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CRIME, URBAN FLIGHT, AND THE CONSEQUENCES FOR CITIES

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Abstract—This paper analyzes the link between rising city crime rates and urban flight. Each additional reported crime is associated with a roughly one-person decline in city population. Almost all of the crime-related population decline is attributable to increased out-migration rather than a decrease in new arrivals. Households that leave the city because of crime are much more likely to remain within the Standard Metropolitan Statistical Area (SMSA) than those that leave the city for other reasons. Migration decisions of highly educated households and those with children are particularly responsive to changes in crime. Causality appears to run from rising crime rates to city depopulation.

I. Introduction

THE DIFFICULTIES confronting large American cities in recent decades are well documented (e.g., Bradbury et al., 1982; Gottdeiner, 1986, Wilson, 1987; Inman et al., 1994). Crime is one of the greatest challenges facing large American cities. Violent crime rates in U.S. cities with populations over 500,000 in 1993, were four times higher than in cities with populations below 50,000, and seven times greater than in rural areas.[1] The level of crime in large cities is even more remarkable when one considers that both per capita expenditures on police and the level of victim precaution (e.g., locked doors, private security guards, alarm systems) are much greater in large cities.[2] Recent estimates suggest that the average crime victimization cost per resident in large cities is over $1,000 annually (Miller et al., 1993).

This paper examines the link between crime and urban flight. Anecdotal evidence suggests that rising crime rates in cities like Detroit drove residents to the suburbs, but there has been little formal analysis of the issue. A number of studies have included the crime level as an explanatory variable in determining city population (e.g., Frey, 1979; Grubb, 1982; Katzman, 1980; Sampson & Wooldredge, 1986), but the role of crime has generally not been the primary focus.[3]

It is important to note that economic theory does not necessarily predict a strong link between rising crime and urban flight. If the costs of crime are fully capitalized into property values, then unexpected rises in crime impose costs on property holders, but need not lead to depopulation. Even with full capitalization, however, some population decline might be expected, since lower housing costs may lead residents to demand more housing per person (leading to a smaller equilibrium population level). Rises in crime could also lead to urban flight if there are fixed costs of upkeep on housing. Then, crime-related declines in values may lead some housing units to fall below a critical level, leading to abandonment. Rising crime will also lead to city depopulation if disamenities are not fully capitalized.

The results we obtain are consistent with a strong relationship between changes in crime rates and urban flight. Regardless of the time-scale of the observations (i.e., annual data, 5 yr. differences, or 10 yr. differences), the level of aggregation (city-level versus household-level data), or the control variables included in the analysis, our basic finding is remarkably robust. Each additional reported index crime in a central city is associated with a net decline of approximately one resident. A 10% increase in crime corresponds to a 1% decline in city population. Using household-level data, we are able to determine the relative responsiveness of different population subgroups. Our results suggest that almost all of the impact of crime on city population results from increased out-migration; the link between changes in crime and in-migration appears weak.

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[1] The ***Uniform Crime Reports,*** which reflect only those crimes reported to the police, are likely to understate the actual difference in crime rates across city types because of the greater likelihood a crime will be reported to the police in smaller cities (Levitt, 1998).

[2] In 1990 to 1991, cities with populations over 1,000,000 spent an average of $210 per capita on police protection, whereas cities with populations below 75,000 expended an average of $97 per capita (U.S. Bureau of the Census, 1993).

[3] There is an extensive literature analyzing urban flight more generally (e.g., Taeuber & Taeuber, 1964; Bradford & Kelejian, 1973; Frey, 1979; Marshall, 1979; Marshall & O'Flaherty, 1987). This literature has considered both the role of the increasing attractiveness of suburbs due to declining transportation costs and higher incomes (e.g., Mieszkowski & Mills, 1993) and city disamenities.

The Review of Economics and Statistics, May 1999, 81(2): 159–169

Highly educated households and households with children are most responsive to crime.

The results described in the preceding paragraph are based on correlational analysis. We attempt to distinguish between correlation and causality using lagged changes in the punitiveness of the ***state*** criminal justice system as instrumental variables for changes in a city's crime rate. These state criminal justice variables are demonstrated to affect city-level crime in the predicted manner and are plausibly excluded from the city population equation. Using either 2SLS or LIML, the instrumental variables estimates are at least as large as the OLS coefficients, suggesting that the correlational results may understate the true causal impact of crime rates on city population.

The remainder of the paper is structured as follows. Section II describes the methodology and data used in the analysis. Section III demonstrates the strong empirical relationship between changes in crime rates and changes in city population, as well as exploring the sensitivity of the results to changes in specification. Section IV uses household-level data from the 1980 census to isolate the responsiveness of different population subgroups to crime. Section V concludes.

II. Methodology and Data

Our empirical strategy involves regressing various measures of urban flight on changes in crime rates and an extensive collection of covariates and indicator variables (e.g., year dummies and city-fixed effects). We focus primarily on the link between changes in population and changes in crime rates. There are both theoretical and methodological justifications for examining changes in crime rates. From a theoretical perspective, it seems more logical to look at changes. If a city has a historically high crime rate, then that information will already have been incorporated into the past location decisions of residents. Only as crime rises (or as expectations of future crime rise) will there be an increased incentive for residents to flee the city. On a practical level, focusing on changes mitigates the problems associated with noncomparabilities in crime-reporting rates, crime definitions, and police department practices across cities (O'Brien, 1985).

The analysis is based on three different data sets. Table 1 presents the summary statistics for the variables used in each of the data sets. The appendix describes in detail the sources and construction of the variables.

