equal to zero in all previous years. The variable U_{it} captures the period of uncertainty. For the central city of the ith MSA, it is equal to one during the earlier introduction year and in all subsequent years up to the last year prior to the latter introduction date. For cities with no period of uncertainty, U_{it} equals zero in all years, and I_{it} equals one for all years including and after the (single) introduction date.[3] The absence of the variables I_{it} and U_{it} from the equation for the suburban areas reflects the identifying assumption that the effects of the introduction of crack are limited to the central cities.

The terms δ_t^c and δ_t^s are economy-wide period effects influencing crime rates in the central cities and suburbs, respectively, independently of the introduction of crack. These terms account for trends that may affect all urban or suburban areas of the country similarly, such as the decline in the mean wages of low-skill workers. Note, however, that the central cities and suburbs are each allowed their own independent period effects. This formulation is capable of accounting for labor market trends, for example, that do not vary across different regions of the country, but which affect urban and suburban areas differentially. Because crack was introduced across the country in the later part of our sample period, models that failed to account for economy-wide trends would confound those trends with the effects of the introduction of crack.

The μ_{it} terms are fixed effects that are MSA- and year-specific, and common to both the urban and suburban areas in the MSA. These terms account for influences such as statewide judicial rulings, the state of other illicit drug markets, or local labor market shocks. If these factors (which may be difficult to observe) contribute to a favorable climate for the introduction of crack, then μ_{it} may be correlated with I_{it} in equation (1), and least-squares estimates of equation (1) or simple before-and-after comparisons may yield inconsistent estimates of the effect of the introduction of crack.

The terms γ^c and β^c are parameters to be estimated. In particular, γ^c gives the effect of the introduction of crack cocaine on urban crime rates. The terms ε_{it}^c and ε_{it}^s are

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[3] For example, in Atlanta, $U_{it} = 1$ in 1981, 1982, and 1983, and equals 0 in all other years; $I_{it} = 1$ in all years from 1984 to 1991 inclusive, and equals 0 in all other years.

idiosyncratic error terms that vary by MSA, year, and between the central city and suburb of each MSA. There are N MSA's and T time periods in the sample.[4]

Subtracting equation (2) from equation (1) yields an estimating equation of the form:

$$(3) \qquad Y_{it}^{c} - Y_{it}^{s} = I_{it}\gamma^{c} + U_{it}\beta^{c} + \Delta_{t} + \varepsilon_{it}^{c} - \varepsilon_{it}^{s}$$

where $\Delta_{t} = \delta_{t}^{c} - \delta_{t}^{s}$. Differencing the equations eliminates the MSA- and year-specific fixed effects μ_{it} from the model. Regressing the difference between central-city and suburban crime rates on the crack introduction dummy, the period-of-uncertainty dummy, and a set of year dummies will yield consistent estimates of the effects of the introduction of crack cocaine on urban crime rates γ^{c} provided that the difference in urban and suburban idiosyncratic error terms, $\varepsilon_{it}^{c} - \varepsilon_{it}^{s}$, is uncorrelated with the year in which crack was introduced. We will provide some limited evidence on this point after discussing our basic results.

IV. Results

A. Basic Estimates

Table 4 reports results from estimating equation (3) by ordinary least squares for each type of crime. The row labeled "After" gives our estimates of the effect of the introduction of crack on urban crime rates, or γ^{c} from equation (3). The row labeled "Uncertain" gives estimates of the coefficient on the period-of-uncertainty dummy, or β^{c}

[4] Strictly speaking, the missing data problems discussed in footnote 1 mean that we have an unbalanced rather than balanced panel. Treating the unbalanced nature of the data explicitly would only complicate the notation, however, while adding no new insights.

from equation (3). The omitted category is the before-crack period. In addition to the two variables shown, all equations include a full set of year dummies.

Most of the violent crime coefficients are at least marginally significant and many are substantial in magnitude. The estimate in column (1) indicates that urban murder rates were higher by 4.8 per 100,000 population after the introduction of crack. Though only marginally significant, this is a sizeable magnitude. Compared to the before-crack urban murder rate of 23.5 per 100,000 (see Table 3), it indicates that central-city murder rates rose by 20 percent in response to the introduction of crack. The rape coefficient is also positive and marginally significant, although it amounts to a smaller increase as a fraction of the base. Relative to the before-crack urban average, rape rose by 15 percent.

