

Measuring Crack Cocaine and Its Impact*

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Abstract

A wide range of social indicators turned sharply negative for Blacks in the late 1980s and began to rebound roughly a decade later. We explore whether the rise and fall of crack cocaine can explain these patterns. Absent a direct measure of crack cocaine's prevalence, we construct an index based on a range of indirect proxies (cocaine arrests, cocaine-related emergency room visits, cocaine-induced drug deaths, crack mentions in newspapers, and DEA drug busts). The crack index we construct reproduces many of the spatial and temporal patterns described in ethnographic and popular accounts of the crack epidemic. We find that our measure of crack can explain much of the rise in Black youth homicides, as well as more moderate increases in a wide range of adverse birth outcomes for Blacks in the 1980s. Although our crack index remains high through the 1990s, the deleterious social impact of crack fades. One interpretation of this result is that changes over time in behavior, crack markets, and the crack using population mitigated the damaging impacts of crack. Our analysis suggests that the greatest social costs of crack have been associated with the prohibition-related violence, rather than drug use *per se*.

I. Introduction

Between 1984 and 1994, the homicide rate for Black males aged 14-17 more than doubled and homicide rates for Black males aged 18-24 increased almost as much, as shown in Figure 1. In stark contrast, homicide rates for Black males 25 and older were essentially flat over the same period. By the year 2000, homicide rates had fallen back below their initial levels of the early 1980s for almost all age groups.¹

Homicide was not the only outcome that exhibited sharp fluctuations over this time period in the Black community. Figure 2 presents national time series data by race for fetal death rates, low birth weight babies, weapons arrests, and the fraction of children in foster care.² All of these time series exhibit noticeable increases for Blacks--typically followed by offsetting declines—starting in the late 1980s or early 1990s. The fraction of Black children in foster care more than doubled, fetal death rates and weapons arrests of Blacks rose more than 25 percent, and Black low birth weight babies increased nearly 10 percent.³ Among Whites, there is little evidence of parallel adverse shocks. The poor performance of Blacks relative to Whites represents a break from decades of convergence between Blacks and Whites on many of these measures.⁴

The concurrent rises and declines in outcomes as disparate as youth homicide, low birth weight babies, and foster care rates presents a puzzle, especially when many standard economic

¹ Homicide rates for young white males (with Hispanics included as whites) followed a similar pattern, although the fluctuations were far more muted. Homicide rates for white males over age 25 have steadily fallen since 1985.

² We describe the data sources, definitions, sample availability, and precise construction of these variables and others used in the paper in the data appendix.

³ Neal (2004) provides further evidence of a downturn in black educational outcomes.

⁴ Over the past thirty years, for instance, the black-white ratio of median earnings for male full-time workers increased from .5 to .73 (Welch 2003), the black infant mortality rate fell by two-thirds (Almond, Chay, and Greenstone 2003), the fraction of blacks between the ages of 25-29 with four-year college degrees has increased nearly 3 fold (Blank 2001), and Black academic achievement (as measured by NAEP scores) has increased 0.6 standard deviations relative to whites (Grissmer, Flanagan, and Williamson 1998). The number of black entrepreneurs has more than doubled (Boston 2001). The number of blacks in Congress has increased five-fold.⁴ Similar advances have been made among high-level executives, professors and administrators at elite colleges and universities, and the fraction of blacks living in middle class neighborhoods.

and labor market measures for Blacks show no obvious deviations from trend over the same period (Blank 2001). In this paper, we examine the extent to which one single underlying factor – crack cocaine – can account for the fluctuations in all these outcomes.⁵

Crack cocaine is a smoked version of cocaine that provides a short, but extremely intense, high. The invention of crack represented a technological innovation that dramatically widened the availability and use of cocaine in inner cities. Virtually unheard of prior to the mid-1980s, crack spread quickly across the country, particularly within Black and Hispanic communities (Bourgois 1996, Chitwood, et al. 1996, Johnson 1991). Many commentators have attributed the spike in Black youth homicide to the crack epidemic's rise and ebb (Blumstein 1998, Cook and Laub 1998, Cork 1999, and Grogger and Willis 2000). Sold in small quantities in relatively anonymous street markets, crack provided a lucrative market for drug sellers and street gangs (Bourgois 1996, Jacobs 1999). Much of the violence is attributed to attempts to establish property rights not enforceable through legal means (Bourgois 1996, Chitwood, et al. 1996). With respect to other outcomes, the physiological evidence regarding the damage that crack cocaine does to unborn babies suggests that crack usage might explain the patterns in fetal death and low birth weight babies (Frank et. al. 2001, Datta-Bhutata 1998), although there is no consensus (Zuckerman 2002). The highly addictive nature of crack, combined with relatively high crack usage rates by women (Bourgois 1996, Chitwood, et al. 1996), could contribute to dysfunctional home environments leading to placement of children into foster care.

In spite of the general appreciation of the potential role that crack may have played in driving the patterns observed in the data (e.g., Bennett et al. 1996, Wilson 1990), especially with respect to the Black youth homicide spike (Cook and Laub 1998, Blumstein and Rosenfeld 1998,

⁵ Other competing explanations have also been proposed. Ferguson (2001) argues that the rise in popularity of hip-hop music is to blame for the divergence in black-white test score gaps in 1988. McWhorter (2003) makes a similar argument.

Levitt 2004), there has been remarkably little rigorous empirical analysis of crack's rise and its corresponding social impact. The scarcity of research appears to be due in part to the great difficulty associated with constructing reliable quantitative measures of the timing and intensity of crack's presence in local geographic areas. Baumer et al. (1998), Cork (1999), and Ousey and Lee (2004) use cocaine-related arrests as a proxy for crack. Ousey and Lee (2002) supplement arrest data with the fraction of arrestees testing positive for cocaine. Grogger and Willis (2000) use breaks from trend in cocaine-related emergency room visits in a sample of large cities, as well as survey responses from police chiefs in these cities to measure the timing of crack's arrival. Corman and Mocan (2000) use drug deaths, but the data do not specify which drug is responsible.

In this paper, we take a somewhat different approach to measuring crack cocaine. Rather than relying on a single measure, we assemble a range of indicators that are likely to proxy for crack. These include cocaine arrests and cocaine-related emergency room visits as in the previous literature, but also the frequency of crack cocaine mentions in newspapers, cocaine-related drug deaths, and the number of DEA drug seizures and undercover drug buys that involve cocaine. While each of these proxies has important shortcomings, together they paint a compelling story for capturing fluctuations in crack. As demonstrated in Figure 3, the national time-series aggregates for these variables tend to follow a similar pattern, rising sharply around 1985, peaking between 1989 and 1993, and in most cases declining thereafter. In spite of the aggregate similarities, using just one of the proxies does not appear to be sufficient for describing crack: the average cross-city correlation in the measures is only about .35. By combining the various measures together into a single factor, however, we are able to generate a crack cocaine index that is not particularly sensitive to any one of the individual measures and corresponds

well to the ethnographic and media accounts of crack cocaine's spread and prevalence. Our measure captures the intensity of crack's presence in a particular place and time and can be constructed for a wide variety of geographic areas. We estimate our crack index annually for large cities and states over the period 1980-2000. These data available to other researchers.⁶

We find that crack rose sharply beginning in 1985, peaked in 1989, and slowly declined thereafter. Our estimated crack incidence remains surprisingly high over time – in the year 2000 crack remains at 60-75 percent of its peak level. Crack is concentrated in central cities, particularly those with large Black and Hispanic populations. The cities experiencing the highest average levels of crack are Newark, San Francisco, Philadelphia, Atlanta, and New York. Although crack arrived early to the West Coast, the strongest impacts were ultimately felt in the Northeast and the Middle Atlantic States. The Midwest experienced relatively low rates of crack.

Our index of crack is strongly correlated with a range of social indicators. We find that the rise in crack from 1984-1989 is associated with a doubling of homicide victimizations of Black males aged 14-17, a 30 percent increase for Black males aged 18-24, and a 10 percent increase for Black males 25 and over, and thus accounts for much of the observed variation in homicide rates over this time period.⁷ The rise in crack can explain 20-100 percent of the observed increases in Black low birth weight babies, fetal death, child mortality, and unwed births in large cities between 1984 and 1989. In contrast, the measured impact of crack on Whites is generally small and statistically insignificant. We estimate that crack is associated

⁶ Data can be found on Roland Fryer's web page [<http://post.economics.harvard.edu/faculty/fryer/fryer.html>] , or Steven Levitt's web page [<http://pricetheory.uchicago.edu/levitt/home.html>].

⁷ Victimization data are used instead of offender data because the identity of some offenders is unknown. Among homicides with a known offender, there is a high correlation between the race and age of the victim and offender.

with a 5 percent increase in overall violent and property crime in large U.S. cities between 1984 and 1989.⁸

The link between crack and adverse social outcomes weakens, however, over the course of the sample. Even though crack use does not disappear, the adverse social consequences largely do. Thus, by the year 2000, we observe little impact of crack, which accounts for much of the recovery in homicide rates and child outcomes for Blacks over the period. We hypothesize that the decoupling of crack and violence may be associated with the establishment of property rights and the declining profitability of crack distribution. The fading of adverse child outcomes may be attributable to the concentration of crack usage among a small, aging group of hardcore addicts (MacCoun and Reuter 2001, page 123).

The remainder of the paper is structured as follows. Section II provides a brief history of crack cocaine. Section III describes the data we use. Section IV presents our methodology for combining the crack proxies into a single index, presents the results of that exercise, and assesses the determinants of the timing and intensity with which crack hits a city or state. Section V analyzes the extent to which crack can account for the observed fluctuations in social indicators since 1985. Section VI concludes. The appendix outlines the sources of data used and the precise construction of the variables and crack cocaine index.

Section II: A Brief History of Crack Cocaine

Cocaine is a powerful and addictive stimulant first extracted from the coca plant in 1862. During the 19th century, cocaine had a variety of medical uses and could be purchased over the counter, including in the original version of Coca-Cola (Bayer 2000). In the 1970s, inhaled

⁸ All of these conclusions regarding the relationship between crack and social outcomes must be qualified with the important caveat that we are describing correlations in the data, rather than clear causal links.

cocaine emerged as a popular but high-priced recreational drug. The street price of pure powder cocaine was roughly \$100 to \$200 per gram (which is equivalent to \$300-\$600 per gram in 2004 dollars). The high price of cocaine had two important implications: (1) cocaine use was concentrated among the affluent, and (2) retail cocaine purchases required hundreds of dollars because it was impractical to transact in fractions of grams.⁹

Crack cocaine is a variation of cocaine made by dissolving powder cocaine in water, adding baking soda, and heating. The cocaine and the baking powder form an airy condensate, that when dried, takes the form of hard, smokeable “rocks.”¹⁰ A pebble-sized piece of crack, which contains roughly one-tenth a gram of pure cocaine, sells for \$10 on the street and provides an intense high, but one that lasts only fifteen minutes.

Crack is an important technological innovation in many regards. First, crack can be smoked, which is an extremely effective means of delivering the drug psychopharmacologically. Second, because crack is composed primarily of air and baking soda, it is possible to sell in small units containing fractions of a gram of pure cocaine, opening up the market to consumers wishing to spend \$10 at a time. Third, because the drug is extremely addictive and the high that comes from taking the drug is so short-lived, crack quickly generated a large following of users wishing to purchase at high rates of frequency. The profits associated with selling crack quickly eclipsed that of other drugs. Furthermore, unlike most other drugs, crack is often sold in open-air, high-volume markets between sellers and buyers who do not know one another.

There are three primary reasons why crack may have been so devastating to the Black community. First, street gangs, which already controlled outdoor spaces, became the logical sellers of crack (Venkatesh and Levitt 2000). Gang violence, primarily as a means of

⁹ A gram weighs about as much as a dime.

¹⁰ Crack differs from freebase cocaine because the creation procedure lacks the final step of removing the base from the mixture.

establishing and maintaining property rights, grew dramatically, and potentially accounts for the sharp rise in Black youth violence. Second, the increased returns associated with drug dealing attracted young Black males to gangs and may have reduced educational investment. Third, a large fraction of crack users were young women. Prostitution was common among female crack addicts, potentially accelerating the spread of AIDS and the unwanted birth of low birth weight “crack babies.”¹¹ Crack addicted mothers and fathers are unlikely to provide nurturing home environments for their children (and often ended up incarcerated), leading to the relinquishment of parental rights.

Section III: Data

We analyze data separately at the city-level and the state-level. The city-level analysis is carried out on the 144 cities with population greater than 100,000 in 1980. These cities are of particular interest because anecdotal evidence suggests that the problems associated with crack were concentrated in large urban areas. In addition, a number of the variables we use are collected at the city-level, making it a natural unit of analysis. Focusing on the state-level allows us to analyze outcome variables that are not available at the city level, and facilitates a linkage between our work and the large empirical literature carried out using state-level data. In all cases, annual data are used for the period 1980 to 2000.

As noted earlier, we utilize a range of measures to proxy for the prevalence of crack.¹² At the city-level, these outcomes are crack-related emergency room visits, cocaine-related

¹¹ Note, however, that the consensus in the recent medical literature is that there are few long term effects of crack exposure in utero after controlling for the mother’s alcohol and tobacco consumption. (Frank et. al. 2001, Zuckerman, Frank, and Mayes 2002).

¹² The exact data sources, definitions, and construction of each of the variables are described in greater detail in the appendix.

arrests, the frequency of crack cocaine mentions in newspapers, DEA drug buys and seizures involving cocaine, and cocaine-related deaths. The emergency room data are based on information from the Drug Abuse Warning Network (DAWN). These data initially covered 14 cities, with that number growing to 19 by the end of the sample. In later years, these data distinguish between crack and powder cocaine, but for consistency over the whole period, we do not exploit this variation.¹³ The proxy we use is cocaine-related emergency room visits per capita in the metropolitan area. Arrest data are collected by city police departments and are available through the FBI's Uniform Crime Reports. Because of incomplete reporting, we follow Levitt (1998) and define our cocaine arrest measure as cocaine arrests as a fraction of total arrests in the city.¹⁴ Our measure of crack cocaine mentions in newspapers is the number of news articles in Lexis-Nexis with a city's name and the words "crack" and "cocaine," divided by the total number of articles with the city's name and the word "crime." By constructing the variable as a ratio, we avoid obvious problems associated with the fact that large cities and those with local newspapers included in Lexis-Nexis will appear much more frequently in the database. The frequency of DEA drug buys and seizures per capita is taken from the System to Retrieve Drug Evidence (STRIDE) data base, which catalogs undercover drug buys and seizures carried out by DEA agents and informants, typically in support of criminal prosecutions. These data include approximately 274,000 cocaine transactions. The city in which the transaction occurred is recorded in the data set. STRIDE does not allow one to definitively distinguish between powder and crack cocaine.¹⁵ The final proxy for crack that we use is the rate per capita

¹³ In an earlier version of this paper, we presented estimates in which we did attempt to differentiate between powder and crack cocaine, obtaining similar results.

¹⁴ Arrests for powder versus crack cocaine are not reported separately in the FBI data.

¹⁵ The data set includes separate drug codes for cocaine, cocaine hydrochloride, and a variety of cocaine salts. There does appear to be a pattern of classifying crack cocaine, which has the hydrochloride portion of the molecule removed, as cocaine. It seems, however, that powder cocaine is also sometimes classified under the code "cocaine."

of cocaine-related deaths, drawn from the annual Mortality Detail File produced by the National Center for Health Statistics. The death data include accidental poisonings, suicides, and deaths due to long-term abuse for which cocaine use was coded by physicians as a primary or contributing factor. We cannot distinguish between crack cocaine and powder cocaine drug deaths in these data.

Each of these proxies suffers from important weaknesses. First, with the exception of the newspaper citations, the measures are unable to clearly differentiate between powder and crack cocaine. Second, both the cocaine arrest and DEA drug buy data are affected not just by the prevalence of crack usage, but also by the intensity of government enforcement efforts (see, for example, Horowitz 2001). Third, the DAWN emergency room data covers only a small set of metropolitan areas and the sample of hospitals that participates changes over time (Substance Abuse and Mental Health Services Administration 2003 Appendix B). Both the emergency room data and the drug death data are potentially affected by the subjective nature of physician determination of the contribution of cocaine to an emergency room visit or a death. Finally, the newspaper citation measure is the output of a relatively crude algorithm and suffers both from the criticism that in the early years of the epidemic there were other terms such as “rock cocaine” that were sometimes used to describe the product before crack cocaine became the agreed upon nomenclature, and also that the newsworthiness of crack-related stories may have declined over time, while consumption continued to rise.

The number of observations, means, and standard deviations for all of these city-level crack proxies are presented in the top panel of Table 1. Values are reported separately for the period prior to and after 1985, the year when crack use is believed to have become widespread. All of these indicators are much higher in the post-1985 period, even for those measures that do

not directly distinguish between powder and crack cocaine. Crack mentions in newspapers are extremely low prior to 1985; these instances likely represent false positives in our Lexis-Nexis algorithm.¹⁶ Note that the number of observations available varies dramatically across measures due to differences in the cities covered by the data, as well as the years in which data are collected. The data appendix describes the statistical corrections that are done to account for missing values in the construction of our crack index.

When conducting our analysis at the state level, we drop the emergency room and crack citation variables since these measures are available only for a limited number of large cities. The rest of our city-level measures are available at the state-level. The state-level crack proxies are shown in the second panel of Table 1. The absolute levels of the crack proxies are generally lower in states than in large cities, but the patterns are otherwise similar.

The final two panels of Table 1 report the criminal, social, and economic outcomes that we are trying to explain using our crack index at the city-level and state-level respectively. These outcomes include age specific homicide rates, the full set of violent and property crimes tracked in the FBI's Uniform Crime Reports, fetal death, low-birth weight babies (singleton births only), teen births and unwed births, death rates of children aged one to four, weapons arrests, the number of new admissions to prison, the per capita number of children in the foster care system, the unemployment rate, and the poverty rate. When the data are available we analyze these variables separately by race. Some of the variables are available at the state-level only.