The first data set consists of city-level data covering the last three decennial census years for 127 U.S. cities with populations greater than 100,000 in 1970. The benefit of limiting the sample to census years is the wealth of city-level variables that are available only in census years: median family income, racial breakdowns, education levels, employment by sector, percentage in owner-occupied housing, etc. These data allow us to examine the long run (10 yr.) relationship between city population and crime rates. The availability of such an extensive list of covariates lessens the

Table 1.—Summary Statistics

Variable	Census Year Data: 1970, 1980, 1990 (127 cities; 10 yr. changes)	Annual Data: 1976–1993 (127 cities; 1 yr. changes)	PUMS Data: 1980 (81 cities; 5 yr. changes)
City population	405,937 (745,899) [39,506]	414,809 (742,274) [44,014]	483,231 (924,740)
Δln(city population)	0.035 (0.154) [0.063]	0.0035 (0.0315) [0.0283]	−0.081[a] (0.091)
Per capita city crime	0.097 (0.026) [0.009]	0.091 (0.026) [0.013]	0.086 (0.021)
Δ (Per capita city crime)	0.018 (0.021) [0.017]	0.0007 (0.0084) [0.0083]	0.012 (0.014)
Unemployment rate	0.054 (0.021) [0.015]	0.066 (0.024) [0.018]	0.086 (0.021)
Median family income	33,668 (4,592) [1,827]	33,375 (5,378) [1,923]	35,083 (3,729)
% black	0.204 (0.151) [0.029]	0.232 (0.168) [0.020]	0.200 (0.143)
% aged 0–17	0.314 (0.036) [0.031]	0.276 (0.026) [0.017]	0.310 (0.017)
% aged 18–24	0.126 (0.011) [0.007]	0.123 (0.012) [0.011]	0.129 (0.008)
% aged 25–44	0.257 (0.024) [0.021]	0.295 (0.030) [0.024]	0.252 (0.012)
% aged 45–64	0.199 (0.014) [0.005]	0.191 (0.014) [0.006]	0.204 (0.014)
Per capita suburban crime	—	0.047 (0.016) [0.006]	—
Δ (Per capita suburban crime)	—	−0.0001 (0.0048) [0.0048]	—
% manufacturing	0.216 (0.091) [0.021]	—	0.232 (0.101)
% home owner	0.538 (0.110) [0.018]	—	0.522 (0.125)
% high-school graduate	0.593 (0.114) [0.066]	—	0.526 (0.097)
Average July temperature (°F)	76.8 (5.1) [0.0]	—	75.5 (5.2)
Average January temperature (°F)	37.9 (11.7) [0.0]	—	37.8 (12.9)
Average yearly precipitation (inches)	35.5 (13.0) [0.0]	—	35.5 (14.1)

Notes: [a] This entry corresponds to net migration, rather than overall population changes, which also includes births and deaths.

Column 1 presents city-level data from the 1970, 1980, and 1990 censuses for 127 U.S. central cities with populations greater than 100,000 in 1970. Column 2 presents annual observations from 1976 to 1993 for the same set of cities. Column 3 presents city-level data for the 81 cities in the preceding sample for which 1980 PUMS data are available. See the appendix for more-detailed variable definitions. For the variables in levels that are used as controls in the regressions, the reported values are for the base year (i.e., 1980 if we are considering changes between 1980 and 1990 in the decadal data). Standard deviations are in parentheses. Within-city standard deviations are in square brackets. Since the 1980 PUMS data are a single cross section, there is no within-city variation.

concerns about the importance of omitted variables. The mean population for cities in the sample is roughly 400,000. These cities are growing slowly (approximately 3.5% per decade). Roughly nine index crimes are reported annually per 100 city residents, a number which increases slightly over time.

The second data set is a yearly city-level panel for the same set of cities described above, covering the years 1976 to 1993. Using this annual frequency data, it is possible to estimate the short-run (within a year) relationship between city population and crime rates. These yearly data will also prove useful in testing the sensitivity of our results to alternative specifications and instrumental variables approaches. The primary shortcoming of the data is the limited collection of city-level variables that is available on an annual basis. Both city population data and crimes reported to the police are available yearly. It should be noted, however, that in noncensus years the population data are not exhaustive counts, but rather estimates that are derived from Current Population Reports and birth and death records. The other variables that we use are either for more-aggregated geographic areas or interpolated between census years. Lacking other covariates, we utilize year and region dummies—and, in some cases, city-fixed effects and/or region-year interactions—in an attempt to control for omitted factors.

The final data set is drawn from household-level data in the Public Use Microdata Sample (PUMS) 5% sample of the 1980 census. Half of those households included in the PUMS data were asked the place of residence of the household head in 1975 and 1980, which allows us to construct measures of net migration. Due to census data-collection methods, we are able to identify the city of residence for only 81 of 127 cities included in the city-level data sets described above. In the other cities, census areas do not correspond to city boundaries. These 81 cities are on average larger than the overall sample, but appear otherwise representative.[4] We divide households within these cities into three migration categories: stayers, comers, and goers. Households that do not move, or move but remain within city limits, are categorized as ***stayers.*** Those who arrive in a city or leave the city are classified as ***comers*** or ***goers,*** respectively.

Despite the drawback that these data represent only a single cross section, they allow us to conduct an expanded analysis of the migration response. Initially, we aggregate this net migration variable to the city level in order to confirm the results of the other two data sets and to explore the responsiveness of population subgroups. We then conduct household-level analysis for the nearly 400,000 households in these 81 cities, including detailed information on the household itself.

For all three data sets employed, the measure of crime used is the per capita number of index crimes that are reported to the police and collected in the Federal Bureau of Investigation's ***Uniform Crime Reports.***[5] In a previous version of this paper, we attempted to disaggregate crimes into violent and property, obtaining similar coefficients on both types. In the current version, we present only estimates aggregated over all crime categories in the tables.

The proxy used for urban flight depends on the data set. When using city-level aggregates (the first two data sets described), we are limited to net population changes, which include not only migration in and out of cities, but also births, deaths, and immigration. Empirically, however, the primary factor that drives city population changes is migration. Roughly 6% of the U.S. population moves across county lines each year (Schwartz, 1987), compared to the annual rates of birth (1.5), death (0.9), and immigration (0.2) per hundred annually. When we use household-level data, we are able to focus directly on net migration and obtain similar results.

III. Correlation Between Changes in Crime and Changes in City Population

We begin our analysis by looking at simple correlations between changes in crime and city population using data from the 1970, 1980, and 1990 censuses (the first data set described above). Figure 1 plots 10 yr. changes in per capita crime rates against the log change in city population over the same period. Although visual inspection of the data does not reveal an obvious pattern, the slope of a simple regression (which is overlaid in the figure) is -1.20 (standard error equal to 0.48). The regression coefficient can be interpreted as the reduction in city residents per crime.

Much of the variation in city populations in figure 1 represent systematic differences in city growth rates over time (e.g., sun-belt cities growing much more quickly than rust-belt cities). Figure 2 is identical to figure 1, except that city-fixed effects have been removed. The slope of the

[4] In table 1, there are significant differences between the means of some variables in columns 1 and 2 compared to the PUMS data in column 3. This is primarily because the PUMS data are only for 1980 (the variables in changes are between 1975 and 1980), but the other columns cover an extended time period. For instance, unemployment is high in column 3 because national unemployment was unusually high in 1980. The most significant notable difference is in the row corresponding to changes in population. In the first two columns, city populations are growing; in the last column, populations are shrinking. The explanation is that the population change corresponds to total population in the first two columns (the only data available), but is limited to ***net migration*** (which more closely corresponds to what we wish to test) in the final column. The growth in overall city population is due to births outpacing deaths, not to net migration.