The rates of robbery and aggravated assault also rose substantially in response to the introduction of crack. Robberies were up by 195.2 per 100,000, an increase of 27 percent. The increase in aggravated assault—by 275.5 per 100,000 population—amounts to an increase of nearly 50 percent compared to the average pre-crack level in the central cities. Unlike the murder and rape increases, the effects on robberies and aggravated assaults are highly significant.

For the property crimes—burglary, larceny, and auto theft—the results are quite different. All of the coefficients are positive, but they are small in relation to their base. An increase in the burglary rate of 108.6 amounts to only 4.5 percent of the pre-crack burglary rate of 2401.4 (see Table 3). An increase in the larceny-theft rate of 167.8 amounts to only a 4 percent increase. Moreover, none of these coefficients is significant. In fact, none of the coefficients is even as large as its standard error. From these results, we conclude that the introduction of crack had no effect on property crimes.

Not only do these property crime estimates stand in contrast to those for the violent crimes, but in the case of larceny and auto theft, they also stand in contrast to the estimates obtained from the simple difference-in-difference procedure. In Table 3, both the larceny and auto theft estimates were positive and significant, in contrast to the estimates in Table 4. The difference has to do with the way time trends are accounted for by the two estimation procedures. In the simple difference-in-difference approach, time trends are implicitly assumed to be the same between the central cities and suburbs. In the regression model reported in Table 4, the urban and suburban areas are allowed to have different trends. This indicates that the significant difference-in-difference estimates were attributing to the introduction of crack a trend toward increasing property crime in the central cities that was actually independent of crack but steeper than the corresponding trend in suburban property crime.[5]

Finally, we note that all but one of the coefficients on the period-of-uncertainty dummy are positive. This is to be expected, since in many cities, crack was likely to be present already at the earlier introduction date.

B. A Robustness Check

The results in Table 4 exhibit a clear pattern: positive and largely significant effects on violent crime, insignificant effects on property crime. In this section we offer an admittedly limited test of an important assumption underlying our results. As discussed in section IV above, consistent estimation of the effects of the introduction of

[5] The joint *F* statistics for the year dummies are insignificant in these models even though several of the coefficients are individually significant. When the year dummies are replaced with a time trend, however, the coefficients on the time variable are significant and the estimates of the crack coefficients are essentially the same as those reported in Table 4.

crack requires that the difference in idiosyncratic error terms between the urban and suburban parts of each MSA be uncorrelated with the date at which crack was introduced in the MSA. This assumption could be violated if, within an MSA, differences between features of the urban and suburban areas made the central city of that MSA more susceptible than other central cities to the introduction of crack.

One way to handle this problem would be to add such characteristics to the regression models in the hope of controlling for them explicitly. The problem with this approach is that, for the most part, annual data on metropolitan areas, disaggregated by their urban and suburban components, are difficult to come by.

One potential source of such data is the Current Population Survey (CPS). This survey satisfies the minimal requirements of providing annual data that can be disaggregated by MSA and by urbanicity within MSA. In many respects, however, the CPS is less than ideal for our purposes. First, the survey is designed to provide estimates representative of the entire United States and the larger states. Only in the two largest MSA's are the CPS samples representative of the area; even in these large MSA's however, the urban and suburban components of the sample may not be representative of those separate parts of the city. Furthermore, the CPS sampling procedure changed at various times over our sample period, so the representativeness of the MSA-specific subsamples changed over time as well [Zimmerman and Robison 1996]. The result is that MSA- and urbanicity-specific variables constructed from the CPS are likely to be measured with substantial error. Although the effects of measurement error in the case of a single regressor are well known, it is unclear how adding a number of mis-measured

covariates from the CPS would affect our estimates of the effect of the introduction of crack.

Nevertheless, it would be desirable to assess whether our results are robust at least to the introduction of a few variables widely believed to influence crime rates. For this reason we re-estimate equation (3), this time adding the fraction of blacks and the fraction of males aged 16 to 29 in the local population.[6] These variables are widely regarded as important predictors of crime [Blumstein et al. 1986].