Section III: Identifying Crack

¹⁶ For instance, a newspaper story that reported a cocaine addict, while in the process of committing a crime, got cracked over the head by a police baton, would erroneously register as a crack mention using our methodology.

The prevalence of crack cocaine is not directly observable. Instead, we must rely on noisy proxies in an attempt to measure crack. The primary approach that we take for extracting the information available in these proxies is to construct a single index measure of crack using factor analysis.¹⁷ In particular, we estimate an equation of the form:

$$(1) \quad Y_{ist} = \beta_i Crack_{st} + \varepsilon_{ist}$$

where the subscripts i , s , and t correspond to particular proxy measures, geographic units, and years respectively. The left-hand-side variables are the proxy measures all of which are stacked into a single vector. The variable $Crack$ is not directly observed, but rather estimated along with the β 's. One could also include covariates on the right-hand side of equation (1) – indeed we allow for city-fixed effects in our baseline estimates – but for simplicity we omit these covariates from the formal discussion.

Estimation of equation (1) generates predicted values both for a set of factors ($Crack_{st}$) and a set of coefficients (also known as loadings) β_i . We focus our analysis on the single factor that has the greatest explanatory power. Because our proxies are highly correlated, our data are well-described by a one-factor model which captures roughly 50% of the variation in the proxies.¹⁸ Additional factors contribute little in terms of explaining the observed variation in our data. The factor with the greatest explanatory power is what we will call “crack,” but more accurately it is the single index that explains the largest share of the variation in our crack proxies. The loadings tell us the degree to which each estimated factor influences the different

¹⁷ This is similar to how psychometricians measure “intelligence” (g) – taking the results of several individual aptitude tests and determining the single factor that best explains the covariance in these related proxies. Mathematically, factor analysis identifies the eigenvectors (the scores) and corresponding eigenvalues (the loadings) of the variance-covariance matrix of the Y variables.

¹⁸ We follow standard practice of normalizing proxy measures included on the left-hand side to have mean zero and variance one whenever we do factor analysis.

outcome variables. The crack index we obtain is a weighted average of the proxy variables underlying it, with weights given by the squares of the loadings on each proxy.

There are three advantages to combining our multiple measures into a single index. First, we are interested in describing the observed patterns of crack's arrival and fluctuations. Having one summary measure of crack rather than five separate proxies greatly simplifies this task. Second, because each of our individual proxy measures is quite noisy, combining them into a single index substantially increases the signal-to-noise ratio. For instance, in the simplest case where $\beta_i=1$ for each proxy, the share of the variance in a given measure that is attributable to a true signal is $\sigma_{crack}^2 / (\sigma_{crack}^2 + \sigma_{\varepsilon_i}^2)$, where σ_{crack}^2 and $\sigma_{\varepsilon_i}^2$ are the variance of the latent crack factor and the measurement error in proxy i respectively. Under the assumption that the measurement errors across proxies are i.i.d, the signal-to-total variance ratio of an equally-weighted index of N

proxies is $\frac{\sigma_{crack}^2}{\sigma_{crack}^2 + \frac{\sigma_{\varepsilon_i}^2}{N}}$.¹⁹

A third possible benefit of using a single crack index arises when we turn to estimating the impact of crack on outcomes such as low-birth weight babies or crime rates. Although it might seem that putting each of the individual proxies directly on the right-hand side of such regressions would be preferable (see, for example Lubotsky and Wittenberg 2004), in the plausible scenario in which one or more of our individual proxies may be endogenous to a particular outcome of interest (e.g. when Black youth homicide is on the rise, police departments may respond by intensifying enforcement against drug sellers, holding constant overall crack use), use of an index provides potential benefits by imposing the restriction that each of the proxies has an identical impact on the outcome variable. If the proxies were each entered

¹⁹ If measurement error is positively correlated across proxies, then the improvement in the signal-to-noise ratio is less pronounced. The opposite is true if the measurement error is negatively correlated across proxies.

separately as explanatory variables, one might greatly overstate the role of crack in explaining fluctuations in social outcomes.

In estimating the impact of crack on social outcomes, an attractive alternative to constructing a single index is to instead use the various proxies as instrumental variables for one another. To the extent that the proxies are correlated with the underlying latent variable crack, but the measurement error in the proxies is uncorrelated, the various crack measures are plausible instruments for one another. We present results both using our single index proxy and using an instrumental variables approach.²⁰

One unique feature of our data that we have not yet emphasized, but proves extremely valuable in our analysis, is the fact that crack cocaine was a technological innovation which was virtually unknown until around 1985. This provides us with a well defined pre-crack period. To the extent that our proxies/index are truly reflecting crack, they should have values near zero in the pre-1985 period. In addition, variation in the proxies prior to 1985 is likely to be almost purely measurement error. Comparing the variation in the proxies before and after crack arrives will provide useful insights into the extent to which fluctuations in our proxies after 1985 can plausibly be viewed as signal rather than noise.²¹

Section IV: The Prevalence of Crack Across Time and Space

Table 2 presents correlations across the various crack proxies we use in the analysis. The top panel of the table reports correlations across time for the national aggregates of the proxies.

²⁰ Note, however, that this instrumental variables strategy is a possible solution to the measurement error problem, but not to any possible endogeneity in the crack measure, as we discuss later.

²¹ The existence of a pre-crack period also allows us the opportunity to estimate our factor analysis on the pre-period data only, isolating any common factors that are moving the crack proxies before crack arrives. One can then remove these pre-existing factors in constructing a crack index. In practice, this has little impact on our results. An earlier version of this paper, available from the authors, describes this exercise and the underlying assumptions in detail.

Given how similar the time-series patterns are for these variables in Figure 3, it is not surprising that these correlations are high, ranging from .225 to .951. The mean of the off-diagonal elements is equal to .71. The middle panel of the table presents correlations using either the city-year or the state-year as the unit of analysis. City-fixed effects and state-fixed effects have been removed to eliminate systematic and persistent reporting differences across areas. The correlation across the proxies falls, but remains substantial. For both the city and the state sample, all the pairwise correlations remain positive and the mean of the off-diagonal elements is .32 for cities and .36 for states. In other words, when a city or state is high relative to its usual value on one of the proxies in a given year, it tends to be high on all of them – consistent with the hypothesis that a single factor is driving the increase. The bottom panel of the table reports correlations at the city-year and state-year level after removing not only city or state fixed-effects, but also all of the aggregate time series variation using year dummies. Consequently, the correlations in the bottom panel reflect whether a city-year or state-year observation that is high relative to the rest of the sample in that year on one proxy also tends to be high on the other proxies. These correlations are much lower than the others shown in the table. The mean off-diagonal element in the city sample falls to only .07; in the state sample it is .15. The DEA cocaine busts and the newspaper citation index perform particularly poorly. These results highlight the fact that the co-movement of our proxy variables is due in large part to the fact that across many areas, all the proxies tend to be high in some years and low in others.

Table 3 presents our baseline estimates of the loadings obtained using factor analysis. The greater is the value corresponding to a particular proxy, the more influence it is given in constructing the crack index.²² The factor loadings can be negative, although that is not the case

²² The scaling of the loadings is arbitrary; we follow the standard normalization which is to make the square of the loadings sum to one. In constructing a crack index that is a weighted average of the underlying proxies, the weights

for any of our analysis. We report five sets of estimates corresponding to the correlation matrices in Table 3: national aggregates (column 1), city-level data (columns 2 and 3), and state-level data (columns 4 and 5). At the city and state level, we report results before and after year-fixed effects have been removed. For the national aggregates, the loadings are relatively equal across the five proxies. The same is true at the city level before removing year-fixed effects (column 2), except that the DEA cocaine busts proxy receives less weight than the others. When year-fixed effects are taken out, more weight is given to cocaine deaths at the expense of cocaine-related ER visits and, to a lesser extent, crack-related newspaper citations. At the state level, cocaine arrests and cocaine deaths both get high weight and DEA drug busts are given more influence after year-fixed effects are removed.

Figure 4 presents population-weighted crack indexes that correspond to the factor analysis loadings for the national-level, city-level and state-level analysis in Table 3. We show results for the specifications without year-fixed effects; the patterns are similar for the other specifications. The crack index is identified only up to a scale of proportionality, so the absolute units of the crack measure are not directly interpretable, nor can they be directly compared across the three figures.

Our results regarding the time-series pattern of crack are not particularly sensitive to the level of aggregation used in the analysis. In all three cases, the crack index is low but rising slightly until 1985, at which point there is a sharp increase to a peak in 1989. The timing of crack's rise that we estimate corresponds nicely with the anecdotal evidence regarding the introduction of crack cocaine in the mid-1980s and its rapid proliferation. Our estimation technique in no way constrains the estimated crack prevalence to be low in the early years of the

one would use are the square root of the loadings we report in the table. After taking the square root of these values, the sum of the weights would add to one.

data; this result is driven purely by the data. The one noticeable difference between the three indexes is the pattern from 1989-2000. In the top figure using national aggregate data, the index falls almost 50 percent between 1989 and the end of the sample. In the city-level and state-level samples the decline is about 25 percent, with much of the decline coming in latter half of the 1990's. Regardless of the index, one perhaps surprising result is that our crack index remains so high in 2000, a time in which many casual observers had declared the crack epidemic to have faded. Survey measures of crack usage, however, reinforce our conclusion that crack has not disappeared. The percentage of high school seniors reporting having used crack in the last twelve months fell roughly 30 percent (from 3.1 to 2.2 percent) between 1989 and 2000 (Johnston et al 2004). Eighth and tenth graders in the same survey, who were not asked about crack usage until 1990, reported the highest incidence of annual crack usage in 1999. There is also evidence that sharp declines in the price of crack have led those who use crack to consume it in greater quantities (MacCoun and Reuter 2001).

Existing evidence suggests that the impact of crack has been much greater on Blacks and Hispanics than on Whites. Because most of our proxy variables are not available separately by race, we are forced to take an indirect approach to identifying a race-specific crack index. Under the assumption that the loadings on the crack proxies are the same for Blacks and Whites, using the available data we can estimate a model in which the impact of crack varies by race. The overall per capita impact of crack in a city (or state) and year can be decomposed into

$$(2) \quad Crack_{st} = \lambda_t^{Black} P_{st}^{Black} + \lambda_t^{Hispanic} P_{st}^{Hispanic} + \lambda_t^{White} P_{st}^{White} + \epsilon_{st}$$

where the P variables represent population shares by race and the λ coefficients are race- and city-specific crack estimates. λ captures how our crack index varies across cities at a given point of time as a function of the racial composition of the city; λ is the value the crack index would

take in a hypothetical city all of whose residents were of the race in question. That coefficient does not necessarily directly reflect the relative rates of crack usage across individuals of different races if, for example, the presence of more Blacks in a city is associated with higher crack use by Whites. To estimate the relative impact of crack by race, we run a separate cross-sectional regression for each year with the crack index as the left-hand-side variable and race proportions as the right-hand-side variables, omitting a constant.

The results of this estimation are reported in Figure 5. For both city- and state-level analyses, crack among Blacks rises until 1989 and then remains relatively steady thereafter. In large cities, the estimated crack index for Whites is consistently 5-10 times lower than Blacks. In the state-level sample, Blacks are again much higher than Whites, and in both samples Hispanics appear roughly comparable to Blacks.

Figures 6 and 7 present crack estimates by region and size of central city respectively. In Figure 6, the Northeast experienced the greatest crack problem, followed by the West. In Figure 7, the time series pattern for crack in cities above and below 350,000 residents is quite similar, except that the crack levels are more than twice as high in the larger cities.²³

Table 4 reports the cities and states in our sample with the highest and lowest estimated average crack prevalence over the period 1985-2000.²⁴ Because our estimates are noisy at the city-level and the state-level due to substantial measurement error in our proxies, precise rankings must be viewed with the appropriate caution. The set of cities with the greatest crack problem includes cities one might expect: Newark, Philadelphia, New York, and Oakland, for

²³The patterns observed in Figures 5-7 continue to hold if we simultaneously control for racial composition and the other factors like region and city size.

²⁴ Results for the full set of cities and states in the sample, for the years 1985, 1989, 1993, 1997, and 2000 are reported in Appendix Table 1.

instance. Boston, San Francisco, and Seattle, however, are perhaps surprising.²⁵ Other cities one would expect to rank high such as New Orleans, Baltimore, Washington D.C., and Los Angeles also rank highly, but are not in the top ten. Among states, Maryland and New York head the list. The cities with the least evidence of crack tend to be smaller, geographically isolated cities, but not exclusively cities with low Black populations. Huntsville and Jackson, two of cities with the very low crack estimates, for example, are thirty and seventy percent Black respectively. The states with low crack tend to have large rural populations and few minorities.

Section V: The Impact of Crack Cocaine

In this section, we attempt to measure the impact that crack had on society by regressing a variety of outcome measures on our estimated crack index and varying combinations of covariates:

$$(3) \quad Outcome_{st} = \beta * CrackIndex_{st} + Z_{st}\Gamma + \lambda_s + \gamma_t + \varepsilon_{st}$$

where *CrackIndex* is one of the crack indices we estimated above, and *s* corresponds to a geographic area (either national, state, or city), and *t* represents time. One important point to note is that our crack index is a measure of the severity of crack in an area as a whole. This severity can represent both the composition of the population as well as the intensity of use per person. For instance, since crack use appears to be more prevalent among Blacks than Whites, if two cities have the same value on the crack index, but one city has a higher proportion of Whites, the implication is that crack use per Black and crack use per White are likely to be higher in that city than the other city. Consequently, when we examine socio-economic outcomes as dependent variables, the logical specification involves defining outcomes in terms of rates per

²⁵ Recent work by Beckett et. al. (2006) in fact argues that Seattle has an acute crack problem relative to other cities.

overall city population. For example, when we examine Black youth homicide, the dependent variable we use is Black youth homicides per 100,000 city residents, not Black youth homicides per Black youth.²⁶

There are two obvious shortcomings associated with the simple OLS approach that we adopt. The first is that our crack index may suffer from measurement error, which will bias the estimates of crack's impact, most likely in a downward direction. The second weakness of this approach is that the estimates we obtain reflect correlations, rather than true causal impacts. It is possible that omitted variables such as the erosion of social networks or the decline of two-parent households affects both crack and outcomes like homicide or children in foster care.

Instrumenting one proxy using the others provides a means of dealing with the issue of measurement error, under the assumption that the measurement error in the different proxies are uncorrelated (conditional on the other controls included in the regression). It is important to note, however, that this instrumenting strategy is unlikely to help in providing estimates that are directly interpretable as causal in nature. To the extent that omitted variables or reverse causality lead one of the crack proxies to be correlated with the error term in equation (3), it is likely that all of the crack proxies will suffer the same weakness.

Table 5 shows results from estimating equation (3) on our city-level sample using the city-level crack index. Each row of the table corresponds to a different outcome variable. The first column of the table reports the mean of the dependent variable in the sample; because our outcomes are denominated by the entire city population (not just Blacks or Whites depending on which race we are looking at), the reported means for both races are less than if the variables

²⁶ Imposing the further assumption that the ratio of crack's incidence across Whites and Blacks is constant across areas in a given year, we have also constructed an index of the crack intensity in a city controlling for racial composition. This measure of intensity more closely corresponds to the crack variable that one would use as a right-hand-side variable when using individual-level data, and is available for download at our website. The results we obtain are quite similar.

were per member of the group. Because Blacks make up a smaller percentage of the population, the reported means are particularly small relative to a rate per capita for Blacks. We allow the estimated coefficient on the crack index to vary by time period; columns 2-5 of the table report the coefficients for the periods 1985-1989, 1990-1994, and 1995-2000 respectively.²⁷ All specifications include city-fixed effects, year dummies, and controls for percent of the population that is Black and Hispanic, log population, and log per capita income. Standard errors, shown in parentheses, take into account AR1 serial correlation within cities over time.

The top panel of Table 5 reports outcomes for Blacks. The crack index is positively associated with eight of the nine outcomes we examine in the 1985-1989 time period, with statistically significant estimates at the .01 level in five of the cases. A similar pattern of estimates is present in the 1990-1994 period. After 1995, however, the link between the crack index and these social outcomes for Blacks disappears--more than half of the point estimates become negative in the last period, and only the male age 18-24 homicide rate has a positive and significant coefficients. The middle panel of Table 5 shows city-level estimates for Whites. Although the crack index is generally positively correlated with these outcomes after 1985 (21 of the 27 point estimates are positive), only 5 of the 27 coefficients are statistically different than zero. The bottom panel of the table analyzes results for overall crime rates, which are not separately available by race. The crack index is positively correlated with eight of nine crime categories from 1985-1989, six significantly, and seven of the nine categories from 1990-1994, but the estimated coefficients decline in magnitude and statistical significance in the final period for all categories of crime.

²⁷ The crack index is close to zero and exhibits little variation prior to 1985, leading to unstable, imprecisely estimated coefficients in the early part of our sample. Thus, we do not report results for 1980-1984.

To aid in interpreting the magnitude of the effects implied by the coefficients in Table 5, we report graphically the fraction of the observed variation in the outcomes that can be accounted for by the crack index over the period in which crack rose sharply (1984-1989) in Figure 8, and from the peak of crack to the end of the sample (usually 1989-2000) in Figure 9. In these figures, we compare the observed percent changes for the crime and birth-related outcomes over these time periods to the implied impact of crack calculated in one of two ways: (1) using the crack index as in Table 5, and (2) instrumenting for cocaine arrests using the other crack proxies as instruments.²⁸ The implied impact of crack from the OLS specification in a particular year is the product of the regression coefficient in Table 5 multiplied by the average value of the crack index in that year. The impact of crack between 1984 and 1989 is simply the difference between the measured impact of crack in 1989 and in 1984. Calculating the impact of crack in the instrumental variables regressions is done in a similar manner, with the added complication related to measurement error in the cocaine arrests proxy.²⁹ The corresponding standard error bands are shown in the figure as well.