[5] UCR data are subject to a number of criticisms. In particular, a large number of victimizations are not reported to the police, departments differ as to how they classify crimes, department recording practices appear to have changed over time, and the aggregate trends do not closely match that of victimization data (O'Brien, 1985; Donohue & Siegelman, 1994; Levitt, 1998). Ideally, one would like to test the sensitivity of the results using victimization data in place of reported crime data. Unfortunately, existing victimization data is not disaggregated below the region level, precluding such a test. Note that, in the specifications that include city-fixed effects, any cross-department differences in crime reporting or recording are eliminated, although changes in a given city's practices over time will affect the estimates.

FIGURE 1.—CITY CRIME AND POPULATION CHANGES BY DECADE

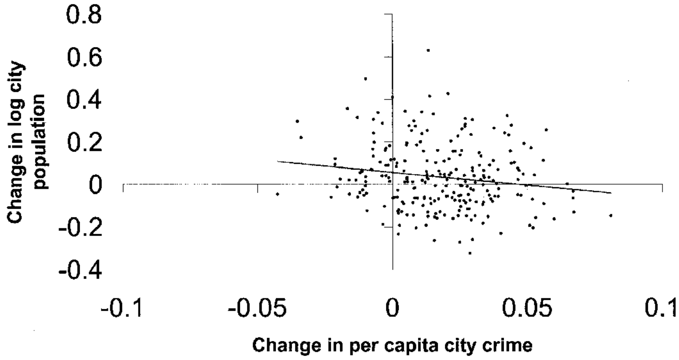
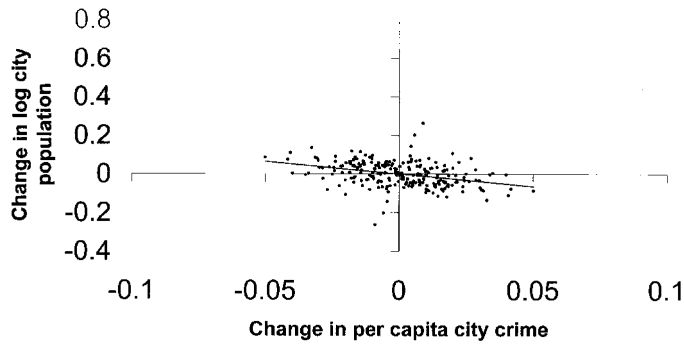


FIGURE 2.—CITY CRIME AND POPULATION CHANGES BY DECADE (WITHIN-CITY VARIATION ONLY)



regression line is virtually unchanged (− 1.29 with a standard error of 0.23), but the points are now much more tightly clustered.

The multiple regression equivalent of figures 1 and 2 adds a range of covariates to capture socioeconomic, economic, and demographic characteristics of the city, Standard Metropolitan Statistics Area (SMSA) and state:

$$\Delta \ln(\boldsymbol{CITY\_POP_{it}}) = \beta\Delta \boldsymbol{CITY\_CRIME_{it}} + + X'_{it}\Gamma + \lambda_t + \gamma_r + \epsilon_{it} \tag{1}$$

where the subscripts $\boldsymbol{i}$, $\boldsymbol{r}$, and $\boldsymbol{t}$ index cities, regions, and years. $\boldsymbol{X}$ represents a vector of covariates that differs according to specification and data set. One-year lags are used for all of the covariates to reduce potential endogeneity problems.[6] λ and γ represent year and region dummies, respectively. In some specifications, city-fixed effects and/or region-year interactions replace region dummies. Since the dependent variable is in changes, including city-fixed effects is equivalent to removing a city-specific trend.

Because the population variable is in log changes (whereas the two crime variables are in changes in per capita rates), this specification allows the impact of changes in crime on mobility to be independent of the level of crime. Other specifications such as log changes in both crime and population, or changes in levels of both variables, yield similar results when evaluated at the sample mean. We present results from this particular specification solely to ease interpreting the coefficients. It is straightforward to demonstrate that the crime coefficient is roughly interpretable as the decline in the number of city residents associated with each additional crime.[7] Our estimation technique is weighted least squares with weights proportional to city population.[8]

[6] We have experimented with including the covariates in either levels or changes, or both levels and changes simultaneously. The crime coefficients are not sensitive to this choice.

[7] In practice, this interpretation slightly exaggerates the magnitude of the impact. The larger the variation in crime rates relative to the variation in city populations, the closer the approximation. In our data, the standard deviation of percent changes in year-to-year crime rates is five to six times larger than the corresponding value for city populations.

[8] The results are not sensitive to weighting.

Table 2 presents the basic findings for each of our three data sets. The first two columns of the table report results from 10 yr. changes based on decennial censuses, columns 3 and 4 present results using annual changes, and column 5 shows results using the 1980 PUMS data, aggregated to the city level. The PUMS data captures mobility between 1975 and 1980. Columns 2 and 4 include city-fixed effects. City-fixed effects cannot be included in the 1980 PUMS sample because the only source of variation is cross-sectional.

The coefficients on changes in the crime rate are in the top row. They range from − 0.50 and − 1.21. These estimates are of the same order as those reported in figures 1 and 2 (which did not include any control variables), but are generally somewhat smaller. The crime coefficients are generally statistically significant at the 0.05 level, except in column 5 where the number of observations is limited. Evaluated at the sample means, a change of one standard deviation in city crime rates (roughly a 10% change in crime) translates into a decline in city population of slightly less than 1%. Somewhat surprisingly, the coefficients based on 1 yr. changes (columns 3 and 4) and 10 yr. changes (columns 1 and 2) are not that different in magnitude, suggesting that much of the link between crime and population appears to occur without a substantial lag.