The results are presented in Table 5. The additional variables are significant in most cases, but not always with the expected sign. The fraction of young males is strongly significant in the property crime models, as one would expect from previous research. In the violent crime models, however, the fraction of young males is negative. This is contrary to much previous work, although it is consistent with a recent finding that there is little link between the fraction of youths and violent crime (Cook and Laub 1997).

Adding these variables to the model has two main effects on the cocaine coefficients. First, they reduce the coefficients of the period-of-uncertainty dummy. This suggests that the discrepancy between the estimated introduction dates is correlated with demographic characteristics of the MSA's, although the reason for such correlation is by

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[6] With regressors X_{it}^{j} in the model, equations (1), (2), and (3) become

(1') $Y_{it}^{c} = I_{it}\gamma^{c} + U_{it}\beta^{c} + X_{it}^{c}\alpha^{c} + \mu_{it} + \delta_{t}^{c} + \varepsilon_{it}^{c}$

(2') $Y_{it}^{s} = \quad + X_{it}^{s}\alpha^{s} + \mu_{it} + \delta_{t}^{s} + \varepsilon_{it}^{s}$

(3') $Y_{it}^{c} - Y_{it}^{s} = I_{it}\gamma^{c} + U_{it}\beta^{c} + X_{it}^{c}\alpha^{c} - X_{it}^{s}\alpha^{s} + \Delta_{t} + \varepsilon_{it}^{c} - \varepsilon_{it}^{s}$.

In estimating equation (3'), we imposed the restriction that $\alpha^{c} = \alpha^{s}$, although relaxing that constraint had little effect on the estimates.

no means clear. The second effect of adding the demographic variables to the model is to increase the precision with which the effect of the introduction of crack is measured. The standard error in the murder model falls from 2.8 to 2.0, with the result that the effect of the introduction of crack on murder rates is significant at conventional levels.

The estimated effect of the introduction of crack itself, however, is practically unchanged by adding the demographic variables. The coefficient estimates for murder, rape, robbery, and aggravated assault are nearly identical in tables 4 and 5. The estimates for burglary and auto theft change somewhat more, but remain statistically insignificant.

The estimated effect of the introduction of crack is thus robust to the addition of two variables known to predict crime. This hardly constitutes a comprehensive test, but in the absence of better data, it gives us a bit more confidence in the validity of our estimates. The pattern in the results in Table 5 is the same as that in Table 4: the introduction of crack led to substantial increases in violent crime, but had little if any effect on property crime.

C. Explaining the Rise in Crime during the 1980s

Crime is largely a young man's pursuit, and as noted above, the overall crime rate is correlated with the fraction of the population in that demographic group. Several analysts have attempted to exploit this fact by using the age distribution of the population to forecast aggregate crime, arrest, and incarceration rates [Blumstein et al 1980; Fox 1978; Steffensmeier and Marer 1987]. The problem is that these models predicted decreases in crime over the 1980s due to the aging of the large baby-boom cohorts beyond their crime-prone teens and twenties. In fact, as seen in Figure 1, crime rose after about 1983.

Here we assess the extent to which the introduction of crack can explain the unexpected rise in crime. The evidence is presented in Figure 2, where we plot two series. The first is the predicted annual crime rate for our sample, constructed by summing offense-specific predicted crime rates based on the models reported in Table 5. Because the offense-specific rates sum to the index and because the model contains a full set of year dummies, the predicted annual crime rate equals the actual annual crime rate (and is so labeled).

The second series is from a prediction exercise that removes the effect of the introduction of crack. We again use the coefficients from the models reported in table 5 to construct the predictions, but this time we replace the crack variables (I_{it} and U_{it} in equation 3) entirely with zeroes. This provides a prediction of what the crime rate would have been in our sample metropolitan areas in the absence of crack.

The introduction of crack explains a substantial fraction of the increase in crime after 1983. In 1986, the modal year for the introduction of crack, the index crime rate in our sample MSA's was 9961; we predict that it would have been 9225 in the absence of crack. By 1988, when crack had reached all but one of the metropolitan areas in our sample, the crime rate was 9971. Our prediction in the absence of crack is 9109. Thus by 1988, the introduction of crack had resulted in a crime rate that was 9.5 percent higher than it otherwise would have been. Put differently, the crime rate rose from 9058 in 1983 to 9971 in 1988, a rise of 10 percent. Our predictions indicate that, in the absence of crack, crime would have risen by only 1.5 percent.