²⁸ One could also instrument with each of the remaining crack proxies individually, but because of missing data in some of our proxies, the index approach is preferable in our setting. The results are not sensitive to using a different one of the crack proxies as the right-hand side variable.

²⁹ More specifically, only a portion of the observed variation in cocaine arrests is attributable to variation in crack usage if there is measurement error in cocaine arrests. Assume that cocaine arrests are determined by a latent variable crack and noise, and that our estimated crack index using all of the proxies except cocaine arrests also reflects a combination of movements in crack and noise. Further assume that the error terms in these two measures are uncorrelated, and that these errors are also uncorrelated with the error term in equation (3). Then a consistent estimate of the impact of cocaine arrests can be obtained from two-stage least squares using the index as an instrument. In the standard application, one would then compute the overall impact of a change in cocaine arrests as the product of the change in cocaine arrests multiplied by the estimated coefficient from two-stage least squares. In computing the impact of crack (as opposed to cocaine arrests *per se*) in equation (3), however, we only want to use the portion of the variation in cocaine arrests driven by crack. It can be shown that algebraically this equates to scaling down the full variation in cocaine arrests by the signal to signal-plus-noise ratio in cocaine arrests. This signal to signal-plus-noise ratio can be computed from the variance-covariance matrix of the crack proxies, combined with a scaling adjustment across proxies that can be inferred from the ratio of the IV estimates when one proxy is used as the instrument and the other variable is instrumented versus when the roles of the two variables are reversed.

A number of important points emerge from Figure 8. First, comparing the columns shaded white (OLS estimates) and the columns shaded black (instrumental variables estimates), in most cases the IV estimates are larger than the OLS estimates, although less precisely estimated. These generally larger IV estimates are consistent with the presence of measurement error in our index, leading to attenuation bias in our OLS results. Second, the magnitude of the actual percentage increase in homicide rates among young Black males is far greater than for the other variables considered. Our measure of crack cocaine explains a substantial part of this increase, particularly in the instrumental variables specifications. According to our IV estimates, crack can account for a 100-155 percent increase in Black male homicides among those aged 18-24, and a change of 55-125 percent for Black male homicide among those aged 14-17. In contrast, our crack measure accounts for only small changes in older Black male homicide and White homicide. Third, for the birth/childhood outcomes, the impact of crack is larger for Blacks than for Whites, but the results are not as stark as for homicide. We estimate that the rise in crack between 1984 and 1989 accounts for roughly one-third of the increase in low birth weight Black babies, less than one-third of the Black rate of unwed births, much or all of the increase in Black child mortality and fetal death. For Whites, there is some apparent positive association between crack and low birth weight babies and child mortality. Finally, we find a positive relationship between crack and a wide range of crimes, although the magnitude is small when compared to the impact on Black youth homicide. In the OLS specifications, violent crime and property crime are both estimated to have increased by roughly 4 percent due to crack over the period 1984-1989; in the IV specifications the increase is approximately 10 percent, but very imprecisely estimated.

Figure 9 shows the estimated impact of changes in crack on the same set of outcomes for the period 1989-2000. One-half to three-fourths of the decline in homicide by Black males aged 14-17 can be attributed to the combined impact of a decline in the level of the crack index, and more importantly, the weakening of the link between crack and violence. By the year 2000, most of the crack-related spike in youth homicide in the late 1980s was gone--because the baseline level of youth homicide is almost three times higher in 1989 than in 1984, a 34 percent decrease in the latter period is equal and opposite to almost a 100 percent increase in the earlier period in terms of number of homicides. For older criminals and Whites, the impact of receding crack does not consistently explain a substantial fraction of the observed homicide declines in the 1990s. For Blacks, the adverse effects of crack on birth outcomes in the 1980s are essentially undone in the 1990s. The impacts on White birth outcomes are small and carry mixed signs. For city-level crime measures, the reductions attributable to crack in the 1990s erase much, but often not all, of the crack-driven increases in the 1980s. The notable exception to this pattern is the IV estimate on violent crime, which suggests that violent crime *rose* (although not statistically significantly) in the 1990s as crack receded (because the estimated impact of crack on violent crime is negative in the 1990s).

Table 6 replicates the analysis of Table 5, but using states as the unit of analysis rather than our sample of large cities. The regression results in Table 5 are quite similar to what we found for large cities; crack has the greatest impact on Black youth homicide, tends to be positively related to adverse birth outcomes for Blacks and is not significantly related to most outcomes for Whites. The impact of crack once again weakens over time. One important difference relative to the city sample is that overall crime is not positively and statistically related to crack in the state sample. In addition, there is less evidence of a strong impact of crack on

Black birth outcomes outside of the large cities. A number of additional outcome measures are available at the state level: foster care rates, new prison commitments, unemployment rates, and poverty rates. None of these outcomes reveals a pattern suggestive of an important impact of crack in the expected direction. The negative relationship between crack and new prison commitments, while perhaps surprising given the enormous increase in drug-related incarceration over this period, hints at the possibility that aggressive punishment of drug sellers may have reduced the severity of the crack epidemic. In other words, the negative coefficient in the prison regression may primarily reflect reverse causality running from imprisonment to crack, rather than vice versa.

Figures 10 and 11 report the fraction of the observed variation in the outcomes at the state level that can be explained by the crack index for the periods 1984-1989, and 1989-2000. Not surprisingly given that crack was concentrated in large cities, the rise and fall of crack has less explanatory value at the state level. For instance, the crack index explains less than one-third of the overall rise in young Black male homicide at the state level, and only one-fifth of the increase in Black low birth weight babies. Overall, comparing the results in Figures 8-11, and noting that about 16 percent of the U.S. population resides in cities included in our city sample, we estimate that about 70 percent of the adverse impact of crack was felt in large cities, implying that the rates per capita were at least 10 times higher in large cities than in the rest of the country.

Section VI: Conclusion

A number of social, criminological, and economic variables experienced negative shocks in the late 1980s and early 1990s, particularly among Blacks. We find evidence consistent with the hypothesis that the rise of crack cocaine played an important contributing role. To overcome

the absence of a reliable quantitative measure of crack, we construct a crack index based on a set of imperfect, but plausible proxies. This crack index reproduces many of patterns described in journalistic and ethnographic accounts including the timing of the crack epidemic and the disproportionate impact on Blacks and Hispanics. We find a strong link between our measure of crack and increased homicide rates by the young, especially among Blacks, in the late 1980s. During that time period, our crack index is also associated with adverse outcomes for babies – especially Black babies. By the early 1990s, however, the relationship between crack and unwelcome social outcomes had largely disappeared. Thus, though crack use persisted at high levels, it did so with relatively minor measurable social consequences. This finding is consistent with an initially high level of crack-related violence as markets responded to the changes in distribution methods associated with the technological shock that crack represented. After property rights were established and crack prices fell sharply reducing the profitability of the business, competition-related violence among drug dealers declined.

One explanation for the weakening relationship between the crack index and birth outcomes is the changing composition of crack users. Following its introduction, crack use was overwhelmingly a drug of adolescents and young adults, and its use was widespread. For instance, 7.2 percent of respondents in the National Household Survey on Drug Use and Health (SAMHSA 2003b) who were 18-22 in 1985 report lifetime crack usage, compared to only 2.8 percent of those who were 33-37 years old in 1985. Later cohorts also use crack at much lower rates than the first cohorts exposed to crack. In 2002, 0.6 percent of the age group that was 18-22 in 1985 (and by 2002 was 35-39 years old) had used crack in the last month. In stark contrast, less than 0.2 percent of the 18-22 year olds in 2002 report using crack in the prior month. As crack addicts aged, fewer were in the high fertility age group. Presumably, as the dangers of

crack to the fetus became clear, women intending to get pregnant may have avoided crack and those using crack may have been less likely to take a pregnancy to term.

If the rise of crack indeed exerted an important influence on social outcomes over the last two decades, then an obvious concern is that studies examining these outcomes which fail to adequately control for crack may generate misleading conclusions. Ayres and Donohue (2003), for instance, conjecture that the findings of Lott and Mustard (1997) and Lott (2000) regarding the impact of concealed weapons laws are spurious, driven by the omitted variable crack cocaine. Sailer (1999) and Joyce (2004) level the same charges at Donohue and Levitt's (2001) analysis of the impact of legalized abortion on crime. An important application of the crack index we construct is as a control variable in future research.

Appendix

Data

This paper uses data from the 144 cities with population above 100000 in 1980 and the 50 U.S. States. The following table describes the data used in paper.

Measure	Explanation	Availability	Years Covered	Source	Analyzed by race?	City (C), State(S), or Both (B)
Cocaine arrest rate	Percentage of all arrests made for possession or distribution of opium/cocaine and their derivatives, minimum of 100 total arrests	Most cities, almost all states	1980-2000	Federal Bureau of Investigation (FBI) Uniform Crime Reports (UCR)	N	B
Cocaine death rate	Per capita number of cocaine-related deaths*	Almost all cities, all states	1980-2000	National Center for Health Statistics (NCHS) Mortality Detail Files	N	B
Cocaine bust rate	Per capita number of busts involving cocaine; minimum of 15 busts**	60 cities in 1980 increasing to 110 cities by 1999, almost all states	1980-1999	Drug Enforcement Administration (DEA) System to Retrieve Information From Drug Evidence (STRIDE)	N	B
Cocaine-related ER visits	Number of cocaine-related emergency department visits per 100000 population	17 cities in 1980 increasing to 21 cities by 1999	1980-2000	Drug Abuse Warning Network (DAWN)	N	C
Newspaper citation ratio	Number of articles drawn from 341 U.S. periodicals containing a city name, "crack", and "cocaine" divided by the number of articles containing the city name and "crime", minimum of 30 crime articles	52 cities in 1980 increasing to 132 cities by 2000	1980-2000	Lexis-Nexis	N	C
Male homicide rate ages 14-17	Male homicide victims ages 14-17 per 100000 population	Most cities, almost all states	1980-2000	FBI UCR Supplemental	Y	B

				Homicide Report		
Male homicide rate ages 18-24	Male homicide victims ages 18-25 per 100000 population	Most cities, almost all states	1980-2000	FBI UCR Supplemental Homicide Report	Y	B
Male homicide rate age 25 and over	Male homicide victims ages 25 and over per 100000 population	Most cities, almost all states	1980-2000	FBI UCR Supplemental Homicide Report	Y	B
Violent crime rate	Violent crimes per 100000 residents	Almost all cities and states	1980-2000	FBI UCR	N	B
Homicide rate	Homicides per 100000 residents	Almost all cities and states	1980-2000	FBI UCR	N	B
Rape rate	Rapes per 100000 residents	Almost all cities and states	1980-2000	FBI UCR	N	B
Assault rate	Assaults per 100000 residents	Almost all cities and states	1980-2000	FBI UCR	N	B
Robbery rate	Robberies per 100000 residents	Almost all cities and states	1980-2000	FBI UCR	N	B
Property crime rate	Property crimes per 100000 residents	Almost all cities and states	1980-2000	FBI UCR	N	B
Burglary rate	Burglaries per 100000 residents	Almost all cities and states	1980-2000	FBI UCR	N	B
Larceny rate	Larcenies per 100000 residents	Almost all cities and states	1980-2000	FBI UCR	N	B
Auto theft rate	Auto thefts per 100000 residents	Almost all cities and states	1980-2000	FBI UCR	N	B
Weapons arrest rate	Percentage of all arrests made for weapons violations, minimum 100 total arrests	Most cities, almost all states	1980-2000	FBI UCR	Y	B
Rate low birth weight babies	Per capita number of singleton births <2500 grams	Almost all cities, all states	1980-2000	NCHS Natality Detail Files	Y	B
Child mortality rate	Per capita number of child deaths ages 1-4	Almost all cities, all states	1980-2000	NCHS Mortality Detail Files	Y	B
Rate teen birth	Per capita number of teen births	Almost all cities, all states	1980-2000	NCHS Natality Detail Files	Y	B
Rate unwed birth	Per capita number of unwed births	Almost all cities, all states	1980-2000	NCHS Natality Detail Files	Y	B

Fetal death rate	Per capita number of fetal deaths	117 cities before 1996, 57 cities after 1996, most states	1980-1998	NCHS Fetal Death Files	Y	B
Foster care rate	Per capita number of children in state-managed foster-care	Most states	1983-1995	American Public Welfare Association (APWA) Voluntary Cooperative Information System (VCIS)	N	S
Female prison rate	Proportion of new court commitments that are female	All states	1980-1998	Bureau of Justice Statistics (BJS) Correctional Populations in the United States	N	S
Total new prisoners	Total annual new court commitments	All states	1980-1998	BJS Correctional Populations in the United States	N	S
Unemployment rate	Fraction of the labor-force population unemployed	All states	1980-2000	Bureau of Labor Statistics (BLS)	N	S
Poverty rate	Fraction of the population below the federal poverty level	All states	1980-2000	Census Bureau Poverty Estimates	N	S
Per-capita income	Per capita income in 2000 dollars	All cities and states	1980-2000	Bureau of Economic Analysis (BEA) Regional Economic Accounts	N	B
Population by age, sex, and race	City-level population measures are constructed by linearly interpolating across decennial Census years; state-level data use annual estimates	All cities and states	1980-2000	Census Bureau Population Estimates	Y	B

* Cocaine deaths include accidental poisonings, suicides, and other deaths for which cocaine use was coded as a primary or contributing factor. Prior to 1989, deaths were classified using the International Classification of Diseases 9th revision (ICD-9); starting in 1999 deaths were coded using the 10th revision. Cocaine death entries under ICD-9 include ICD codes 8552, 3042, and 3056 as well as ICD codes 8501-8699, 9501-9529, 9620-9629, 972, 9801-9879, 3050-3054, 3057-3059 with a secondary code of 9685. Cocaine deaths under ICD-10 include codes F140-F149 and F190-F199, X42, X44, X62, X64, X85, Y12, and Y14 with secondary code T405. For more information on counting drug-related deaths see Lois Fingerhut & Christine Cox, "Poisoning mortality, 1985-1995", *Public Health Reports* 113:3, 1998.

** Cocaine busts were defined as busts with primary drug code 9041 and secondary drug codes L000, L005, L010, L269, L900, and L920

Estimating the Crack Index

The procedure for estimating the crack index is:

1. Remove city or state fixed effects from each of the crack proxies. Readjust each proxy to have a grand mean of 0 during the period from 1980-1984.
2. Normalize each of the proxies to have unit variance. This eliminates differences in units of measure across proxies.
3. The factor loadings (Γ_i) and scores (Z_{st}) satisfy the relationship:

$$Y_{ist} = Z_{st}\Gamma_i + \varepsilon_{ist} \quad (1)$$

Here i indexes a proxies, s a location, and t a time period. We require a scale restriction to separately identify the loadings and scores. In our analysis, we impose that the sum of the squared loadings is one.

4. Select an initial value for the loadings.
5. Stack each of the available proxies at a particular location/time. Use least squares regression across the proxies to estimate the value of the crack index (score) at each location/time. These regressions are within a location/time, across measures.
6. The squared loadings measure the extent to which each of the proxies contributes to the overall crack index. To account for missing data, at each location/time, multiply the scores calculated in step 5 by $\sum_i \gamma_i^2$, where γ_i represents the loading associated with proxy i and the summation is made over all available proxies at that location/time.
7. Regress each proxy on the scores calculated in step 5 to generate a new estimate of the loading associated with that proxy. These regressions are within a particular measure, across locations/times.
8. Re-normalize the estimated loadings to satisfy the scale restriction.
9. Repeat steps 5-8 until the loadings converge.³⁰
10. Test multiple initial choices for loadings to ensure that the convergent result is optimal in the sense of minimizing the sum of the squared residuals in (1).

It is important to note that constructed in this manner the absolute mean and variance of the crack index are arbitrary.

³⁰ Although the paper reports estimates of a single factor model, for verification purposes we also estimated models allowing for multiple factors (i.e. Γ_i and Z_{st} are vectors). With multiple factors the estimated loadings and scores are unique only up to a rotation. The algorithm described will not converge unless a specific rotation is imposed at each stage of estimation.