The other covariates enter in a plausible manner, although the standard errors are generally quite large except when using the annual data set. Changes in SMSA unemployment are associated with a decline in city population. The coefficients in columns 3 and 4 translate into a decrease of roughly 15 to 40 city residents for each 100 additional persons unemployed. That estimate is roughly similar in magnitude to the state-level estimates in Blanchard and Katz (1992). There is mixed evidence on the impact of median family income in a city. The evidence is also unclear as to whether cities with a higher initial fraction of black residents grow more slowly. The age coefficients—which are relative to the omitted category "over age 65"—flip sign with the inclusion of city-fixed effects. Using the decennial census data in columns 1 and 2, there is some evidence that the percent employed in manufacturing, a high proportion of

TABLE 2.—WEIGHTED LEAST-SQUARES ESTIMATES OF THE RELATIONSHIP BETWEEN CITY POPULATION AND CRIME

Variable	Census Years (10 yr. differences) (1)	(2)	Annual Data, 1976–1993 (1 yr. differences) (3)	(4)	1980 Census (5 yr. differences) (5)
Δ (Per capita city crime)	− 1.21	− 0.50	− 0.92	− 0.96	− 1.20
	(0.38)	(0.34)	(0.08)	(0.08)	(0.69)
Unemployment rate	− 0.066	− 0.096	− 0.110	− 0.284	− 0.280
	(0.448)	(0.671)	(0.034)	(0.045)	(0.722)
Median family Income $* 10^6$	− 0.93	− 3.37	0.04	0.12	0.96
	(0.25)	(0.38)	(0.02)	(0.04)	(0.40)
% black	− 0.371	− 0.441	− 0.028	0.074	0.062
	(0.0678)	(0.248)	(0.005)	(0.041)	(0.091)
% aged 0–17	2.27	− 3.25	− 0.23	− 0.64	2.37
	(1.00)	(2.73)	(0.08)	(0.20)	(1.27)
% aged 18–24	2.58	− 3.44	0.46	− 0.66	1.32
	(1.61)	(3.18)	(0.14)	(0.27)	(2.57)
% aged 25–44	2.47	− 1.30	− 0.12	− 0.69	2.92
	(0.91)	(2.15)	(0.06)	(0.23)	(1.29)
% aged 45–64	4.84	− 4.81	− 0.12	− 0.58	5.61
	(2.07)	(4.63)	(0.15)	(0.24)	(2.55)
% manufacturing	0.086	0.402	—	—	− 0.213
	(0.121)	(0.349)			(0.159)
% home owner	0.003	0.152	—	—	0.010
	(0.066)	(0.326)			(0.088)
% high-school graduate	0.829	0.484	—	—	0.288
	(0.143)	(0.253)			(0.190)
Average July temperature (°F)	0.013	—	—	—	0.001
	(0.002)				(0.003)
Average January temperature (°F)	0.001	—	—	—	0.003
	(0.001)				(0.002)
Average yearly precipitation (inches)	− 0.0003	—	—	—	− 0.0012
	(0.0008)				(0.0013)
City Fixed Effects?	No	Yes	No	Yes	No
Adjusted ***R***-squared	0.700	0.853	0.282	0.327	0.431
Crime coefficient, adding region-year interactions to specification	− 0.54	− 0.67	− 1.03	− 1.07	—
	(0.40)	(0.35)	(0.08)	(0.08)	
Crime coefficient, only the 81 cities for which 1980 PUMS data are available	− 1.74	− 0.71	− 0.95	− 0.99	− 1.20
	(0.51)	(0.46)	(0.10)	(0.09)	(0.69)

Notes: Dependent variable is Δln(city population). Columns 1 and 2 are 10 yr. differences using the years 1970, 1980, and 1990 for 127 cities with populations greater than 100,000 in 1970. Columns 3 and 4 are first differences using annual observations from 1976 to 1993 for the same sample of cities. Column 5 is 5 yr. differences (1975 to 1980) for the 81 cities (out of 127) for which 1980 PUMS data are available. Number of observations is equal to 241 in columns 1 and 2; 2,044 in columns 3 and 4; and 81 in column 5. Year dummies are included in all regressions. All variables are available annually, except for % black, which is linearly interpolated between decennial census years in columns 3 and 4, and median family income, which is interpolated between census years using fluctuations in state per capita income. Control variables are once-lagged to minimize endogeneity. See the appendix for further information about the level of geographic disaggregation of the covariates. The method of estimation is weighted least-squares with the weights proportional to city population. Standard errors are in parentheses. The bottom two rows of the table respectively present estimates of the crime coefficient including region-year interactions and limiting the sample to the 81 1980 PUMS cities.

high-school graduates, warm temperatures, and low precipitation are all associated with city population growth.

In order to test the sensitivity of the crime coefficients to different choices of specification, we present results from a range of alternative regressions. The penultimate row of table 2 presents the crime coefficients from regressions that are identical to those in the table, except that region-year interactions (based on the nine census regions) are also included. The decadal results in columns 1 and 2 are somewhat sensitive, with the crime coefficient shrinking in the specification that does not include fixed effects and increasing in the second column, which includes fixed effects. In specifications using the annual data, the crime coefficient increases slightly. The bottom row of table 1 presents estimates limiting the sample to the 81 cities in column 5 to test for evidence of sample selection in the PUMS data set. While the coefficients from the 10 yr. analysis are larger, there is no apparent difference when the restricted sample of cities is used with the annual data.

Table 3 presents a range of other specification checks performed using the annual data set. The small number of observations and long elapsed periods between observations (10 yr. years in the decennial census data and 5 yr. in the PUMS data) make it difficult to test alternative specifications.[9] The first column of table 3 is simply a baseline regression correponding to column 3 of table 2. The next column adds three lags of the ***level*** of crime to test the hypothesis that levels of crime matter, rather than just the ***changes*** in crime. The inclusion of lagged levels of crime has almost no impact on the coefficient on changes in crime. Although the individual lags are statistically significant, the cumulative effect of the three lags (i.e., the sum of the three coefficients) is virtually zero. The absence of a cumulative effect of lags of crime is robust to the number of lags included.

Up to this point, we have focused exclusively on changes in city crime rates, and have ignored changes in suburban crime. As suburban crime rates fluctuate, the relative attractiveness of leaving the city will be affected. If changes in central city and suburban crime are positively correlated, then omitting suburban crime from the regression may understate the impact of crime on urban flight. Column 3 of table 3 adds crime rates in the rest of the Standard Metropolitan Statistical Area (SMSA) excluding the central city as a proxy for suburban crime. As predicted, the city-crime coefficient increases somewhat with the inclusion of suburban crime. The positive coefficient on suburban crime implies that higher crime rates outside the city tend to keep residents in the city. Although the absolute magnitude of the coefficients on city and suburban crime are the same, the differing construction of the two variables means that the interpretation of the coefficients is not the same. In particular, the suburban crime measure is per suburban resident, rather than per city resident. Thus, the interpretation of this coefficient depends on the relative sizes of the city and suburban populations. In our data, suburbs on average have three times as many residents as central cities. To determine

[9] For instance, our instrumental variables lose almost all power when these longer lags are used. More generally, it should be noted that the estimates obtained using the annual data set are more robust than those based on the decennial censuses.