Although the introduction of crack explains a substantial fraction of the unexpected increase in crime after 1983, inspection of Figure 2 reveals that crack alone

does not fully explain why crime failed to drop, as the demographic models had forecast. The patterns that remain in the data after removing the influence of crime merit some discussion in their own right.

First, crime rose gradually between 1983 and 1987, even after accounting for the effects of crack. This may be attributable to deteriorating low-skill labor markets. Between 1983 and 1987 the real wage paid to males between 16 and 24 fell slightly [U.S. Bureau of Labor Statistics 1989], and Grogger [1997] has shown that property crimes—which account for a large fraction of the overall crime index—are responsive to wage incentives.

More striking is the increase in crime after 1988. In just one year, the crime rate in our sample MSA's rose by 10.6 percent. After removing the effect of the introduction of crack, the increase was actually slightly higher, at 11.6 percent.

This suggests that the post-1983 increase in crime may have occurred in two distinct phases that are attributable to two (or more) different causes. The first is the 1983-1987 phase, which our analysis suggests is largely attributable to the introduction of crack. The second is the post-1988 phase, which is essentially independent of crack. To our knowledge, we are the first to report that the post-1983 rise in urban crime may consist of two distinct components.[7] Although we currently have no explanation to offer for the post-1988 increase, it is clear that this phenomenon warrants further research attention.

[7] Data presented by Blumstein (1995) are broadly consistent with this observation. He notes that drug arrests and youth homicides rose in tandem between 1984 and 1988, but that after 1988, murders continued to rise although drug arrests fell.

The post-1988 increase in crime, which like the post-1983 increase was missed by demographic forecasting models, leads us to make this observation regarding the use of age as a predictor of crime trends. Although age is generally an important predictor of crime, it is clear that there are other, largely unpredictable factors that have important effects on the aggregate crime rate. Even after accounting for factors such as crack, which are important but unlikely to be repeated with any regularity, excessive reliance on the age distribution of the population is likely to lead to unreliable forecasts.

VI. Interpreting the Results

In this section we offer an interpretation of the central result from our analysis: that the introduction of crack had substantial effects on violent crime but little if any effect on property crime. Since it is an explanation offered to rationalize the data, the results above cannot be regarded as a test of the explanation. Rather, we offer this interpretation as a way of thinking about the crack problem in a way that may shed further light on it or on similar events in the future.

Our results are consistent with an explanation comprising two hypotheses. The first hypothesis is that violent crimes and property crimes play substantially different roles in the market for crack cocaine. On the supply side, dealers have incomplete property rights since they cannot avail themselves of the police or the courts to resolve disputes with trading partners. In the absence of complete property rights, trading parties must enforce their own agreements, and violence may serve this function well. Property crimes, in contrast, may largely support the demand side of the market, providing users with the income they need to purchase the drug. The hypothesis that different types of

crimes play different roles in illicit drug markets has been proposed by other researchers as well [Goldstein 1985; Johnson, et al 1994; Fagan and Chin 1990].

The second hypothesis is that the introduction of crack cocaine amounts to a technological innovation in the market for cocaine intoxication. Crack cocaine is a derivative of powdered cocaine, made by dissolving cocaine powder in water, adding baking soda, and boiling the mixture until a solid base—the cocaine "rocks"—separates from the solution. This process does not change the chemical composition of the active cocaine alkaloid, but it does change the manner by which it may be ingested. Once converted into crack, the cocaine can be smoked, which allows the cocaine molecules to concentrate in the brain much more rapidly than is possible by taking powdered cocaine intranasally [U.S. Sentencing Commission 1995, p. 19]. Because the euphoric effects of cocaine have more to do with the speed at which the alkaloid concentrates in the brain than with the level of the drug in the body [Schuster 1986, p. 16; Jones 1985, p. 40], crack is the more intoxicating form of the drug. Moreover, the price of crack is the same as powdered cocaine when measured on a molecule-for-molecule basis (Kleiman 1992). Thus the process of synthesizing crack from powdered cocaine reduces the unit cost of cocaine intoxication, satisfying the usual economic definition of a technological innovation.