Appendix Table 1: Estimated Crack Indices for Cities and States

City	Crack Index				
	1985	1989	1993	1997	2000
Akron	0.006	0.055	0.045	0.024	0.047
Albuquerque	0.019	1.370	1.557	1.944	2.168
Allentown	0.158	0.964	1.012	1.175	1.136
Amarillo	-0.015	0.203	0.622	0.242	0.286
Anaheim	0.362	1.239	1.165	0.707	0.420
Anchorage	0.047	0.258	-0.155	0.250	0.284
Ann Arbor	0.021	0.000	0.115	-0.015	-0.016
Arlington Tx	0.041	2.440	0.817	0.845	0.785
Atlanta	0.432	4.344	3.180	4.230	3.995
Aurora Co	0.005	0.086	0.444	0.257	0.588
Austin	-0.026	0.596	0.617	0.823	0.661
Baltimore	0.095	2.156	2.640	2.980	1.184
Baton Rouge	0.151	1.297	0.852	1.224	0.880
Beaumont	0.148	0.160	0.000	0.777	0.766
Birmingham	0.082	0.419	0.493	0.502	0.624
Boston	0.912	3.662	3.810	3.501	3.129
Bridgeport	0.540	1.143	2.918	2.311	2.208
Buffalo	0.536	2.687	4.376	4.563	3.214
Cedar Rapids	-0.035	-0.013	0.000	0.043	0.060
Charlotte	0.427	2.273	1.222	0.352	0.434
Chattanooga	0.024	0.064	0.501	0.829	0.523
Chesapeake	0.093	1.334	1.494	0.725	0.943
Chicago	0.134	2.689	1.795	1.805	2.284
Cincinnati	0.203	1.401	1.234	0.462	1.181
Cleveland	0.045	2.935	2.426	1.835	0.837
Colorado Springs	-0.025	0.109	0.308	0.074	0.231
Columbus Ga	0.007	0.298	0.457	0.399	0.541
Columbus Oh	0.033	2.120	2.276	2.144	2.198
Corpus Christi	-0.007	0.045	0.166	0.068	0.156
Dallas	0.161	1.946	1.884	1.951	2.103
Dayton	0.028	0.721	0.435	0.838	1.578
Denver	0.176	1.322	1.571	2.028	2.785
Des Moines	-0.014	1.084	0.104	0.445	0.426
Detroit	0.126	1.939	2.100	1.739	2.057
Durham	-0.060	0.186	0.513	0.892	0.597
El Paso	0.675	2.407	1.347	1.436	1.300
Erie	-0.009	0.631	0.611	0.518	0.882
Eugene	0.009	0.066	0.569	0.550	0.422
Evansville	-0.019	0.055	0.037	0.158	0.063
Flint	-0.021	1.020	0.639	0.443	0.466
Fort Lauderdale	0.254	0.668	2.529	0.343	0.640
Fort Wayne	0.000	1.606	0.738	1.024	0.552
Fort Worth	0.273	2.484	2.068	1.522	1.449
Fremont	0.214	0.794	0.296	0.685	0.369
Fresno	0.302	1.482	1.519	0.817	0.469
Garland	0.013	0.996	0.579	0.900	0.846

Gary	0.042	0.242	0.988	1.200	0.049
Glendale Az	-0.002	0.065	0.013	0.040	0.075
Grand Rapids	0.056	0.944	0.491	0.489	0.112
Greensboro	0.106	0.972	1.383	1.341	1.346
Hampton	0.534	1.171	1.763	1.744	2.068
Hartford	-0.014	0.605	0.924	0.487	0.760
Hialeah	-0.040	0.191	0.013	0.008	-0.016
Hollywood	-0.045	0.187	2.564	0.756	0.587
Honolulu	0.320	0.766	0.827	1.207	0.088
Houston	0.101	1.151	1.687	1.305	0.726
Huntington Beach	0.124	0.654	0.225	0.148	0.293
Huntsville	0.000	0.032	0.000	0.070	0.033
Independence	-0.044	0.356	0.133	0.300	0.204
Indianapolis	0.014	0.833	0.612	0.889	0.858
Irving	-0.023	0.050	0.396	0.371	0.408
Jackson	0.000	0.097	0.051	.	.
Jacksonville	0.236	0.817	1.138	0.408	0.600
Jersey City	0.185	2.652	1.884	2.979	2.604
Kansas City Ks	0.040	2.056	0.644	0.311	1.750
Kansas City Mo	0.140	1.525	0.272	0.550	0.919
Knoxville	0.018	0.275	0.400	0.485	0.598
Lafayette	0.000	2.164	1.161	1.365	0.682
Lakewood	0.070	0.229	0.057	-0.036	0.152
Lansing	0.070	0.815	0.316	0.405	0.387
Las Vegas	0.172	0.513	0.776	0.866	1.226
Lexington	0.181	0.687	0.578	0.157	0.191
Lincoln	0.011	0.649	0.326	0.346	0.281
Little Rock	0.035	1.435	1.095	0.939	0.820
Livonia	0.240	0.407	0.145	0.104	0.557
Long Beach	0.038	2.689	2.574	2.293	1.807
Los Angeles	1.118	3.809	2.626	2.356	2.226
Louisville	0.033	0.929	0.505	1.170	0.665
Lubbock	0.053	0.295	0.032	0.377	0.488
Madison	0.116	0.408	1.178	0.667	0.349
Memphis	0.005	0.849	0.439	0.575	1.468
Mesa	-0.049	0.158	0.029	0.120	0.244
Miami	0.217	1.556	1.011	1.354	1.278
Milwaukee	-0.029	1.294	0.997	1.554	0.790
Minneapolis	0.416	1.677	1.670	2.373	1.630
Mobile	0.194	1.408	0.519	1.195	1.895
Montgomery	-0.035	0.711	0.201	0.946	0.814
Nashville	-0.038	0.464	0.226	0.421	0.356
New Orleans	0.757	4.806	2.629	3.129	1.217
New York	0.266	3.720	4.624	3.975	2.922
Newark	0.148	3.814	3.087	7.438	6.409
Newport News	0.141	0.768	0.721	0.762	0.936
Norfolk	0.071	0.605	0.331	0.465	0.502
Oakland	0.491	4.122	4.286	3.109	3.265
Oklahoma City	0.314	1.907	1.625	1.707	1.272
Omaha	-0.042	2.179	0.682	0.703	0.612

Orlando	0.345	0.686	2.306	0.981	0.583
Pasadena Tx	0.282	0.240	0.383	0.095	0.000
Paterson	0.481	2.515	2.610	4.244	3.947
Peoria Il	0.002	0.269	0.065	0.021	0.113
Philadelphia	0.385	4.794	3.814	3.750	4.087
Phoenix	0.490	2.260	1.431	1.653	2.227
Pittsburgh	0.133	1.169	3.816	2.988	3.522
Portland	0.136	2.664	2.737	2.455	2.253
Providence	0.220	1.409	1.096	3.640	3.180
Raleigh	-0.002	1.255	1.584	1.631	0.978
Richmond Va	0.007	0.810	1.127	0.739	0.626
Riverside	0.308	2.108	1.890	1.685	1.360
Rochester	0.026	0.309	0.181	0.270	0.173
Rockford	-0.030	0.218	0.306	0.082	0.108
Sacramento	-0.059	2.923	1.515	1.043	1.226
Salt Lake City	0.142	1.561	1.807	3.892	4.281
San Antonio	0.033	2.461	1.789	0.687	0.388
San Diego	0.114	3.472	2.108	1.982	2.217
San Francisco	0.162	5.918	4.871	3.550	2.976
San Jose	0.600	2.048	0.834	1.198	0.559
Santa Ana	0.814	0.945	1.623	0.737	0.670
Savannah	0.024	0.001	-0.005	0.099	0.024
Seattle	0.166	3.021	4.290	2.570	2.600
Shreveport	0.008	0.561	0.691	0.365	0.501
South Bend	-0.008	0.262	0.341	0.365	0.528
Spokane	0.125	0.449	0.223	0.216	0.606
Springfield Ma	0.051	0.918	1.057	2.295	1.221
Springfield Mo	0.000	0.099	0.460	1.457	0.005
St. Louis	0.156	1.638	2.167	1.449	1.638
St. Paul	0.212	1.715	1.622	1.259	0.175
St. Petersburg	0.225	0.896	2.050	0.536	0.395
Sterling Heights	0.000	0.000	-0.001	0.096	0.285
Stockton	0.466	1.031	1.337	0.946	0.807
Syracuse	0.283	0.280	0.367	0.353	0.276
Tacoma	0.002	0.146	0.356	0.296	1.459
Tampa	0.407	0.854	1.334	0.647	0.527
Toledo	0.071	0.488	0.328	0.414	0.500
Topeka	0.003	0.037	-0.017	-0.017	0.204
Torrance	0.103	1.173	0.252	0.127	0.564
Tucson	-0.011	1.591	1.045	1.015	2.727
Tulsa	0.065	0.256	0.258	0.108	0.184
Virginia Beach	-0.007	0.007	0.045	0.032	0.044
Warren	0.008	0.396	1.177	0.000	0.106
Washington	0.593	3.183	1.731	0.716	0.807
Wichita	0.015	0.010	0.039	0.029	0.133
Winston-Salem	0.018	0.142	0.169	0.507	0.411
Worcester	0.248	0.747	1.254	0.136	1.356
Yonkers	0.358	3.242	2.048	2.392	1.508

State	Crack Index				
	1985	1989	1993	1997	2000
Alabama	0.265	0.878	0.314	2.009	1.087
Alaska	-0.006	0.690	-0.075	0.644	1.357
Arizona	0.640	1.962	0.701	1.252	1.991
Arkansas	0.134	1.274	1.093	0.947	0.664
California	1.542	3.837	2.220	1.462	1.450
Colorado	-0.076	0.846	0.797	0.798	1.698
Connecticut	0.658	2.250	3.549	3.374	2.273
Delaware	0.106	2.764	3.066	5.266	2.096
Florida	1.241	0.597	2.518	0.842	0.332
Georgia	0.815	3.160	2.333	3.382	2.240
Hawaii	-0.011	2.822	1.893	1.873	0.188
Idaho	0.166	1.157	0.279	0.217	0.276
Illinois	0.489	2.001	1.976	0.823	1.726
Indiana	0.076	0.565	0.670	1.765	0.864
Iowa	-0.045	0.353	-0.069	0.499	0.439
Kansas	0.641	1.513	0.205	0.509	0.652
Kentucky	0.177	0.764	0.735	1.905	1.316
Louisiana	0.742	2.744	2.279	2.796	1.464
Maine	0.402	0.019	0.273	0.939	0.408
Maryland	1.271	4.676	4.351	5.292	3.002
Massachusetts	1.258	3.447	3.451	4.137	2.500
Michigan	0.423	1.145	1.051	1.196	1.383
Minnesota	0.631	0.502	0.251	0.520	0.551
Mississippi	0.029	1.042	1.007	1.657	1.013
Missouri	0.632	1.046	1.232	0.923	1.049
Montana	0.023	0.081	0.002	0.128	-0.050
Nebraska	0.000	0.090	-0.001	0.019	0.079
Nevada	0.757	1.127	1.794	2.233	2.934
New Hampshire	0.303	0.965	0.448	1.551	0.490
New Jersey	0.639	3.300	3.025	5.163	3.417
New Mexico	0.892	3.056	3.021	4.779	3.638
New York	0.705	4.372	4.661	4.141	2.542
North Carolina	0.228	1.587	1.314	2.038	1.505
North Dakota	-0.006	0.048	-0.073	-0.054	0.224
Ohio	0.438	2.531	1.789	2.105	1.493
Oklahoma	0.316	0.942	1.095	1.316	0.930
Oregon	0.552	2.220	2.271	1.987	1.648
Pennsylvania	0.438	2.295	2.609	2.508	2.160
Rhode Island	1.224	3.231	1.827	2.959	2.447
South Carolina	0.400	2.254	0.801	2.356	1.639
South Dakota	0.043	-0.097	0.029	0.067	0.117
Tennessee	0.319	1.305	1.004	1.579	1.328
Texas	0.759	2.271	1.956	2.389	1.818
Utah	0.025	1.355	1.487	2.961	2.069
Vermont	0.216	0.345	-0.020	0.525	0.190
Virginia	0.177	2.281	2.338	2.279	1.393
Washington	0.519	2.824	1.547	1.997	2.094
West Virginia	0.594	1.171	0.590	0.571	0.649

Wisconsin	0.220	0.854	0.662	0.881	0.610
Wyoming	-0.015	0.063	0.056	-0.109	0.061

Table 1: Summary Statistics

Variable	N	Pre-1985		1985-Present	
		Mean	SD	Mean	SD
City-Level					
Crack Proxies					
Cocaine arrest rate	2473	0.0107	0.01273	0.04227	0.03496
Cocaine death rate	2935	3.174E-6	5.936E-6	2.216E-5	2.72E-5
Cocaine bust rate	1770	1.1546E-4	2.1917E-4	2.4198E-4	7.6628E-4
Cocaine-related ER visits	434	11.12	18.28	124.7	80.87
Newspaper citation ratio	2731	0.002005	0.005511	0.03734	0.03358
Homicide Measures					
Male homicide rate ages 14-17	2760	0.3701	0.5428	0.8373	1.097
Male homicide rate ages 18-24	2760	2.639	2.484	3.793	4.121
Male homicide rate age 25 and over	2760	8.634	7.214	8.359	7.233
Crime Measures					
Violent Crime	2616	1020	694.8	1326	827
Homicide rate	2616	15.81	11.95	17.32	14.4
Rape rate	2616	54.92	32.41	61.79	40.89
Assault rate	2616	475.6	308.5	720.7	476.6
Robbery rate	2616	473.5	448.1	525.9	412.4
Property Crime	2616	8337	4032	8570	4685
Burglary rate	2616	2568	1245	2075	1116
Larceny rate	2616	5157	2634	5545	3377
Auto theft rate	2616	611.9	666.9	949.8	826.6
Other Outcome Measures					
Weapons arrest rate	2717	0.01689	0.007768	0.0159	0.008179
Rate low birth weight babies	2935	0.001297	5.9189E-4	0.001456	7.4674E-4
Child mortality rate	2935	5.61E-5	3.042E-5	4.989E-5	3.063E-5
Rate teen birth	2935	0.003078	0.001506	0.003159	0.001596
Rate unwed birth	1862	0.005324	0.003632	0.008013	0.005199
Fetal death rate	1892	2.2081E-4	2.2851E-4	2.2613E-4	2.6331E-4
State-Level					
Crack Proxies					
Cocaine arrest rate	1034	0.005265	0.005751	0.01918	0.01675
Cocaine death rate	1150	1.207E-6	1.549E-6	8.651E-6	8.277E-6
Cocaine bust rate	1106	2.294E-5	2.774E-5	4.54E-5	4.107E-5
Homicide Measures					
Male homicide rate ages 14-17	1275	0.1504	0.1347	0.2282	0.2193
Male homicide rate ages 18-24	1275	1.025	0.7042	1.061	0.8437
Male homicide rate age 25 and over	1275	3.663	2.297	2.869	1.92
Crime Measures					
Violent Crime	946	406.3	216.1	480.4	248.9
Homicide rate	955	6.663	3.859	6.155	3.457
Rape rate	947	29.55	13.39	34.92	13.95
Assault rate	954	231.8	114.6	301.1	158.5
Robbery rate	955	140.7	112.5	142.6	105.2
Property Crime	955	4489	1193	4221	1149
Burglary rate	955	1277	440.9	969.4	362.1

Larceny rate	955	2871	720.1	2834	736.1
Auto theft rate	955	346.8	188.2	418.1	217.4
Other Outcome Measures					
Weapons arrest rate	1034	0.01277	0.006142	0.01151	0.005613
Rate low birth weight babies	1050	9.3487E-4	2.8929E-4	8.8456E-4	2.958E-4
Child mortality rate	1050	4.3E-5	1.507E-5	3.126E-5	1.299E-5
Rate teen birth	1050	0.002318	7.771E-4	0.001935	7.0492E-4
Rate unwed birth	861	0.002764	0.001115	0.004078	0.001596
Fetal death rate	857	2.4683E-4	3.5718E-4	2.2531E-4	3.3293E-4
Foster care rate	381	0.001074	4.1005E-4	0.001245	5.2851E-4
Female prison rate	1149	0.05824	0.02251	0.08528	0.02475
Total new prisoners	1149	2724	3146	5843	7826
Unemployment rate	1150	0.1431	0.04261	0.1277	0.03957
Poverty rate	1250	0.07207	0.02547	0.05529	0.01812

Notes: The unit of observation is a city-year in the top portion of the table and a state-year in the bottom portion. See the data appendix for precise sources and definitions of the variables. For most variables the sample period covered is 1980-2000; for some measures a shorter time series is available. The city sample is restricted to the 144 cities with population greater than 100,000 in 1980. Rates are measured relative to the total city or state population.

Table 2: Correlations in Crack Proxies

National Data

Raw Correlations

	Arrests	Deaths	Busts	ER	Cites
Cocaine arrests	1.000				
Cocaine deaths	0.839	1.000			
Cocaine busts	0.648	0.225	1.000		
Cocaine-related ER visits	0.951	0.881	0.394	1.000	
Newspaper citations	0.922	0.630	0.754	0.812	1.000

City-Level Data

Correlations Removing City Fixed Effects

	Arrests	Deaths	Busts	ER	Cites
Cocaine arrests	1.000				
Cocaine deaths	0.425	1.000			
Cocaine busts	0.147	0.114	1.000		
Cocaine-related ER visits	0.682	0.490	0.194	1.000	
Newspaper citations	0.385	0.185	0.086	0.467	1.000

Correlations Removing City and Year Fixed Effects

	Arrests	Deaths	Busts	ER	Cites
Cocaine arrests	1.000				
Cocaine deaths	0.164	1.000			
Cocaine busts	0.049	0.043	1.000		
Cocaine-related ER visits	0.262	0.123	0.082	1.000	
Newspaper citations	-0.001	0.003	-0.052	0.020	1.000

State-Level Data

Correlations Removing State Fixed Effects

	Arrests	Deaths	Busts
Cocaine arrests	1.000		
Cocaine deaths	0.545	1.000	
Cocaine busts	0.282	0.258	1.000

Correlations Removing State and Year Fixed Effects

	Arrests	Deaths	Busts
Cocaine arrests	1.000		
Cocaine deaths	0.223	1.000	
Cocaine busts	0.097	0.140	1.000

Notes: The national correlations are the correlations across time of national aggregate annual values of the five crack proxies. The city correlations are correlations across location and time for the 144 U.S. cities with population above 100000 in 1980. The state correlations are correlations across location and time for the 50 U.S. states. The data spans the years 1980-2000.

Table 3: Estimates of Factor Loadings

Crack Proxies	National	City-Level		State-Level	
Cocaine arrests	0.492	0.572	0.578	0.649	0.590
Cocaine deaths	0.415	0.495	0.746	0.639	0.668
Cocaine busts	0.351	0.110	0.129	0.414	0.453
Cocaine-related ER visits	0.441	0.509	0.158	.	.
Newspaper citations	0.518	0.396	0.262	.	.
% of variation explained by factor	0.765	0.428	0.310	0.563	0.495
No. Obs.	21	3024	3024	1050	1050
Remove year fixed effects	No	No	Yes	No	Yes

Notes: The table reports results of factor analysis to extract the first principle component of the five crack proxies. Each of the proxies was standardized to have unit variance over the period 1980-2000 and a grand mean of zero from 1980-1984 prior to estimation of the loadings. The loadings are restricted to have a squared sum of 1. The "% of Variation" row reports the percentage of the total variance in the transformed variables that can be explained by the first principle component. The city sample includes U.S. cities with a population above 100000 in 1980. The city and state estimates remove city or state fixed effects prior to factor analysis. Columns 3 and 5 also remove year fixed effects from each of the measures prior to factor analysis.