TABLE 3.—TESTING THE ROBUSTNESS OF THE RELATIONSHIP BETWEEN CRIME AND CITY DE-POPULATION USING THE ANNUAL CITY-LEVEL PANEL, 1976–1993

Variable	Dependent Variable is Δln(city population) in All Regressions				
	(1) Baseline Specification	(2) Adding Lagged-Levels of Crime	(3) Adding Suburban Crime Change	(4) Adding Lagged % Change in State Population	(5) Including the Covariates in Both Levels and Changes
Δ (Per capita city crime)	−0.92 (0.08)	−1.00 (0.08)	−1.11 (0.08)	−0.91 (0.08)	−0.99 (0.08)
Per capita city crime (−1)	—	0.52 (0.08)	—	—	—
Per capita city crime (−2)	—	−0.74 (0.11)	—	—	—
Per capita city crime (−3)	—	0.24 (0.08)	—	—	—
Δ (Per capita suburban crime)	—	—	1.14 (0.15)	—	—
Δ ln(State population) (−1)	—	—	—	0.55 (0.09)	—
All covariates in Table 2, Column 3 included?	Yes	Yes	Yes	Yes	Yes
Changes in all covariates in Table 2, Column 3 also included?	No	No	No	No	Yes
Adjusted R^2	0.282	0.299	0.303	0.294	0.295
2SLS coefficient on Δ (Per capita city crime)	−1.19 (0.60)	−1.78 (0.71)	−1.82 (0.76)	−1.18 (0.60)	−1.78 (0.78)
LIML coefficient on Δ (Per capita city crime)	−1.24 (0.65)	−2.21 (0.90)	−1.99 (0.84)	−1.21 (0.64)	−1.84 (0.80)

Notes: The dependent variable in all specifications is Δln(city population). The baseline specification is identical to that of table 2, column 3. The remaining columns in the table are variations on that baseline. All regressions use the city-level annual panel data from 1976 to 1993. In addition to the listed variables, the full set of covariates included in table 2, column 3, are also included here. Method of estimation is weighted least squares with the weights proportional to city population. Due to occasional missing data, the number of observations vary between 1,954 and 2,044. The bottom two rows of the table report 2SLS and LIML estimates, respectively, with once- and twice-lagged changes in state prison commitments and releases serving as instruments for the change in city crime rates. (See table A-1 in the appendix for the first-stage and reduced-form regressions.)

the change in city residents per additional suburban crime at the mean of our sample, one must divide the suburban crime coefficient by three.

Column 4 adds once-lagged state population changes to the specification. To the extent that city population is influenced by broader patterns of migration, state population changes may be an important determination of city growth rates. Although this variable enters the regression very strongly, the crime coefficient is virtually unchanged. The last column of the table includes not only all of the covariates in the baseline specification, but also changes in all of those variables as further controls. Once again, the crime coefficient is not greatly affected.

The bottom two rows of table 3 present instrumental variables estimates using 2SLS and LIML on each of the specifications.[10] Unlike the correlational estimation techniques, the instrumental variables (IV) approaches can provide a possible causal interpretation. Valid instruments for the crime variable must affect city crime rates, but not otherwise belong in the equation determining city population changes. The particular instruments used are once-lagged changes in the commitment and release rates of state prison systems per reported crime in the state.[11] Commitments include both new prison terms resulting from criminal convictions and commitments resulting from probation and parole violations.[12] These variables capture both incapacitation effects and deterrence via the certainty and severity of punishment in the state. A high commitment rate implies a high likelihood of detection and conviction. A low release rate translates into a longer mean punishment per conviction. Because the instrumental variable approaches are not the main focus of this paper, we limit the discussion of the justifications of this choice of instruments, as well as their potential shortcomings. An exhaustive discussion of the issue is presented in an earlier version of this paper; interested readers should consult Cullen and Levitt (1996).

The first-stage and reduced-form relationships are reported in table A-1 of the appendix. The instruments perform very well in the first stage, entering strongly and with the expected sign. Lagged increases in prison commitment rates in a state are associated with decreases in city crime; lagged increases in state prison releases lead to rising city crime. The reduced-form estimates mirror the patterns in the first stage, further increasing our confidence in the instruments. The 2SLS and LIML estimates are reported in the bottom of table 3.[13] Across all of the specifications, the instrumental

[10] Recent research suggests that 2SLS frequently has poor small sample properties and converges slowly to asymptotic values (Bound et al., 1995; Staiger & Stock, 1997). Thus, we present LIML estimates as well for comparison purposes.

[11] Prison overcrowding litigation, used as an instrument in Levitt (1996) is not effective here because the overcrowding litigation is concentrated in small, mostly rural states, and thus has little explanatory power in the first stage on our current data set.

[12] When entered separately, new commitments and parole- and probation-related commitments had similar coefficients in the first-stage regression, and the 2SLS results were not substantially affected.

[13] None of the standard errors we report on the instrumental variables estimates take into account the correlation in errors across different cities in the same state because of the difficulty in doing so with LIML. For two-stage least squares, allowing for such a correlation increases the standard errors by approximately 15%.