With these two hypotheses in place, the effects of the introduction of crack both on the market for cocaine intoxication and on crime can be readily analyzed. In response to a technological innovation in the production of cocaine intoxication, the supply curve for cocaine intoxication shifts out, raising the quantity traded and opportunities for profit. Since property rights are incomplete, violent crime increases. The technology-driven

expansion of supply also causes the price of cocaine intoxication to fall. Since we would expect a habit-forming good such as cocaine to be inelastically demanded [Grieson 1989; Becker, Grossman, and Murphy 1994; Rydell and Everingham 1994], the price reduction results in lower total expenditures on cocaine intoxication. To the extent that the demand for property crimes on the part of users is derived from the demand for cocaine intoxication, we would expect property crimes to fall, or at least not to rise significantly.

The one bit of evidence potentially at odds with this explanation is the significant robbery effect. The problem is that robbery has characteristics of both a violent and a property crime. The FBI classifies it as a violent crime, which makes sense in light of the FBI's hierarchical classification rule. In any criminal incident, many separate crimes may be committed, but the FBI will record only the most serious for its crime statistics. If, for example, a crime that was primarily a beating ended with the perpetrator incidentally taking the victim's wallet, the crime would be classified as a robbery, since robbery outranks aggravated assault according to the FBI's coding hierarchy.

Many robberies are doubtless motivated by the desire to seize goods or money, however, and as such would logically be classified as property crimes. The question here is whether the significant positive effect of the introduction of crack on robbery changes the interpretation of our results. For a simple reason, the answer is no. As can be seen in Table 2, property crimes are dominated by larceny and burglary. Robberies are a small enough fraction of property crimes that, in the aggregate, the increases in robbery shown in Tables 4 and 5 are not large enough to lead to significant increases in property crimes as a whole. Regardless how we classify robbery, the basic result is the same: the

introduction of crack led to a significant and sizeable increase in violent crimes, but no significant increase in aggregate property crimes.

Before turning to our conclusions, we delineate precisely what is novel about our interpretation of our findings. As mentioned above, others have suggested that violent and property crimes may play different roles in the market for crack [Goldstein 1985]. Likewise, we are not the first to suggest that the prevalence of violence in drug markets may stem from incomplete property rights [Johnson, et al 1994; Fagan and Chin 1990].

We are the first, however, to offer a single explanation of how the introduction of crack could result in both the rise in violent crime and the relative stability of property crime. The key is to recognize crack as a technological innovation. This technological innovation shifts the supply curve for cocaine intoxication outward. Since the market is characterized by incomplete property rights, the market expansion leads to increased violence. At the same time, however, the supply shift lowers the price of and (assuming inelastic demand) expenditure on cocaine intoxication. The result is that users have less need to steal to support their habits.

VII. Conclusions

Using two different sources of information to date the introduction of crack in 27 metropolitan areas across the U.S., our analysis shows that the introduction of crack cocaine led to more violent crime—but had little effect on property crime—during the 1980's. A model that treats crack cocaine as a technological innovation, and recognizes the different roles played by different types of crime in the market for illicit drugs, is offered to explain those findings. The models we use to estimate the effect of the

introduction of crack show that crack can explain much of the increase in crime in our sample MSA's between 1983 and 1988.

Left unexplained, however, is a substantial increase in crime after 1988. To our knowledge, we are the first to observe that the rise in crime during the 1980's may have taken place in two distinct phases. Whereas the introduction of crack appears to explain much of the earlier phase, we have no explanation for the latter. Explaining the post-1988 increase in crime, which seems largely independent of crack cocaine, is a topic warranting further research attention.