Table 4: Areas With Highest and Lowest Average Crack Levels

Cities With Highest Average Crack Levels

Rank	City Name	Average Crack
1	Newark	3.693
2	San Francisco	2.948
3	Atlanta	2.651
4	Philadelphia	2.651
5	New York	2.609
6	Buffalo	2.361
7	Oakland	2.340
8	Boston	2.306
9	Paterson	2.267
10	Seattle	2.023

States With Highest Average Crack Levels

Rank	City Name	Average Crack
1	Maryland	2.836
2	New York	2.831
3	New Mexico	2.583
4	New Jersey	2.495
5	Massachusetts	2.445
6	Delaware	2.339
7	Connecticut	2.055
8	Rhode Island	1.940
9	Georgia	1.919
10	Pennsylvania	1.723

Cities With Lowest Average Crack Levels

Rank	City Name	Average Crack
1	Huntsville	0.008
2	Hialeah	0.009
3	Jackson	0.014
4	Virginia Beach	0.021
5	Wichita	0.027
6	Cedar Rapids	0.027
7	Akron	0.027
8	Sterling Heights	0.028
9	Topeka	0.030
10	Glendale Az	0.034

States With Lowest Average Crack Levels

Rank	City Name	Average Crack
1	South Dakota	-0.008
2	Montana	0.018
3	Wyoming	0.021
4	North Dakota	0.022
5	Nebraska	0.023
6	Iowa	0.177
7	Maine	0.221
8	Idaho	0.317
9	Minnesota	0.338
10	Vermont	0.374

Table 5: Estimated Effects of Crack on Outcome Measures, City Sample

Outcome	Mean	Coefficient on Crack			
		1980-1984	1985-1989	1990-1994	1995-2000
Black					
Male homicide rate ages 14-17	0.672	0.0753 (0.201)	0.175** (0.0372)	0.108** (0.0301)	0.0351 (0.0278)
Male homicide rate ages 18-24	3.07	-0.244 (0.507)	0.266* (0.107)	0.335** (0.0927)	0.24** (0.0889)
Male homicide rate over age 24	6.39	0.545 (0.727)	0.308* (0.144)	0.307* (0.12)	0.0798 (0.113)
Weapons arrest rate	0.00892	-6.321E-4 (8.043E-4)	-1.605E-4 (1.847E-4)	-1.368E-4 (1.717E-4)	-3.084E-4 (1.739E-4)
Rate low birth weight	7.601E-4	1.042E-5 (2.858E-5)	3.45E-5** (6.311E-6)	2.623E-5** (5.7E-6)	-5.095E-6 (5.78E-6)
Rate teen birth	0.00148	5.231E-6 (4.419E-5)	2.943E-5** (1.004E-5)	9.656E-6 (9.244E-6)	-5.331E-5** (9.605E-6)
Rate unwed birth	0.00482	-8.06E-5 (1.417E-4)	1.361E-4** (2.832E-5)	1.205E-4** (2.535E-5)	-8.96E-5** (2.576E-5)
Child mortality rate	1.702E-5	3.414E-6 (3.429E-6)	1.464E-6** (5.374E-7)	4.061E-7 (4.122E-7)	-2.938E-7 (3.701E-7)
Fetal death rate†	9.025E-5	-1.189E-5 (1.464E-5)	4.713E-6 (2.581E-6)	5.317E-6* (2.323E-6)	-1.305E-6 (2.541E-6)
White					
Male homicide rate ages 14-17	0.359	-0.0462 (0.145)	0.0217 (0.0252)	0.0618** (0.02)	-0.0138 (0.0182)
Male homicide rate ages 18-24	1.69	-0.213 (0.322)	0.0159 (0.0621)	0.212** (0.0512)	0.0869 (0.0476)
Male homicide rate over age 24	4.75	1.04 (0.61)	0.125 (0.116)	0.159 (0.0951)	-0.0918 (0.0883)
Weapons arrest rate	0.0078	-5.612E-4 (7.721E-4)	-2.299E-4 (1.772E-4)	-1.928E-4 (1.65E-4)	-9.048E-5 (1.668E-4)
Rate low birth weight	7.247E-4	-4.681E-5 (3.007E-5)	1.176E-5 (6.496E-6)	5.358E-6 (5.783E-6)	-6.365E-6 (5.774E-6)
Rate teen birth	0.00169	-2.273E-5 (5.396E-5)	4.756E-6 (1.219E-5)	1.36E-5 (1.119E-5)	1.188E-5 (1.157E-5)
Rate unwed birth	0.003	1.174E-4 (1.261E-4)	4.878E-5 (2.545E-5)	5.063E-5* (2.287E-5)	6.173E-6 (2.352E-5)
Child mortality rate	3.782E-5	6.366E-6 (5.432E-6)	2.09E-6* (8.565E-7)	1.101E-6 (6.585E-7)	-5.464E-8 (5.916E-7)
Fetal death rate†	1.818E-4	1.038E-5 (2.845E-5)	4.202E-6 (5.193E-6)	7.56E-6 (4.788E-6)	1.224E-5* (5.248E-6)
Crime Measures					
Violent crime rate	1570	37.8 (60.3)	29.6* (14)	53.1** (13.1)	0.0935 (13.6)
Homicide rate	21.9	-1.29 (1.52)	0.744* (0.326)	0.925** (0.289)	-0.169 (0.283)
Rape rate	58.8	-0.116 (5.4)	2.08 (1.16)	0.0208 (1.03)	-1.59 (1.01)

Assault rate	767	-3.19 (50.3)	29* (11.4)	34.8** (10.6)	9.96 (10.8)
Robbery rate	721	41.4 (25.5)	-2.53 (5.99)	16.8** (5.68)	-5.12 (6.03)
Property crime rate	8280	-390 (236)	172** (55.2)	3.55 (52.2)	-46.3 (55)
Burglary rate	2160	-150 (79.9)	4.85 (18.7)	-12.3 (17.7)	-11.7 (18.6)
Larceny rate	5050	-115 (156)	97.5** (36.6)	-28.4 (34.5)	-9.35 (36.4)
Auto theft rate	1070	-126 (80.6)	72.7** (18.6)	47.1** (17.5)	-29.5 (18.2)

†=data available from 1980 to 1998

Notes: The "Coefficient" columns report estimated coefficients from OLS regressions of the outcome measures on the crack index interacted with indicator variables for the years 1985-1989, 1990-1994, and 1995-2000. The regressions include controls for percent of the population Hispanic, percent of the population Black, log population, and log per capita income as well as city and year fixed effects. Standard errors are in parenthesis. * denotes significance at the 5% level; ** denotes significance at the 1% level. The OLS estimates were corrected to allow AR(1) serial correlation in the error terms. The coefficient on crack in the 1980-84 period is imprecisely estimated due to the small amount of variation in crack during this period and is omitted from the table.

Table 6: Estimated Effects of Crack on Outcome Measures, State Sample

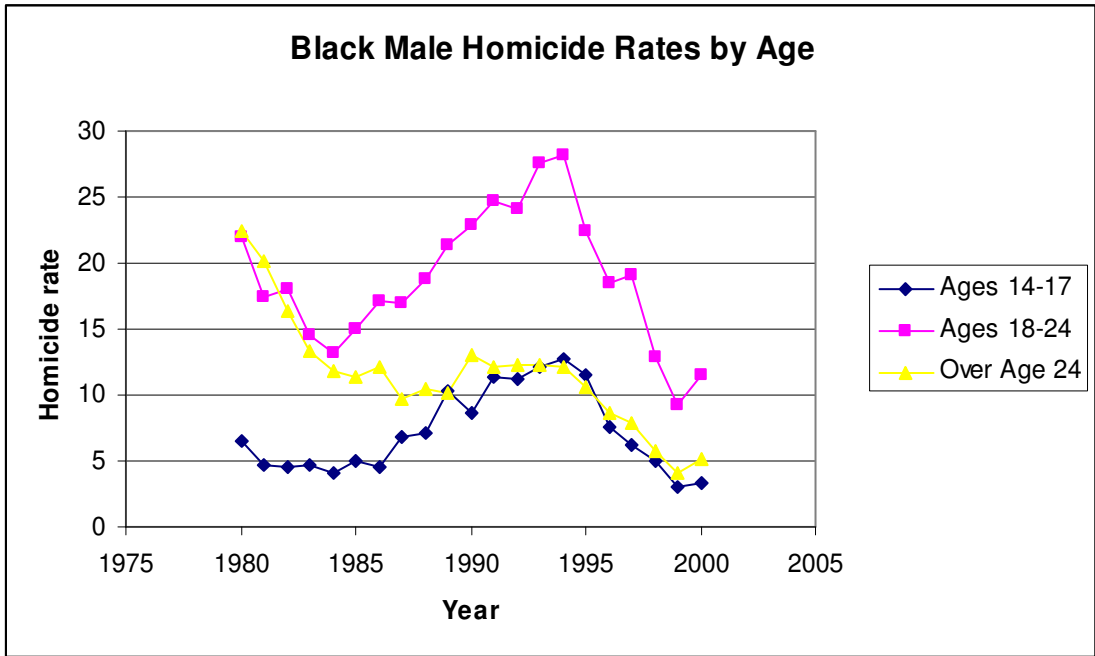
Outcome	Mean	Coefficient on Crack			
		1980-1984	1985-1989	1990-1994	1995-2000
Black					
Male homicide rate ages 14-17	0.184	0.0187 (0.0233)	0.0261** (0.009)	0.0195* (0.00763)	0.0154* (0.00653)
Male homicide rate ages 18-24	0.868	-0.014 (0.0592)	0.0361 (0.0248)	0.0763** (0.0217)	0.0331 (0.0189)
Male homicide rate over age 24	1.88	0.0523 (0.0955)	0.112** (0.0389)	0.0674* (0.0337)	-7.979E-5 (0.0291)
Weapons arrest rate	0.00553	-6.538E-5 (2.659E-4)	-2.531E-5 (1.174E-4)	-1.205E-4 (1.056E-4)	-1.066E-4 (9.371E-5)
Rate low birth weight	2.998E-4	7.088E-6 (5.823E-6)	8.276E-6** (2.465E-6)	9.972E-7 (2.266E-6)	-1.419E-6 (2.011E-6)
Rate teen birth	6.129E-4	5.716E-6 (1.012E-5)	1.289E-5** (4.389E-6)	8.242E-6* (4.087E-6)	-1.192E-6 (3.658E-6)
Rate unwed birth	0.0018	5.891E-6 (2.9E-5)	2.724E-5* (1.256E-5)	2.995E-5** (1.136E-5)	-6.005E-6 (9.791E-6)
Child mortality rate	7.284E-6	3.018E-7 (5.152E-7)	-5.409E-9 (1.77E-7)	-1.53E-7 (1.482E-7)	-3.811E-7** (1.277E-7)
Fetal death rate†	6.935E-5	9.25E-6 (5.361E-6)	1.983E-7 (1.696E-6)	1.602E-6 (1.513E-6)	-6.726E-7 (1.355E-6)
White					
Male homicide rate ages 14-17	0.139	0.0407 (0.0238)	-0.005 (0.00789)	0.00775 (0.00635)	-0.00736 (0.0054)
Male homicide rate ages 18-24	0.654	0.0346 (0.062)	0.0379 (0.0219)	0.0258 (0.018)	-0.0044 (0.0153)
Male homicide rate over age 24	2.11	0.24 (0.152)	0.114* (0.0567)	0.108* (0.0475)	-0.0277 (0.0405)
Weapons arrest rate	0.00774	2.257E-4 (2.52E-4)	-2.095E-4 (1.16E-4)	-7.572E-5 (1.06E-4)	-6.608E-5 (9.551E-5)
Rate low birth weight	6.378E-4	-1.535E-5 (9.235E-6)	-1.103E-7 (3.986E-6)	-8.172E-7 (3.702E-6)	-6.404E-7 (3.307E-6)
Rate teen birth	0.00149	-2.872E-5 (1.93E-5)	-1.721E-6 (8.346E-6)	-7.341E-6 (7.757E-6)	-1.104E-5 (6.934E-6)
Rate unwed birth	0.00233	-2.677E-5 (3.209E-5)	2.792E-5* (1.402E-5)	5.763E-7 (1.274E-5)	-1.167E-6 (1.102E-5)
Child mortality rate	2.831E-5	-9.2E-7 (1.382E-6)	-4.828E-7 (4.26E-7)	8.195E-7* (3.446E-7)	-4.16E-7 (2.958E-7)
Fetal death rate†	1.823E-4	-5.035E-6 (9.29E-6)	3.023E-6 (3.311E-6)	4.952E-6 (3.029E-6)	-6.646E-7 (2.719E-6)
Crime Measures					
Violent crime rate	592	-37.4** (14.3)	0.748 (5.76)	2.47 (5.32)	-0.971 (4.79)
Homicide rate	7.8	-0.164 (0.277)	0.107 (0.108)	0.247* (0.0979)	-0.0755 (0.0871)
Rape rate	35.4	-1.46 (1.74)	-0.0476 (0.655)	-0.992 (0.583)	-0.27 (0.511)

Assault rate	346	-16.6 (8.96)	2.56 (3.63)	-1.34 (3.36)	-1.34 (3.03)
Robbery rate	208	-16.5* (7.95)	-1.95 (3.16)	4.71 (2.89)	-0.248 (2.59)
Property crime rate	4490	-56.5 (67.8)	56.5* (27.8)	6.17 (25.8)	8.1 (23.4)
Burglary rate	1130	-40.2* (20.2)	17.9* (8.3)	-0.385 (7.71)	1.79 (6.99)
Larceny rate	2860	-11.9 (44.9)	25.4 (18.3)	-16.4 (17)	6.33 (15.4)
Auto theft rate	507	-3.56 (13.6)	13.4* (5.58)	23.2** (5.18)	0.235 (4.7)
Other Measures					
Foster care rate	0.00137	4.34E-5 (7.477E-5)	6.613E-6 (2.436E-5)	-3.607E-5 (2.879E-5)	-2.279E-6 (3.865E-5)
Female prison rate	0.0813	0.00345 (0.00393)	-9.288E-4 (0.00148)	-8.443E-4 (0.00131)	-0.00398** (0.00123)
Total new prisoners	11400	-289 (270)	-256* (119)	-72.5 (118)	-90.6 (120)
Unemployment rate	0.0636	-0.00281 (0.00199)	-8.106E-4 (8.258E-4)	0.00121 (7.514E-4)	9.157E-4 (6.636E-4)
Poverty rate	0.136	7.558E-4 (0.00457)	-0.00258 (0.00166)	0.00155 (0.00142)	0.00139 (0.00123)

†=data available from 1980 to 1998

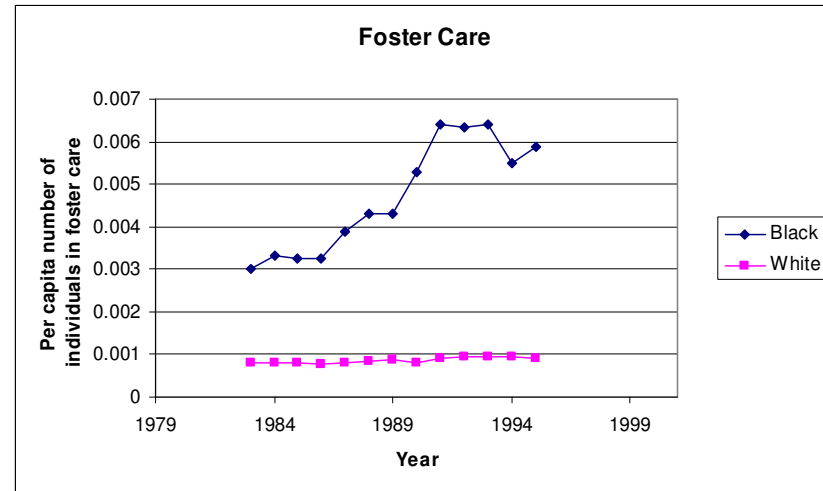
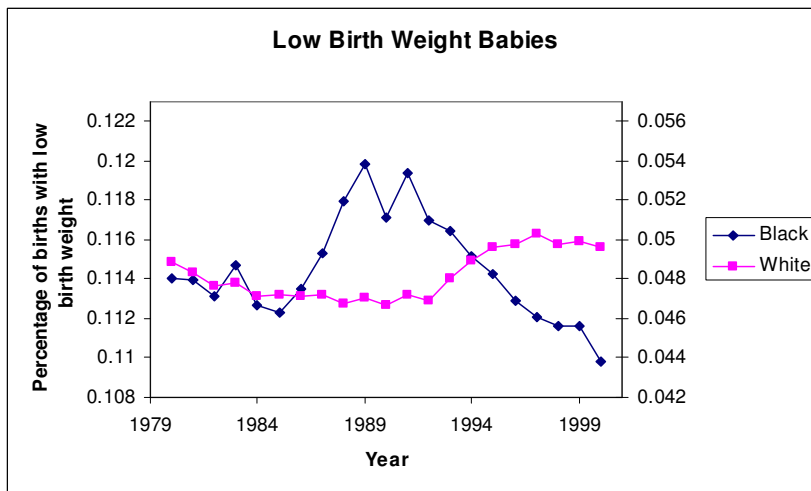
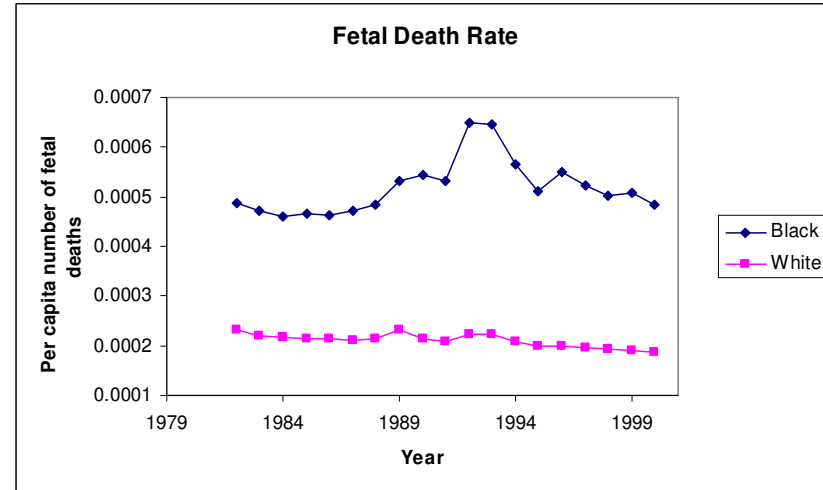
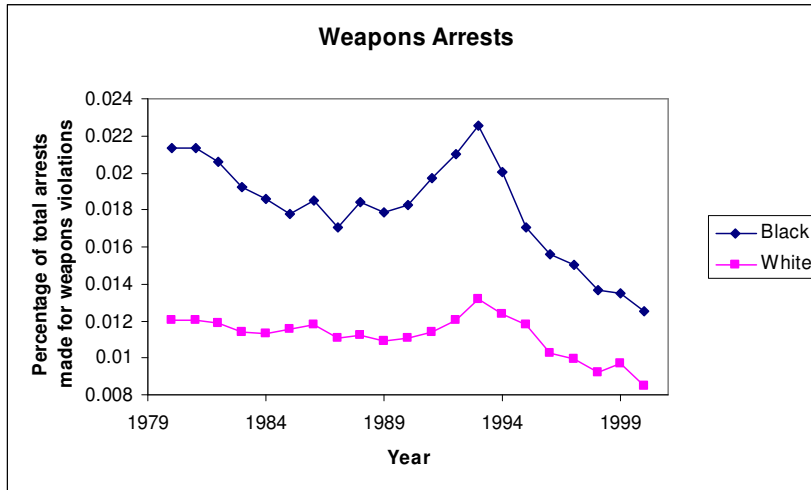
Notes: The "Coefficient" columns report estimated coefficients from OLS regressions of the outcome measures on the crack index interacted with indicator variables for the years 1985-1989, 1990-1994, and 1995-2000. The regressions include controls for percent of the population Hispanic, percent of the population Black, log population, and log per capita income as well as state and year fixed effects. Standard errors are in parenthesis. * denotes significance at the 5% level; ** denotes significance at the 1% level. The OLS estimates were corrected to allow AR(1) serial correlation in the error terms. The coefficient on crack in the 1980-84 period is imprecisely estimated due to the small amount of variation in crack during this period and is omitted from the table.