TABLE 4.—SUMMARY STATISTICS FOR 1980 CENSUS MIGRATION SAMPLE

	All Groups	School > 12 Years	School = 12 Years	School < 12 Years	Black	Nonblack	With Children	No Children
Net migration	−0.081	−0.102	−0.103	−0.048	0.015	−0.100	−0.149	−0.045
within SMSA	−0.065	−0.072	−0.080	−0.043	−0.020	−0.075	−0.105	−0.043
outside SMSA	−0.017	−0.030	−0.023	−0.005	0.036	−0.025	−0.045	−0.002
Comers	0.215	0.311	0.189	0.124	0.188	0.229	0.205	0.219
from within SMSA	0.058	0.075	0.063	0.037	0.038	0.064	0.057	0.059
from outside SMSA	0.156	0.236	0.126	0.087	0.150	0.165	0.148	0.160
Goers	0.295	0.413	0.292	0.172	0.173	0.328	0.354	0.264
to within SMSA	0.123	0.147	0.143	0.080	0.058	0.138	0.162	0.102
to outside SMSA	0.173	0.266	0.149	0.092	0.115	0.190	0.192	0.162

Notes: Data are city-level aggregates based on place of residence for household heads in 1975 and 1980 from the 5% PUMS 1980 sample. Data are for the 81 cities with populations greater than 100,000 in 1975 for which mobility data and covariates are available. The sample excludes those who resided outside the United States in 1975. Net migration is calculated as comers minus goers as a fraction of 1975 population. Within SMSA movers are the subset of total movers who remain within the SMSA.

variables estimates are larger than the corresponding OLS estimates. These results imply not only that the direction of causality runs from changes in crime rates to city depopulation, but that the OLS estimates may in fact understate the magnitude of the true causal relationship. One reason for this understatement is that big cities cause higher crime rates, perhaps due to greater anonymity, more criminal opportunities, or by attracting likely criminals (Glaeser & Sacerdote, 1996).

IV. Using 1980 PUMS Data to Isolate the Relationship Between Crime and Migration Among Population Subgroups

In this section, we attempt to identify differential relationships between crime and migration among subgroups of the population. We consider three dimensions along which to characterize city residents: education, race, and the presence of children. With respect to education, households are divided into three categories depending on whether the household head did not complete high school, completed high school but did not attend college, or attended college. With respect to race, we report results separately for whites and blacks. Each household is also classified either as having children present or absent in 1980.

For each of the 81 available cities, the fraction of stayers, comers and goers among each group is computed. ***Stayers*** are those present in the city in both 1975 and 1980. ***Comers*** are those households that reside in the city in 1980, but not in 1975. ***Goers*** are those that lived in the city in 1975, but left before 1980. Table 4 presents summary statistics on migration patterns for these various groups. For all city residents, net migration (comers minus goers as a fraction of 1975 population) for the 5 yr. period is approximately − 8%.[14] Net migration rates were larger for those with at least a high-school degree (− 10%) relative to high-school dropouts (− 4%). Blacks flowed into cities on net, while the nonblack population declined by 10%. Households with children declined much more sharply than households with no children present. Roughly 30% of households residing in one of these central cities in 1975 had left that city by 1980 (as shown in the row labeled "Goers"), with high-school dropouts and blacks less likely to leave. New arrivals to cities offset three-fourths of these leavers. Sixty percent of city out-migrants left the SMSA, and over 70% of the new arrivals to central cities came from outside the SMSA.

Table 5 presents regression estimates of the responsiveness of the migration decisions of various population subgroups to crime rates. Each entry in table 5 is the coefficient on changes in crime rates from a separate regression based on the specification in table 2, column 5. The top row of each column reports the impact of crime on net migration. (These coefficients parallel those in the earlier tables except that they correspond to population subgroups.) The other rows of table 5 decompose the overall impact of crime on net migration. For instance, the second row reports the impact of crime changes on the number of new arrivals to the city. The third and fourth rows further disaggregate new arrivals based on whether they come from within or outside the SMSA. The last three rows show the impact of crime on the decision of city residents in 1975 to leave the city by 1980, and whether or not they remain in the SMSA. The coefficient on goers (row 5) minus the coefficient on comers (row 2) equals the total crime-related impact on net-migration (row 1).

Net migration in response to crime increases with the education level of the household head. Those with some college are over 50% more responsive to crime than high-school dropouts.[15] There is little apparent difference between blacks and nonblacks. Those with children are twice as responsive to crime as those without. (See also Glendon, 1996.)

Almost all of the crime-related impact on mobility arises from increased out-migration, as evidenced by the large

[14] This number is greater than the observed 3% aggregate decline in city populations for the cities in our sample over the period 1975 to 1980. Most of that gap can be explained by differences in birth and death rates. Annual national birth rates (per 100 population) were approximately 1.5 in this time period; comparable death rate statistics were roughly 0.9. Assuming that the same rates apply to these cities, the differential between birth and death rates accounts for a gap of three percentage points between city population changes and net migration. Overall, the correlation between city population changes and net migration in our sample is 0.45.

[15] According to the National Crime Victimization Survey, the likelihood of victimization declines with educational attainment. Thus, if the migration response to crime is solely based on personal victimizations rather than on official statistics or newspaper reports, then these estimates understate the sensitivity of the highly educated per victimization. Similar arguments would hold for whites relative to blacks.

TABLE 5.—DECOMPOSITION OF IMPACT OF CHANGE IN CITY CRIME ON NET MIGRATION

Dependent Variable	All	School > 12 Years	School = 12 Years	School < 12 Years	Black	Nonblack	With Children	No Children
				Impact of Change in Per Capita City Crime				
Net migration	−1.20	−1.53	−1.25	−0.93	−0.91	−1.17	−1.87	−0.89
	(0.69)	(0.92)	(0.80)	(0.45)	(1.00)	(0.75)	(0.95)	(0.63)
Comers:	−0.08	0.08	−0.14	−0.26	−0.67	−0.09	−0.33	0.03
	(0.55)	(0.69)	(0.59)	(0.40)	(1.11)	(0.56)	(0.64)	(0.57)
within SMSA	−0.09	−0.24	0.10	−0.11	−0.17	−0.06	−0.01	−0.14
	(0.27)	(0.37)	(0.29)	(0.20)	(0.47)	(0.28)	(0.31)	(0.28)
outside SMSA	0.01	0.32	−0.24	−0.14	−0.50	−0.03	−0.32	0.17
	(0.42)	(0.52)	(0.45)	(0.29)	(0.83)	(0.44)	(0.48)	(0.45)
Leavers:	1.12	1.61	1.11	0.67	0.24	1.08	1.54	0.93
	(0.70)	(0.84)	(0.78)	(0.49)	(0.81)	(0.77)	(0.82)	(0.66)
within SMSA	0.91	0.70	1.33	0.78	1.02	0.75	1.47	0.61
	(0.47)	(0.55)	(0.57)	(0.34)	(0.48)	(0.50)	(0.63)	(0.40)
outside SMSA	0.21	0.91	−0.23	−0.11	−0.78	0.33	0.07	0.31
	(0.40)	(0.54)	(0.47)	(0.27)	(0.49)	(0.46)	(0.52)	(0.36)

Notes: Each cell is the coefficient on the change in per capita city crime from a separate regression in which the dependent variable is either the fraction coming to or leaving the central city as indicated. The covariates included are identical to those of table 2, column 5. The method of estimation is weighted least squares with the weights proportional to city population. Within comers and goers, the crime effect is further decomposed according to whether the migration crosses SMSA lines. The number of observations is 81.

magnitudes on goers compared to comers. One possible explanation for this pattern is that current residents are better informed about recent changes in crime than are potential in-migrants. The other notable result that emerges from table 5 is the high proportion of those leaving the city in response to crime who remain within the SMSA. Comparing the bottom two rows of table 5, those leaving cities in response to crime remain in the SMSA roughly 80% of the time overall (less frequently for the well educated, less frequently for blacks and families without children). In contrast, for all out-migrants (as reported in the bottom two rows of the summary statistics in table 4), only 40% remain in the SMSA. This result is consistent with households leaving SMSAs when moves are due to economic or job-related factors, whereas households fleeing to the suburbs in response to crime keep their jobs in the city.