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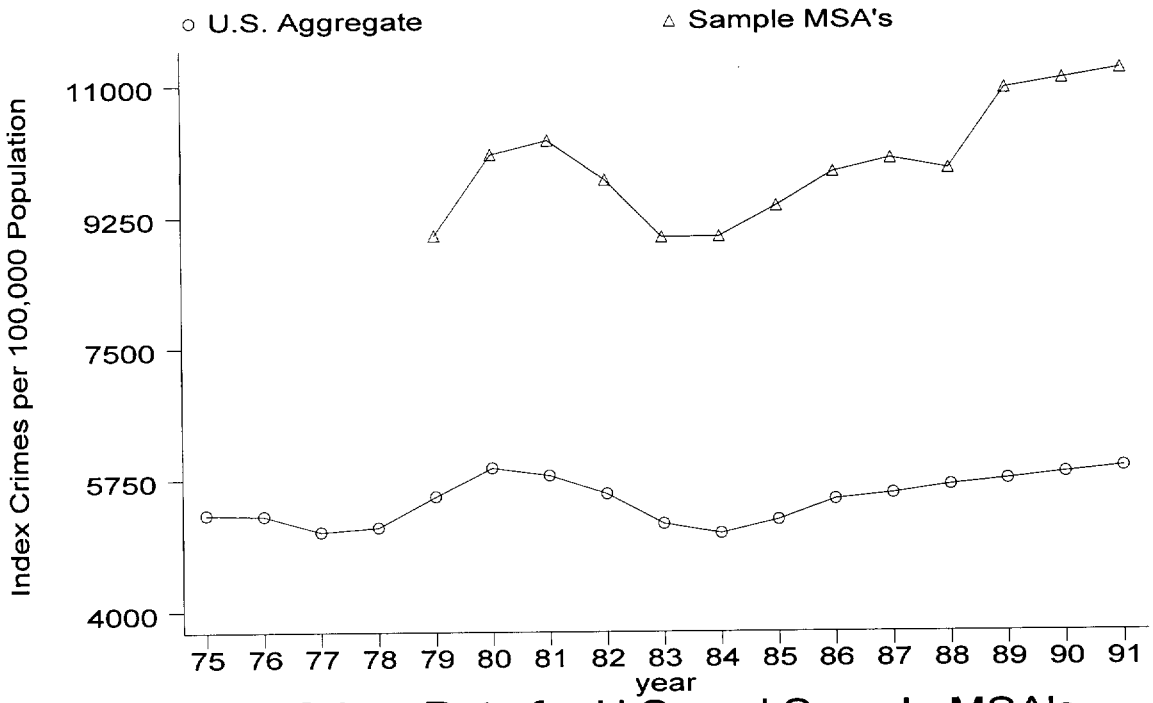
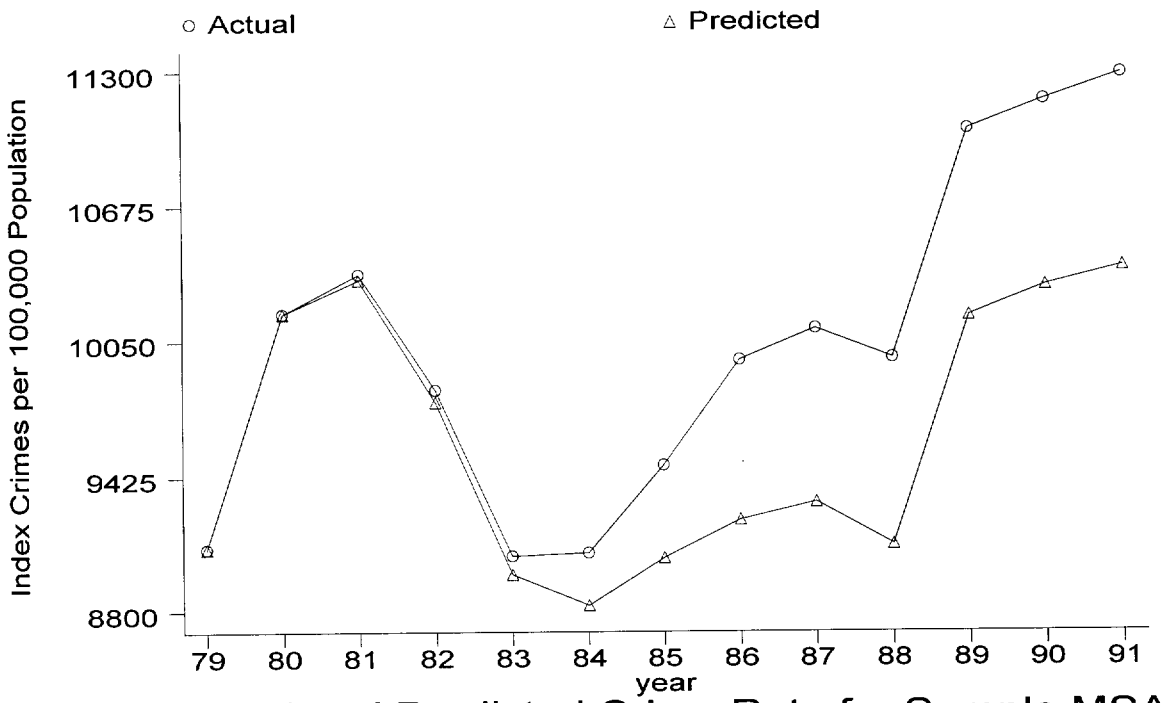