Figure 1: Black Male Homicide Rates by Age



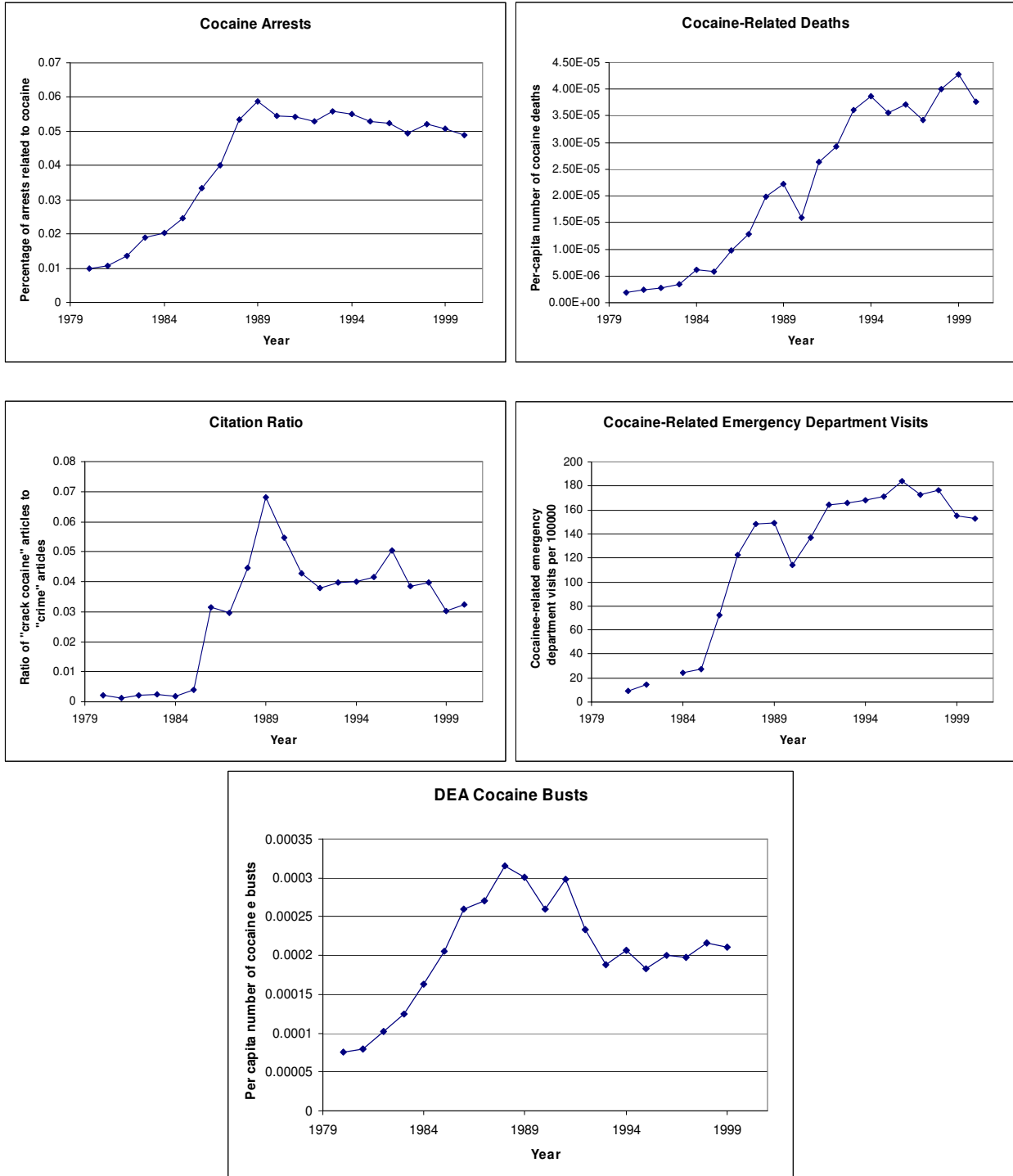
The figure depicts population-weighted national averages derived from state data.

Figure 2: Outcome Measures



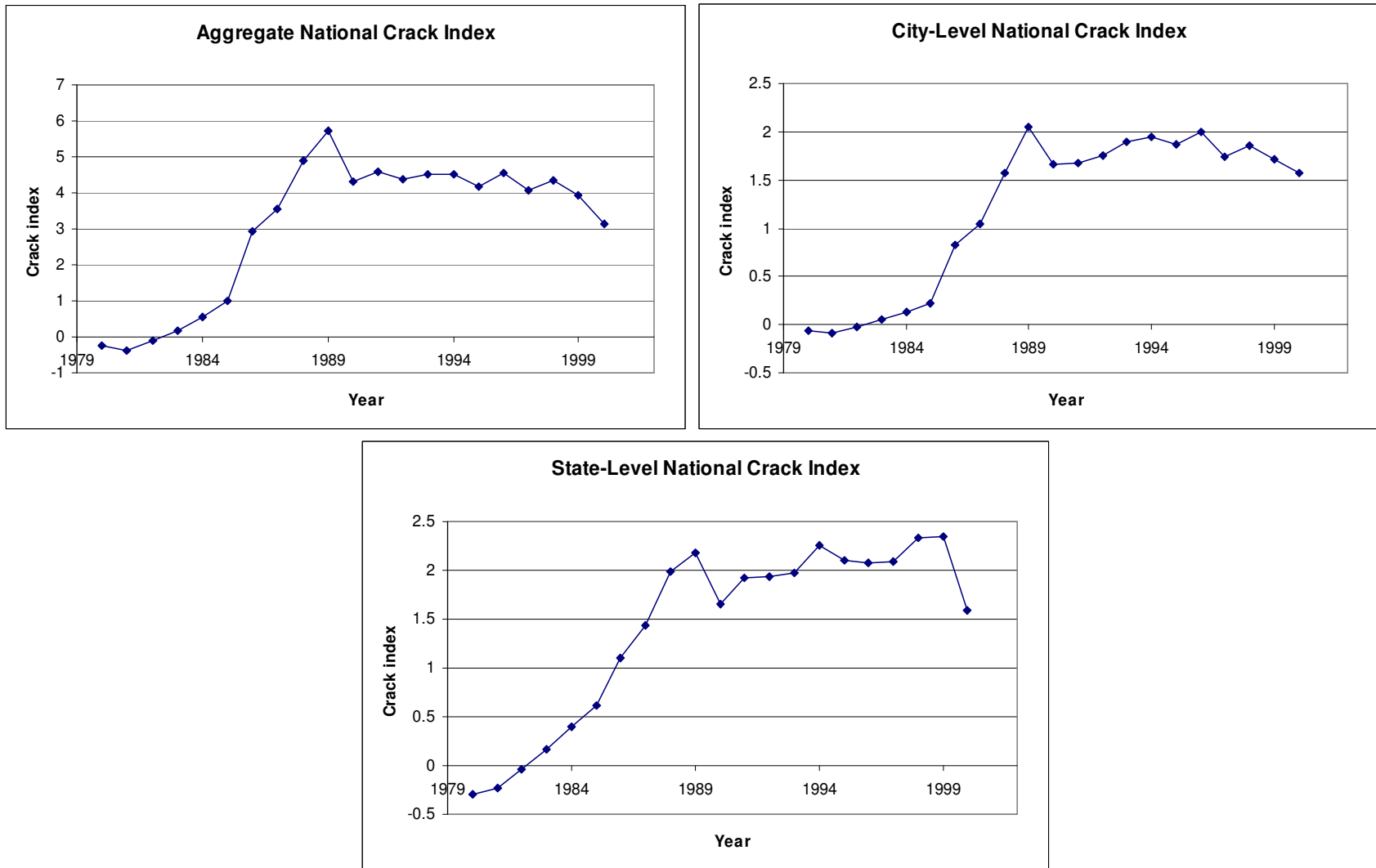
The figures depict population-weighted annual national averages derived from state-level data.

Figure 3: Crack Proxies



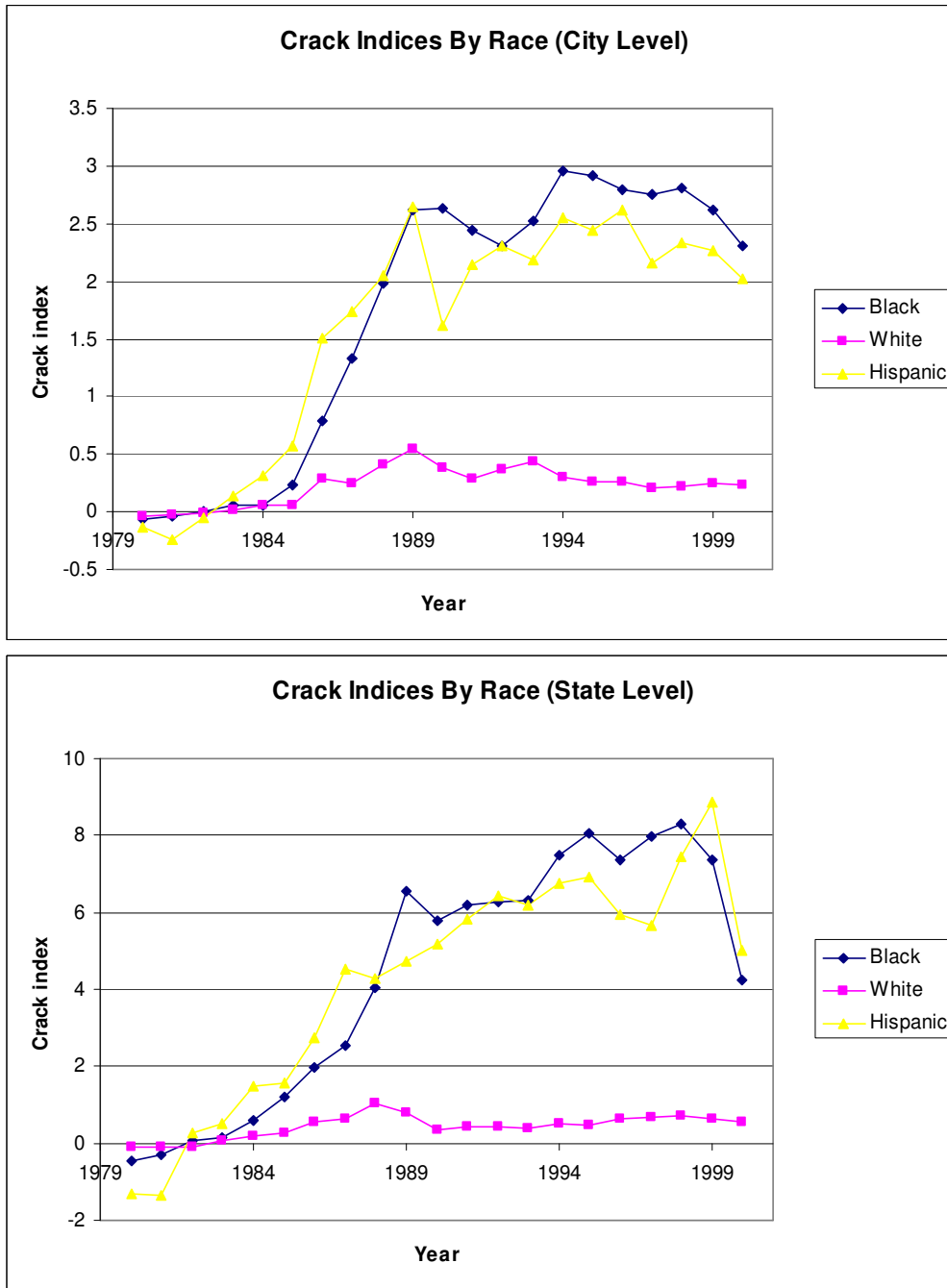
The figures depict population-weighted annual national averages derived from city-level data.

Figure 4: Crack Indices



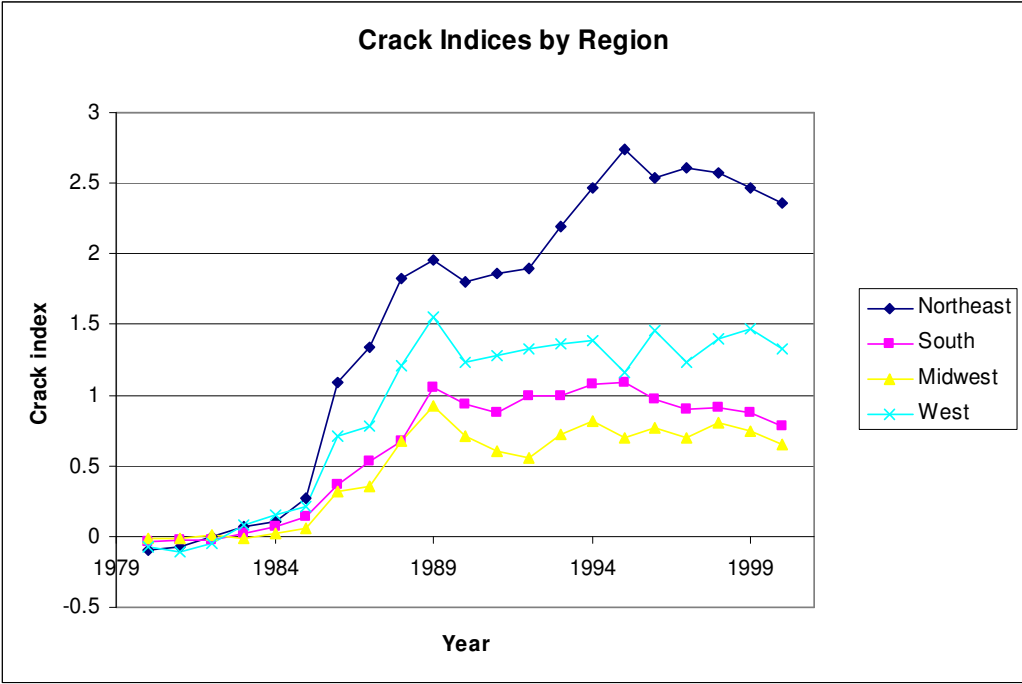
The reported indices are population weighted national estimates of the crack index.

Figure 5: Crack Indices by Race



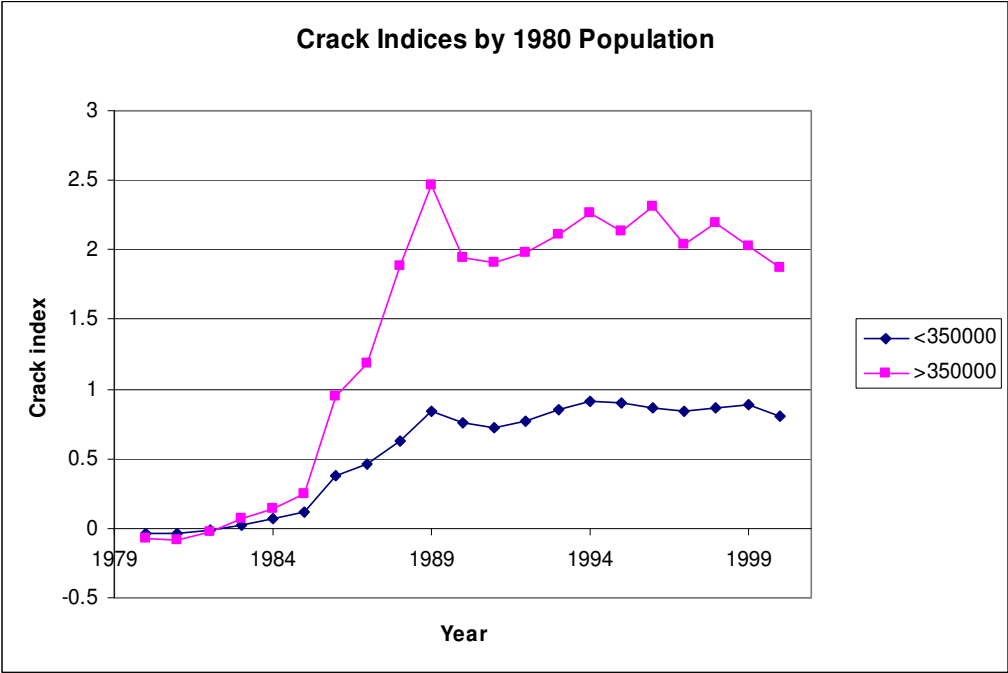
The race-specific indices were estimated using year-by-year cross sectional regressions of the city-level crack index on the population percentages of Blacks, Whites, and Hispanics.