Up to this point, we have focused exclusively on aggregated data. One possible shortcoming of this approach is that it is impossible to include a particular household's characteristics as covariates. Thus, we explore the results from household-level regressions.

We use the results of the preceding city-level analysis to guide our choice of specification. Table 5 demonstrates that almost all of the crime-related net migration from cities is due to increased outflows of residents. Therefore, in the following analysis we focus exclusively on the decision of current city residents to stay or to leave. This restricted focus limits the sample to residents of large cities in 1975, approximately 400,000 observations, or roughly 15% of the 1980 PUMS mobility sample.

The results of the household-level analysis are presented in tables 6a and 6b. For simplicity of interpretation, we present estimates from linear probability models in which the dependent variable is equal to 1 if a household residing in one of the large central cities in our sample in 1975 remains in that city through 1980, and 0 if the household leaves the central city before 1980. As before, the 5 yr. change in the per capita reported crime rate captures the effect of crime. Probit and logit yield similar marginal effects when evaluated at the sample means.[16] All specifications in tables 6a and 6b include the full set of city, state, and region controls that were used in table 5. With the exception of the first column, the regressions also include a wide array of ***household-level*** controls: the education, age, sex, race, and marital status of the household head, and whether the household head is a homeowner, in the armed forces in 1975, or attends college in 1975. The reported standard errors have been corrected to take into account correlation in the error term for households in a given city. Failing to account for within-city correlations leads to standard error estimates that are roughly twenty times too small on the crime coefficients. Because all of the variation in the crime variable is at the city level, there is actually very little information gain in moving from city-level aggregates to household-level estimation, as reflected by the fact that the standard errors in tables 5 and 6 are not very different. For comparison purposes, we report the corresponding coefficient from the city-level regressions in the bottom panel of table 6.

Column 1 of table 6a includes only aggregate controls for the full sample of households. Each additional reported crime is associated with 1.23 residents leaving the city.

Column 2 of table 6a is identical to column 1 except that a full complement of household-level controls are added to the specification. It is interesting to note that, while these variables significantly improve the R^2 of the regression (0.151 versus 0.030), the estimated impact of crime is largely unaffected. This increases our level of confidence in the earlier estimates using city-level aggregates, where there was concern that the set of controls was incomplete. Having controlled for city-level characteristics, household heads who are old, male, black, single, have children, or have

[16] We have also experimented with multinomial logit models that allow for differential effects for those households moving within and across SMSAs. These results suggest that crime has a larger effect on those moving within the SMSA, as would be expected.

TABLE 6A.—HOUSEHOLD-LEVEL ESTIMATES OF THE DECISION TO STAY IN CENTRAL CITIES

Variable	All Household Heads		School > 12 Years	School = 12 Years	School < 12 Years
Δ Per capita crime in city	− 1.23	− 1.18	− 1.54	− 1.27	− 0.77
	(0.72)	(0.57)	(0.75)	(0.63)	(0.34)
School = 12	—	− 0.016	—	—	—
		(0.004)			
School > 12	—	− 0.055	—	—	—
		(0.008)			
Years of education	—	− 0.004	− 0.006	—	− 0.005
		(0.001)	(0.002)		(0.001)
Age	—	0.006	0.009	0.006	0.003
		(0.001)	(0.001)	(0.001)	(0.0005)
Male	—	0.023	0.023	0.027	0.021
		(0.002)	(0.003)	(0.004)	(0.003)
Black	—	0.144	0.162	0.168	0.107
		(0.020)	(0.023)	(0.026)	(0.017)
Has own children	—	0.021	0.023	0.003	0.010
		(0.005)	(0.005)	(0.007)	(0.004)
Married	—	− 0.032	− 0.056	− 0.032	− 0.017
		(0.005)	(0.008)	(0.005)	(0.004)
Homeowner	—	0.019	0.016	0.025	0.023
		(0.023)	(0.034)	(0.022)	(0.015)
Armed forces 1975	—	0.277	− 0.238	− 0.293	− 0.257
		(0.023)	(0.017)	(0.019)	(0.048)
College student 1975	—	− 0.090	− 0.048	− 0.033	—
		(0.008)	(0.006)	(0.015)	
Controls from city level regressions	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.030	0.151	0.142	0.127	0.083
Observations	396,476	396,476	142,465	117,675	136,336
Comparable Coefficient from City-level Regression					
Δ Per capita crime in city	− 1.20	− 1.20	− 1.53	− 1.25	− 0.93
	(0.69)	(0.69)	(0.92)	(0.80)	(0.45)

Notes: The sample includes only households residing in one of the 81 central cities included in the sample in 1975. The dependent variable is an indicator equal to 1 if the household remains in the central city through 1980, and 0 otherwise. The complete set of regressors from table 2 are also included in the specifications. We allow for correlation in the error term across households in a given city so as not to understate the standard errors.

lower educational attainment are more likely to stay in central cities. Members of the military and those attending college are far more likely to leave the city.

The last three columns of table 6a divide the sample according to educational attainment of the household head, which is likely to be highly correlated with household income. Those with more than a high-school education are roughly twice as responsive to crime as are those who did not complete high school. Those with a high-school diploma, but no college, fall in the middle. The other covariates tend to carry similar coefficients across education groups, although being married is a much better predictor of leaving the city among the well educated. The first two columns of table 6b divide the sample between blacks and nonblacks. As before, little differential effect of crime is observed across races. The final two columns of table 5b split the sample into households with and without children. Households with children are more likely to leave central cities in response to rising crime. This result is particularly interesting given that, in the other regressions of this table, households with children are found to be more likely to remain in the city. In other words, the direct effect of having children in the household is to keep people in cities, but the interaction between children and rising crime drives families from the city.