Figure 1: Crime Rate for U.S. and Sample MSA's



gure 2: Actual and Predicted Crime Rate for Sample MSA

Table 1
Crack Introduction Dates

Metropolitan Area	Police Survey (1)	DAWN Data (2)	Period of Uncertainty (3)
Atlanta, GA	1981	1984	1981-1983
Baltimore, MD	1988	1986	1986-1987
Boston, MA	n/a	1986	--
Buffalo, NY	1986	1987	1986
Chicago, IL	1988	1984	1984-1987
Cincinnati, OH	1988	n/a	--
Cleveland, OH	1988	1983	1983-1987
Columbus, OH	1986	n/a	--
Dallas/Fort Worth, TX	1986	1987	1986
Denver, CO	1986	1986	--
Detroit, MI	1986	1984	1984-1985
Indianapolis, IN	1988	1986	1986-1987
Kansas City, MO	1982	1983	1982
Los Angeles, CA	1984	1984	--
Miami, FL	n/a	1984	--
Milwaukee, WI	1991	n/a	--
New Orleans, LA	1986	1987	1986
New York, NY	1985	1986	1985
Newark, NJ	1985	1985	--
Norfolk, VA	1988	1985	1985-1987
Philadelphia, PA	1985	1985	--
Pittsburgh, PA	1987	n/a	--
Saint Louis, MO	1986	1987	1986
San Diego, CA	1984	1984	--
San Francisco, CA	1985	1985	--
Tampa Bay, FL	1985	n/a	--
Washington, D.C.	1986	1986	--

Table 2
Descriptive Statistics

	Observations	Mean	Minimum	Maximum
Violent Crime Rates				
Murder:				
Central-City	347	25.89	4.65	80.60
		(14.18)		
Suburbs	347	5.18	0.62	27.84
		(3.89)		
Rape:				
Central-City	334	93.42	26.62	200.65
		(38.97)		
Suburbs	334	24.65	4.68	59.99
		(11.20)		
Aggravated Assault:				
Central-City	347	747.60	170.67	2386.26
		(423.20)		
Suburbs	347	263.57	62.57	951.15
		(157.63)		
Robbery:				
Central-City	347	846.04	246.78	2337.52
		(424.61)		
Suburbs	347	149.96	26.23	803.40
		(124.75)		
Property Crime Rates				
Burglary:				
Central-City	347	2347.69	999.50	4994.03
		(810.68)		
Suburbs	347	1148.01	412.92	3063.56
		(486.17)		
Larceny-Theft:				
Central-City	347	4543.80	1926.92	10002.77
		(1400.92)		
Suburbs	347	2861.24	964.35	6166.20
		(858.10)		
Auto-Theft:				
Central-City	347	1439.86	291.18	5369.14
		(875.79)		
Suburbs	347	468.26	116.08	1928.02
		(265.11)		

Notes: There are 347 observations because crime rates were not published for Buffalo in 1981, Miami in 1988, or Tampa Bay in 1988 and 1990. Additionally, rape figures were not published for Chicago after 1985. We exclude Chicago in the rape regressions, thus leaving 334 observations. Standard errors are reported in parentheses.