Figure 6: Crack Indices by Region



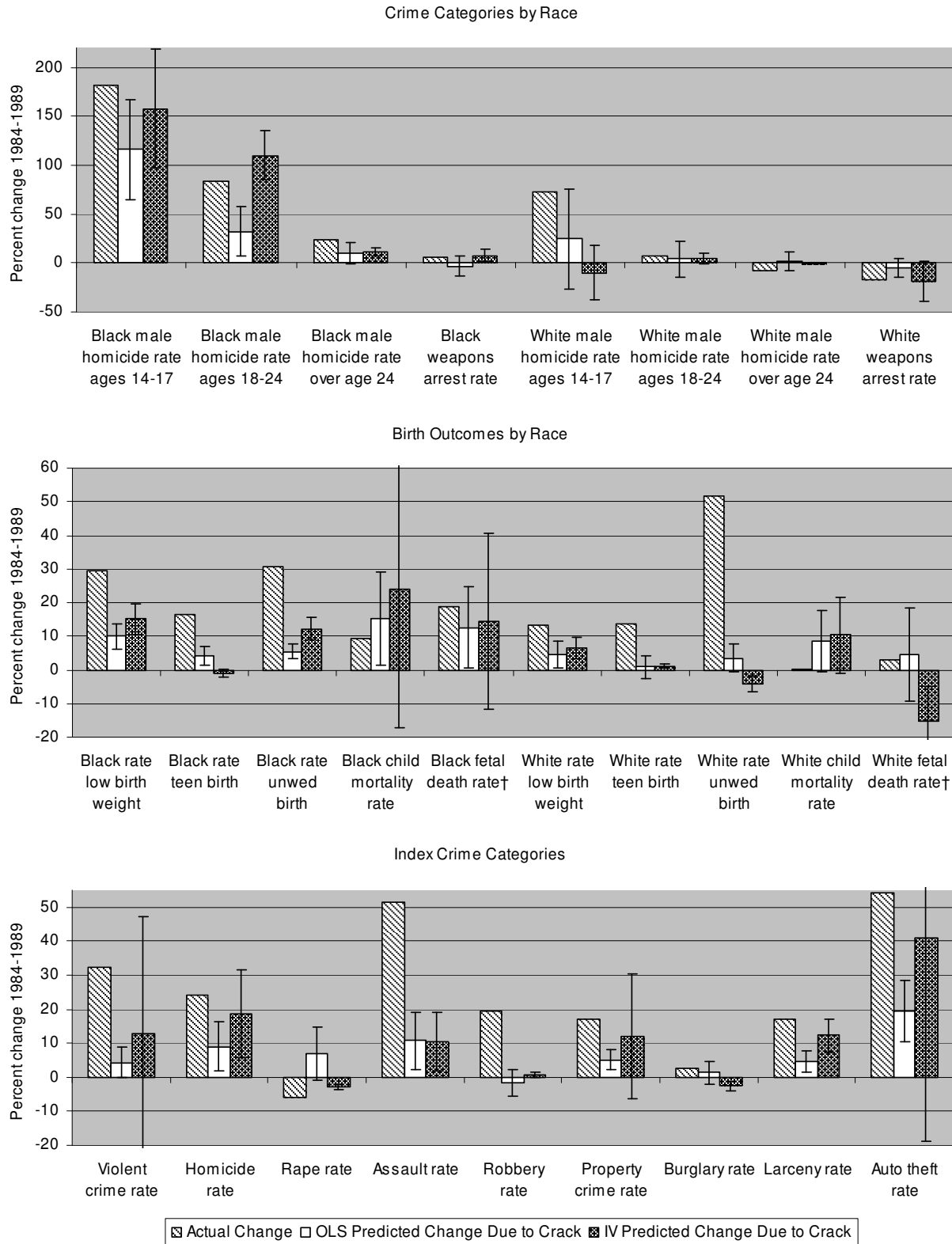
The regional indices were estimated using year-by-year cross sectional regressions of the city-level crack index on indicator variables for the specified regions.

Figure 7: Crack Indices by City Size



The indices were estimated using year-by-year cross sectional regressions of the crack index on indicator variables for the specified city size.

Figure 8: Actual Changes in Social Outcomes and Predicted Changes Due to Crack 1984-1989, City-Level Sample

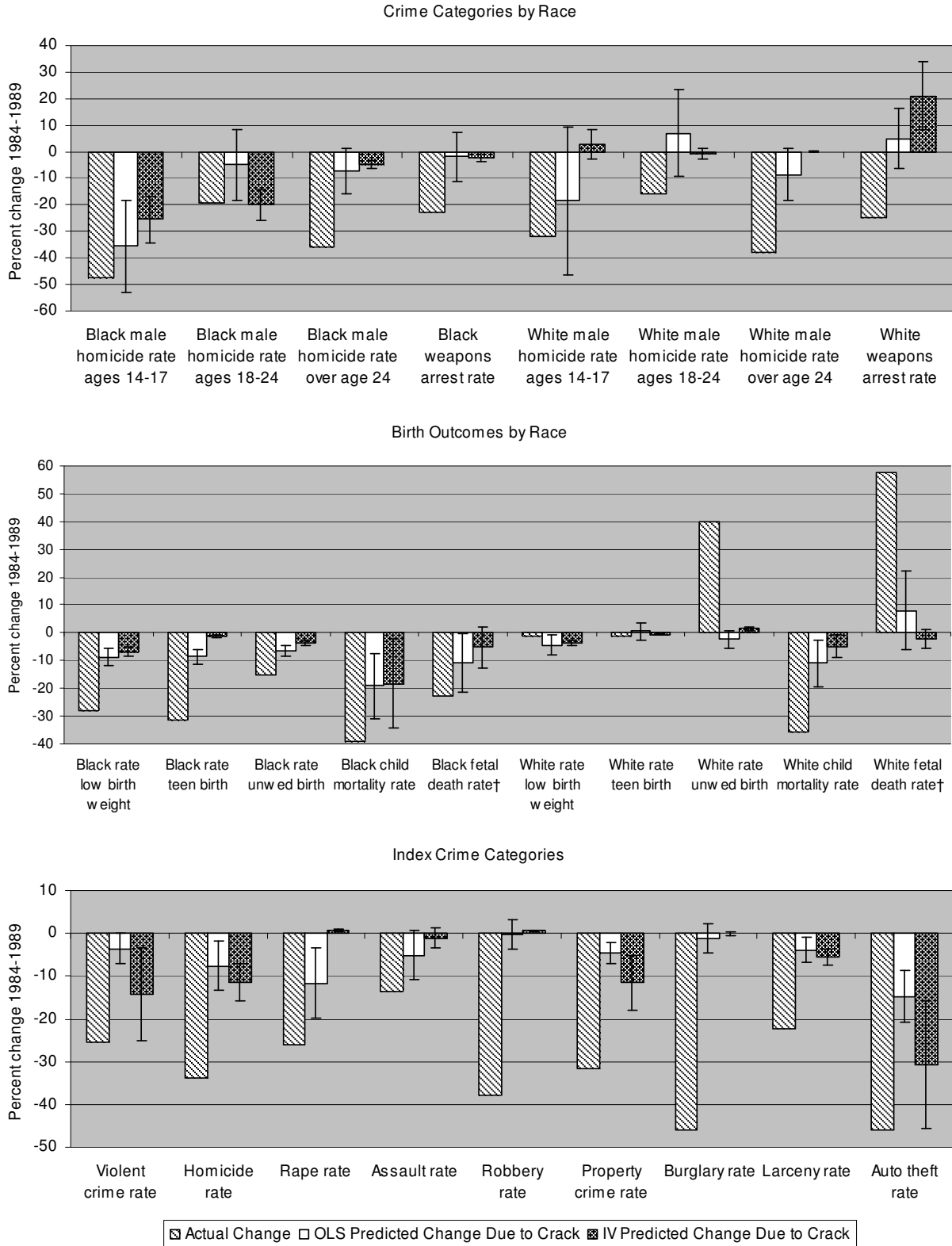


† indicates that data are available from 1980 to 1998 only. The leftmost bar (“Actual Change”) plots the actual percent change in the outcome of interest between 1984 and 1989 with 1984 as the base year. To obtain the “OLS Predicted Change Due to Crack” (middle bar), let

$\hat{\beta}_{85-89}$ denote the estimated effect of crack during the 1985-1989 period, \bar{C}_{89} denote the mean crack index in 1989, and \bar{Y}_{84} denote the mean value of the outcome of interest in 1984. The predicted change is constructed as $\frac{\hat{\beta}_{85-89}\bar{C}_{89} - \hat{\beta}_{80-84}\bar{C}_{84}}{\bar{Y}_{84}}$. The IV predicted

changes are constructed similarly, except that the coefficients are based on an instrumental variables strategy in which cocaine arrests are used as the right-hand-side variable in equation (3) and a crack index constructed using the other crack proxies is used as an instrumental variable. In calculating the implied impact of crack using IV, only the portion of the observed variation in cocaine arrests attributable to variation in crack is relevant. It can be shown that algebraically this equates to scaling down the full variation in cocaine arrests by the signal to signal-plus-noise ratio in cocaine arrests. This signal to signal-plus-noise ratio can be computed from the variance-covariance matrix of the crack proxies, combined with a scaling adjustment across proxies that can be inferred from the ratio of the IV estimates when one proxy is used as the instrument and the other variable is instrumented versus when the roles of the two variables are reversed. OLS and IV regressions include controls for percent of the population Hispanic, percent of the population Black, log population, and log per capita income as well as city and year fixed effects. The whiskers display 95% confidence intervals for the OLS and IV estimated effects. To facilitate comparison of effect sizes across social outcomes, in some cases confidence intervals were permitted to extend beyond the bounds of the plots. The OLS estimates were estimated allowing AR(1) serial correlation in the error terms; IV standard errors were obtained via the bootstrap.

Figure 9: Actual Changes in Social Outcomes and Predicted Changes Due to Crack 1989-2000, City-Level Sample

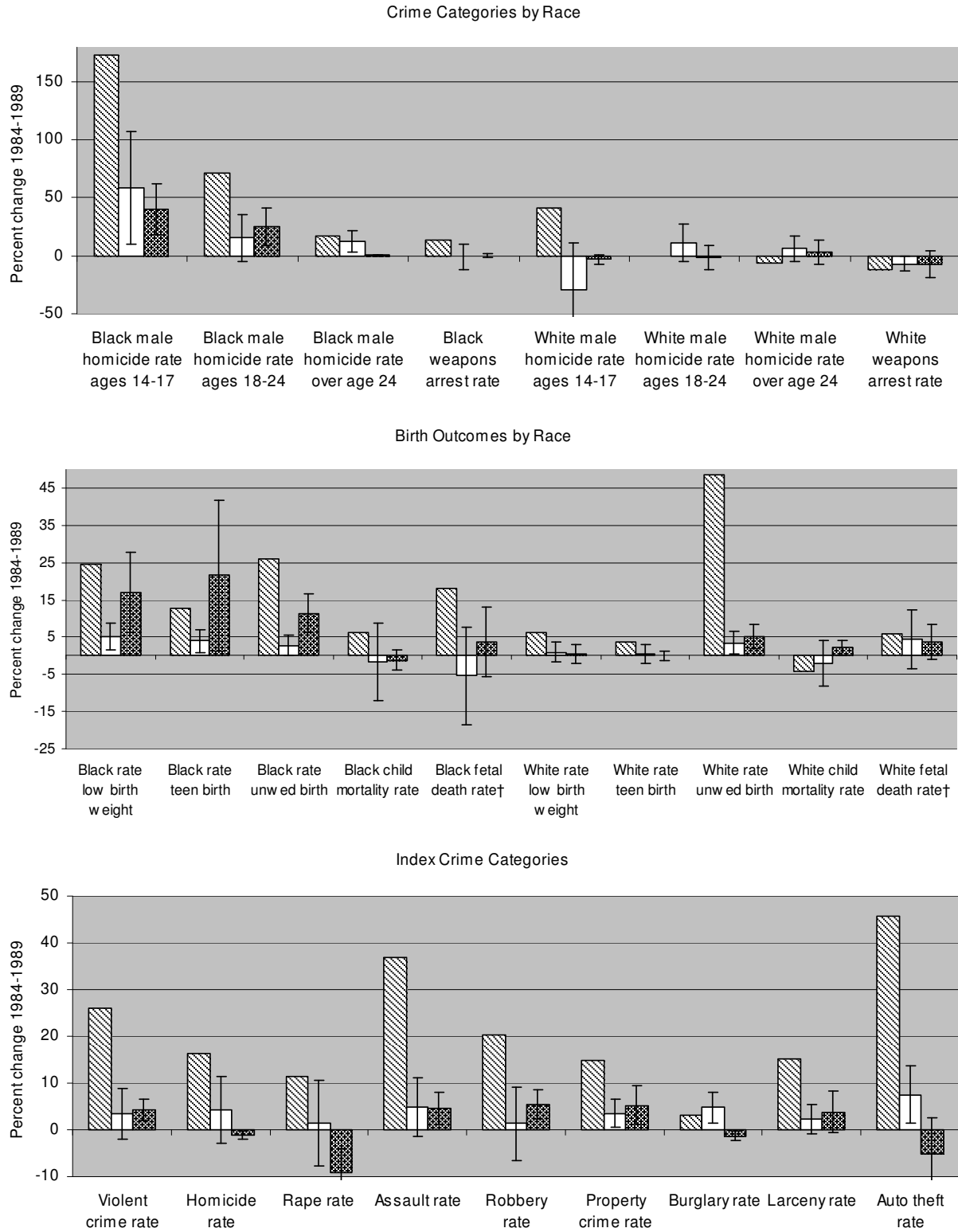


† indicates that data are available from 1980 to 1998 only. The leftmost bar (“Actual Change”) plots the actual percent change in the outcome of interest between 1989 and 2000 with 1989 as the base year. To obtain the “OLS Predicted Change Due to Crack” (middle bar), let

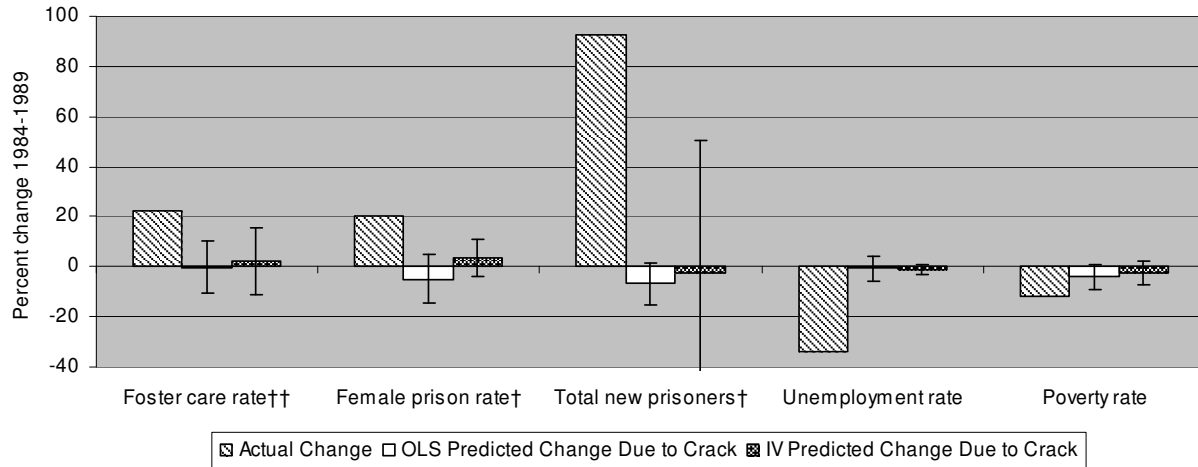
$\hat{\beta}_{85-89}$ denote the estimated effect of crack during the 1985-1989 period, \bar{C}_{89} denote the mean crack index in 1989, and \bar{Y}_{89} denote the mean value of the outcome of interest in 1989. The predicted change is constructed as $\frac{\hat{\beta}_{95-00}\bar{C}_{00} - \hat{\beta}_{85-89}\bar{C}_{89}}{\bar{Y}_{89}}$. For outcomes that were

not available through 2000 the change from 1989 through the final year of available data is reported in the final column. The IV predicted changes are constructed similarly, except that the coefficients are based on an instrumental variables strategy in which cocaine arrests are used as the right-hand-side variable in equation (3) and a crack index constructed using the other crack proxies is used as an instrumental variable. In calculating the implied impact of crack using IV, only the portion of the observed variation in cocaine arrests attributable to variation in crack is relevant. It can be shown that algebraically this equates to scaling down the full variation in cocaine arrests by the signal to signal-plus-noise ratio in cocaine arrests. This signal to signal-plus-noise ratio can be computed from the variance-covariance matrix of the crack proxies, combined with a scaling adjustment across proxies that can be inferred from the ratio of the IV estimates when one proxy is used as the instrument and the other variable is instrumented versus when the roles of the two variables are reversed. OLS and IV regressions include controls for percent of the population Hispanic, percent of the population Black, log population, and log per capita income as well as city and year fixed effects. The whiskers display 95% confidence intervals for the OLS and IV estimated effects. To facilitate comparison of effect sizes across social outcomes, in some cases confidence intervals were permitted to extend beyond the bounds of the plots. The OLS estimates were estimated allowing AR(1) serial correlation in the error terms; IV standard errors were obtained via the bootstrap.

Figure 10: Actual Changes in Social Outcomes and Predicted Changes Due to Crack 1984-1989, State-Level Sample



Other Social Outcomes



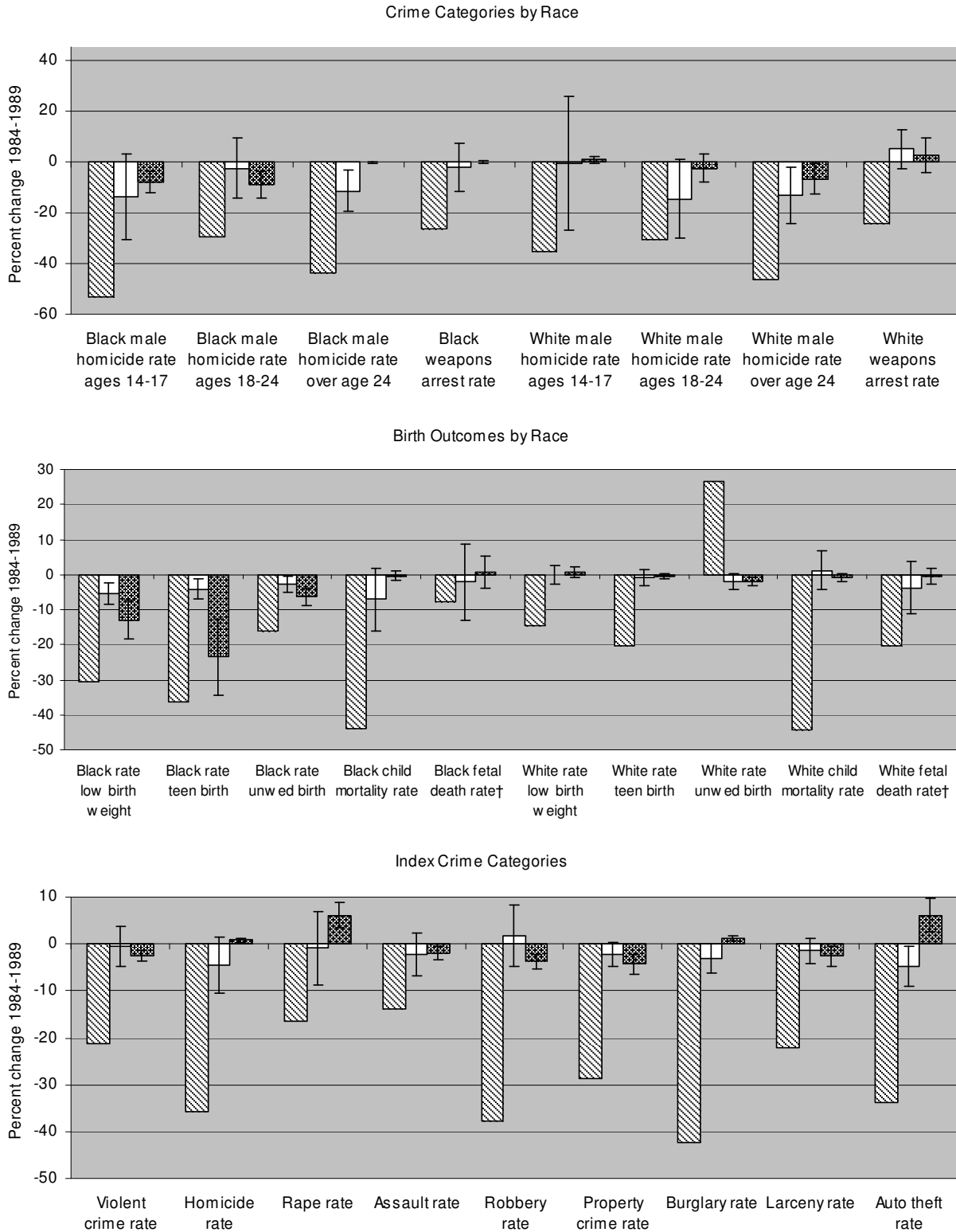
† indicates that data are available from 1980 to 1998 only and †† indicates that data are available from 1983 through 1995 only. The leftmost bar (“Actual Change”) plots the actual percent change in the outcome of interest between 1984 and 1989 with 1984 as the base year. To obtain the “OLS Predicted Change Due to Crack” (middle bar), let $\hat{\beta}_{85-89}$ denote the estimated effect of crack during the 1985-1989 period, \bar{C}_{89} denote the mean crack index in 1989, and \bar{Y}_{84} denote the mean value of the outcome of interest in 1984. The predicted change is constructed as

$$\frac{\hat{\beta}_{85-89} \bar{C}_{89} - \hat{\beta}_{80-84} \bar{C}_{84}}{\bar{Y}_{84}}.$$

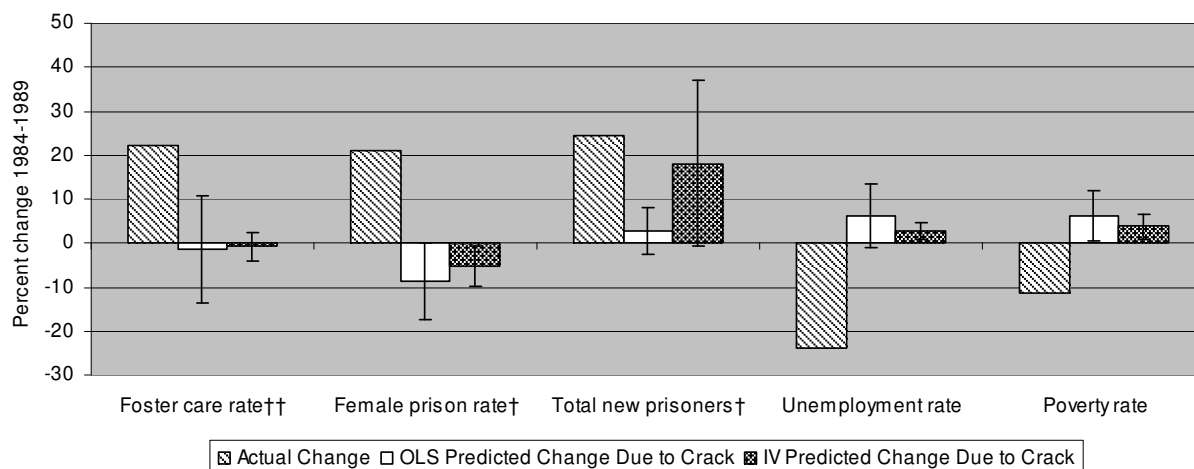
The IV predicted changes are constructed similarly, except that the coefficients are based on an instrumental

variables strategy in which cocaine arrests are used as the right-hand-side variable in equation (3) and a crack index constructed using the other crack proxies is used as an instrumental variable. In calculating the implied impact of crack using IV, only the portion of the observed variation in cocaine arrests attributable to variation in crack is relevant. It can be shown that algebraically this equates to scaling down the full variation in cocaine arrests by the signal to signal-plus-noise ratio in cocaine arrests. This signal to signal-plus-noise ratio can be computed from the variance-covariance matrix of the crack proxies, combined with a scaling adjustment across proxies that can be inferred from the ratio of the IV estimates when one proxy is used as the instrument and the other variable is instrumented versus when the roles of the two variables are reversed. OLS and IV regressions include controls for percent of the population Hispanic, percent of the population Black, log population, and log per capita income as well as state and year fixed effects. The whiskers display 95% confidence intervals for the OLS and IV estimated effects. To facilitate comparison of effect sizes across social outcomes, in some cases confidence intervals were permitted to extend beyond the bounds of the plots. The OLS estimates were estimated allowing AR(1) serial correlation in the error terms; IV standard errors were obtained via the bootstrap.

Figure 11: Actual Changes in Social Outcomes and Predicted Changes Due to Crack 1989-2000, State-Level Sample



Other Social Outcomes



† indicates that data are available from 1980 to 1998 only and †† indicates that data are available from 1983 through 1995 only. The leftmost bar (“Actual Change”) plots the actual percent change in the outcome of interest between 1984 and 1989 with 1984 as the base year. . To obtain the “OLS Predicted Change Due to Crack” (middle bar), let $\hat{\beta}_{85-89}$ denote the estimated effect of crack during the 1985-1989 period, \bar{C}_{89} denote the mean crack index in 1989, and \bar{Y}_{89} denote the mean value of the outcome of interest in 1989. The predicted change is constructed as

$$\frac{\hat{\beta}_{95-00} \bar{C}_{00} - \hat{\beta}_{85-89} \bar{C}_{89}}{\bar{Y}_{89}} .$$

The IV predicted changes are constructed similarly, except that the coefficients are based on an instrumental

variables strategy in which cocaine arrests are used as the right-hand-side variable in equation (3) and a crack index constructed using the other crack proxies is used as an instrumental variable. In calculating the implied impact of crack using IV, only the portion of the observed variation in cocaine arrests attributable to variation in crack is relevant. It can be shown that algebraically this equates to scaling down the full variation in cocaine arrests by the signal to signal-plus-noise ratio in cocaine arrests. This signal to signal-plus-noise ratio can be computed from the variance-covariance matrix of the crack proxies, combined with a scaling adjustment across proxies that can be inferred from the ratio of the IV estimates when one proxy is used as the instrument and the other variable is instrumented versus when the roles of the two variables are reversed. OLS and IV regressions include controls for percent of the population Hispanic, percent of the population Black, log population, and log per capita income as well as state and year fixed effects. The whiskers display 95% confidence intervals for the OLS and IV estimated effects. To facilitate comparison of effect sizes across social outcomes, in some cases confidence intervals were permitted to extend beyond the bounds of the plots. The OLS estimates were estimated allowing AR(1) serial correlation in the error terms; IV standard errors were obtained via the bootstrap.

References

- Almond, Douglas., Chay, Kenneth, and Greenstone, Michael. 2003. "Civil Rights, The War on Poverty, and Black-White Convergence in Infant Mortality in Mississippi." Mimeo. MIT.
- Ayres, Ian., and Donohue, John. 2003. "Shooting Down the More Guns, Less Crime Hypothesis," *55 Stanford Law Review* 1193 (2003)
- Baumer, Eric P. 1994. "Poverty, Crack, and Crime: A Cross-City Analysis." *Journal of Research in Crime and Delinquency* 31:311-327.
- Baumer, Eric P., Janet Lauritsen, Richard Rosenfeld, and Richard Wright. 1998. "The Influence of Crack Cocaine on Robbery, Burglary, and Homicide Rates: A Cross- City, Longitudinal Analysis." *Journal of Research in Crime and Delinquency* 33:316-340.
- Bayer, Linda. 2000. *Crack and Cocaine*. New York: Chelsea House Publishers.
- Beckett, Katherine, Kris Nyrop, and Lori Pflingst, 2006, "Race, Drugs, and Policing: Understanding Disparities in Drug Delivery Arrests." *Criminology* 44:105-137.
- Bennett, William, John DiIulio, and John Walters, 1996, Body Count, New York: Simon and Schuster.
- Blank, Rebecca. 2001. An Overview of Social and Economic Trends, By Race." In *America Becoming: Racial Trends and Their Consequences*. Neil J. Smelser, William J. Wilson, and Faith Mitchell, Editors. Commission on Behavioral and Social Sciences and Education. Washington, DC: National Academy Press, pp. 21-40.
- Blumstein, Alfred, 1995, "Youth Violence, Guns, and the Illicit-Drug Industry," *Journal of Criminal Law and Criminology*, vol 86, no. 1, pp. 10-36.
- Blumstein, Alfred, and Richard Rosenfeld, 1998, "Explaining Recent Trends in U.S. Homicide Rates." *The Journal of Criminal Law and Criminology* 88:1175.
- Boston, Thomas. 2001. Trends in Minority-Owned Businesses. In *America Becoming: Racial Trends and Their Consequences*. Neil J. Smelser, William J. Wilson, and Faith Mitchell, Editors. Commission on Behavioral and Social Sciences and Education. Washington, DC: National Academy Press, pp 190-221.
- Bourgois, Phillip. 2002. *In Search of Respect: Selling Crack in El Barrio*. Cambridge University Press.
- Centers for Disease Control. 2004. "HIV/AIDS among African Americans."
- Chitwood, Dale, James Rivers, and James Inciardi. 1996. *The American Pipe Dream: Crack Cocaine and the Inner City*. Austin: Harcourt Brace College Publishers.

- Cook, Philip, and John Laub, 1998, "The Unprecedented Epidemic in Youth Violence," in Michael Tonry (ed.) *Crime and Justice: An Annual Review of Research*, 26-64, University of Chicago Press.
- Cork, Daniel, 1999, "Examining Space-Time Interaction in City-Level Homicide Data: Crack Markets and the Diffusion of Guns Among Youth," *Journal of Quantitative Criminology* 15(4):379-406.
- Corman, Hope and Mocan, H. Naci, 2000, "A Time-Series Analysis of Crime, Deterrence, and Drug Abuse in New York City." *American Economic Review*, 90 (June): 584-604.
- Datta-Bhutada, S., H. L. Johnson, and T. S. Rosen, 1998, "Intrauterine cocaine and crack exposure: neonatal outcome," *Journal of Perinatology* May-Jun;18(3):183-8.
- Donohue, John, and Steven Levitt, 2001, "Legalized Abortion and Crime", *Quarterly Journal of Economics* 116 (2): 379-420.
- Ferguson, Ronald. 2001. "Test Score Trends Along Racial Lines, 1971-1996: Popular Culture and Community Academic Standards." In *America Becoming: Racial Trends and Their Consequences*. Neil J. Smelser, William J. Wilson, and Faith Mitchell, Editors. Commission on Behavioral and Social Sciences and Education. Washington, DC: National Academy Press, pp.348-391.
- Frank et. al. 2001. "Growth, Development, and Behavior in Early Childhood Following Prenatal Cocaine Exposure: A Systematic Review" *The Journal of the American Medical Association*, 285(12), 1613-1625.
- Grissmer, Flanagan, and Williamson. 1998. Why Did The Gap Narrow? In *The Black White Test Score Gap*. Christopher Jencks and Meredith Phillips, Editors.
- Grogger, Jeff, and Michael Willis, 2000, "The Emergence of Crack Cocaine and the Rise in Urban Crime Rates," *Review of Economics and Statistics* 82(November): 519-529.
- Horowitz, Joel, 2001, "Should the DEA's STRIDE Data Be Used for Economic Analyses of Markets for Illegal Drugs?" *Journal of the American Statistical Association* 96: 1254-1262.
- Jacobs, Bruce. 1999. *Dealing Crack: The Social World of Streetcorner Selling*. Boston: Northeastern University Press.
- Johnston, L.D., P.M. O'Malley, J.G. Bachman, and J.E. Schulenberg, 2004, *Monitoring the Future national survey results on drug use, 1975-2003. Volume I: Secondary school students* (NIH Publication No. 04-5507). Bethesda, MD: National Institute on Drug Abuse.
- Joyce, Ted. 2004. "Did Legalized Abortion Lower Crime?" *Journal of Human Resources* 39(1): 1-28.

- Levitt, Steven, 1998, "Juvenile Crime and Punishment." *Journal of Political Economy*, 106 (December): 1156-1185.
- Levitt, Steven, and Sudhir Venkatesh, 2000, "An Economic Analysis of a Drug-Selling Gang's Finances." *Quarterly Journal of Economics* 115 (August): 755-789.
- Lott, John. R. 2000. *More Guns, Less Crime: Understanding Crime and Gun Control Laws*. Chicago: University of Chicago Press.
- Lott, John., and Mustard, David. 1997. Crime, Deterrence, and Right-to-Carry Concealed Handguns. *Journal of Legal Studies*, 26 (1), 1-68.
- Lubotsky, Darren, and Martin Wittenberg. 2004. "Interpretation of Regressions with Multiple Proxies." Unpublished manuscript, University of Illinois at Champaign-Urbana.
- MacCoun, Robert, and Peter Reuter, 2001, Drug War Heresies: Learning from Other Vices, Times, & Places, Cambridge: Cambridge University Press.
- Neal, Derek. 2004. Why Has Black-White Skill Convergence Stopped? Mimeo. University of Chicago.
- Ousey, Graham, and Matthew Lee, 2002, "Examining the conditional nature of the illicit drug market-homicide relationship: A partial test of the theory of contingent causation. *Criminology* 40 (1, Feb): 73-102.
- Ousey, Graham, and Matthew Lee, 2004, "Investigating the Connections between race, illicit drug markets, and lethal violence, 1984-1997." *Journal of Research in Crime and Delinquency*, 40 (March): 1-32.
- Sailer, Steven, 1999, "Does Abortion Prevent Crime?" *Slate Magazine*, August 23.
- Substance Abuse and Mental Health Services Administration, 2003a, *Emergency Department Trends from the Drug Abuse Warning Network, Final Estimates 1995-2002*, DHHS Publication No. 03-3780, Rockville, Maryland.
- Substance Abuse and Mental Health Services Administration, 2003b, *National Survey on Drug Use and Health, Detailed Tables*. Rockville, Maryland.
- Venkatesh, Sudhir, and Steven Levitt, 2000, "Are We a Family or a Business? History and Disjuncture in the Urban American Street Gang," *Theory and Society*, 29 (Volume 3): 427-462.
- Welch, Finis. 2003. Catching Up: "Wages of Black Men." *The American Economic Review*, 93 (2), pp. 320-325.
- Wilson, James Q. 1990. "Against the Legalization of Drugs," *Commentary* 89, pp. 21-28.
- Zuckerman, Frank, and Mayes. 2002. "Cocaine Exposed Infants and Developmental Outcomes:

“Crack Kids” Revisited.” *The Journal of the American Medical Association*, 287 (15), 1990-1991.