Table 3
Mean Crime Rates for Central Cities and Suburbs, Before and After the Introduction of Crack

I. Violent Crime Rates

	1. Murder			2. Rape			3. Robbery			4. Aggravated Assault		
	Central City (1)	Suburbs (2)	Difference (1)-(2)	Central City (1)	Suburbs (2)	Difference (1)-(2)	Central City (1)	Suburbs (2)	Difference (1)-(2)	Central City (1)	Suburbs (2)	Difference (1)-(2)
Before (B)	23.5	5.1	18.4	87.8	23.3	64.5	792.23	139.9	652.3	569.1	236.1	333.0
	(0.8)	(0.8)	(1.1)	(2.2)	(2.2)	(3.2)	(24.4)	(24.4)	(34.5)	(22.8)	(22.8)	(32.3)
After (A)	28.3	5.4	22.9	95.4	26.4	68.9	914.0	169.8	744.2	948.3	307.2	641.1
	(0.9)	(0.85)	(1.2)	(2.4)	(2.4)	(3.4)	(25.6)	(25.6)	(36.2)	(24.0)	(24.0)	(33.9)
Change (A)-(B)	4.7	0.3	4.4	7.6	3.1	4.5	121.8	29.9	91.9	379.9	71.1	308.1
	(1.2)	(1.2)	(1.7)	(3.3)	(3.3)	(4.6)	(35.4)	(35.4)	(50.0)	(33.1)	(33.1)	(46.1)

II. Property Crime Rates

	5. Burglary			6. Larceny-Theft			7. Auto Theft		
	Central City (1)	Suburbs (2)	Difference (1)-(2)	Central City (1)	Suburbs (2)	Difference (1)-(2)	Central City (1)	Suburbs (2)	Difference (1)-(2)
Before (B)	2401.4	1233.3	1168.1	4373.7	2868.7	1505.0	1136.5	393.7	742.8
	(51.6)	(51.6)	(73.0)	(89.3)	(89.3)	(126.2)	(46.9)	(46.9)	(66.3)
After (A)	2287.6	1078.13	1209.5	4808.7	2895.8	1912.9	1783.6	563.6	1216.3
	(54.3)	(54.3)	(76.8)	(93.8)	(93.8)	(132.7)	(49.4)	(49.4)	(69.8)
Change (A)-(B)	-113.8	-155.2	41.4	435.0	27.1	407.9	647.2	173.6	473.6
	(74.9)	(74.9)	(106.0)	(129.5)	(129.5)	(183.2)	(68.1)	(68.1)	(96.2)

Table 4
Regression Estimates of the Effect of the Introduction of Crack on Urban Crime Rates

Crime: Variable	Murder (1)	Rape (2)	Robbery (3)	Aggravated Assault (4)	Burglary (5)	Larceny-Theft (6)	Auto Theft (7)
After	4.8	13.9	195.2	275.5	108.6	167.8	132.1
	(2.9)	(8.7)	(80.7)	(79.8)	(149.9)	(234.8)	(157.6)
Uncertain	7.5	34.7	155.5	236.6	277.2	-193.2	196.4
	(3.2)	(9.6)	(88.4)	(89.4)	(164.2)	(257.2)	(172.6)
R^2	0.08	0.04	0.07	0.17	0.03	0.06	0.125

Notes: In addition to the variables shown, all models include a full set of year dummies. Standard errors are in parentheses.

Table 5
Further Regression Estimates of the Effect of the Introduction of Crack on Urban Crime Rates

Crime: Variable	Murder (1)	Rape (2)	Robbery (3)	Aggravated Assault (4)	Burglary (5)	Larceny-Theft (6)	Auto Theft (7)
After	4.4	13.8	192.4	263.2	167.6	184.9	190.1
	(2.0)	(8.8)	(69.8)	(77.3)	(146.6)	(235.2)	(154.7)
Uncertain	2.9	32.6	63.7	183.3	221.7	-111.1	140.6
	(2.2)	(10.0)	(76.1)	(84.3)	(159.9)	(256.5)	(168.8)
Percent black	57.5	27.9	1176.9	600.4	1179.7	-939.6	1174.9
	(3.3)	(14.5)	(115.2)	(127.6)	(241.9)	(388.2)	(255.4)
Percent Male, 16-24 years old	-86.7	-30.7	-1368.2	-1526.4	3370.5	2224.8	3296.7
	(21.4)	(94.3)	(750.3)	(831.2)	(1576.0)	(2529.0)	(1663.7)
R^2	0.57	0.06	0.33	0.24	0.09	0.09	0.18

Notes: In addition to the variables shown, all models include a full set of year dummies. Standard errors are in parentheses.