V. Conclusions

This paper examines the connection between crime and urban flight. Across a wide range of specifications and data sets, each reported city crime is associated with approximately a one-person decline in city residents. Almost all of the impact of crime on falling city population is due to increased out-migration rather than a decrease in new arrivals. Households with high levels of education or with children present are most responsive to changes in crime rates. Crime-related out-migrants are much more likely to stay within the SMSA than those who leave the city for other reasons. Instrumenting using measures of criminal justice system severity yields larger estimates than OLS, which suggests that rising city crime rates are causally linked to city depopulation.

Having established a link between crime and urban flight, the logical next step is to understand and quantify how the costs and benefits of such crime-related migration are distributed. To what extent are these costs borne by property owners versus renters? How are city and suburban tax bases affected? If the highly educated are more responsive to crime, does this leave behind a population with a greater dependency on city-provided public services? All of these questions provide avenues for future study.

TABLE 6B.—HOUSEHOLD-LEVEL ESTIMATES OF THE DECISION TO STAY IN CENTRAL CITIES (CONTINUED)

Variable	Black	Nonblack	With Children	No Children
Δ Per capita crime in city	−1.27 (0.61)	−1.12 (0.63)	−1.51 (0.63)	−0.97 (0.55)
School = 12	−0.024 (0.005)	−0.016 (0.005)	−0.032 (0.007)	−0.005 (0.005)
School > 12	−0.078 (0.010)	−0.047 (0.009)	−0.060 (0.009)	−0.045 (0.006)
Years of education	−0.001 (0.001)	−0.005 (0.001)	−0.008 (0.001)	−0.003 (0.001)
Age	0.004 (0.001)	0.006 (0.001)	0.008 (0.001)	0.006 (0.001)
Male	0.022 (0.003)	0.020 (0.003)	0.054 (0.008)	0.013 (0.003)
Black	—	—	0.038 (0.078)	0.125 (0.015)
Has own children	0.034 (0.004)	0.011 (0.006)	—	—
Married	−0.030 (0.004)	−0.032 (0.005)	−0.030 (0.005)	−0.027 (0.004)
Homeowner	0.021 (0.016)	0.021 (0.026)	−0.009 (0.031)	0.033 (0.020)
Armed forces 1975	−0.189 (0.027)	−0.290 (0.019)	−0.258 (0.017)	−0.273 (0.027)
College student 1975	−0.056 (0.009)	−0.095 (0.008)	−0.048 (0.011)	−0.108 (0.008)
Control from city level regressions	Yes	Yes	Yes	Yes
R^2	0.094	0.144	0.144	0.156
Observations	84,105	312,371	134,294	262,182
Comparable Coefficient from City-level Regression				
Δ Per capita crime in city	−0.91 (1.00)	−1.17 (0.75)	−1.87 (0.95)	−0.89 (0.63)

Notes: See notes to table 6a.

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APPENDIX: Data Sources and Variables

The following data sources provided variables used in the paper:

A. *City and County Data Book (Bureau of the Census)*

City-level measures are available in census years (1970, 1980, 1990) for percent black, median family income, percent high-school graduates, percent home owners, and percent of workers employed in manufacturing. In the panel data set of annual observations, percent black is linearly interpolated between census years. City median family income is interpolated using the pattern of changes in state per capita income (which is available annually), constraining the endpoints to match the true values in census years.

In addition, we use mean January temperature, mean July temperature, and mean annual precipitation for each city from this source. Note, however, that there is no within-city variation in the weather variables.

B. *Uniform Crime Reports of the United States (Federal Bureau of Investigation)*

This source provide annual city-level data on the number of crimes reported to police in the seven Index I crime categories (murder, rape, robbery, aggravated assault, burglary, larceny, and auto theft). Our crime measure is simply the total number of reported crimes across all of these categories in a city and year. In those specifications where suburban crime is included as a regressor, suburban crime is calculated as SMSA crime minus central city crime.

These reports also include annual city population estimates. These population data are provided to the FBI by the Bureau of the Census and are estimated using the Current Population Survey and birth and death records.

C. *1980 Census Public Use Micro Sample (PUMS) (Bureau of Census)*

The 1980 PUMS is a 5% sample of the U.S. population. Half of this sample is included in the migration subsample, providing a migration sample covering 2.5% of the U.S. population. Because states are not required to match PUMAs (the basic geographic identifier in the census) with city boundaries, city of residence is only available in a subset of cities (81 out of 127).

The migration sample asks the household head's place of residence in 1975 and 1980. Consequently, we use the household as our unit of analysis. We classify households in a given city in both 1975 and 1980 as ***stayers*** (regardless of whether the household changed residences within the city). ***Goers*** are households within city boundaries in 1975, but not in 1980. ***Comers*** are those that move to the city between 1975 and 1980. We also record whether moves to and from cities cross SMSA boundaries.

The PUMS data also provides all of the household-level variables used in the analysis: race and sex of household head, educational attainment of household head, presence of children, marital status, service in the armed forces in 1975, and college attendance in 1975.

D. *Correctional Population in the United States (Bureau of Justice Statistics)*

This data source, published annually, provides information on state-level prison commitments and releases. Commitments include both new commitments and those returned to prison as a result of probation and parole violations. These numbers include prisoners under the jurisdiction of the state prison system, regardless of where the prisoners are held in custody.

E. *Statistical Abstract of the United States (Bureau of Census)*

This source provides a number of annual, state-level control variables: state population, state per capita personal income, and state age distributions.

F. *Earnings and Employment (Department of Labor)*

This publication provides annual estimates of SMSA-level unemployment rates.

TABLE A-1.—FIRST-STAGE AND REDUCED-FORM ESTIMATES USING STATE PRISON COMMITMENTS AND RELEASES AS INSTRUMENTS

	Δ Per Capita City Crime		% Δ City Population	
Variable	(1)	(2)	(4)	(5)
Δ Prison commitments per crime (− 1)	− 0.392	− 0.425	0.690	0.579
	(0.146)	(0.150)	(0.496)	(0.505)
Δ Prison commitments per crime (− 2)	− 0.152	− 0.160	0.885	0.888
	(0.169)	(0.182)	(0.488)	(0.502)
Δ Prison releases per crime (− 1)	0.399	0.404	− 0.727	− 0.868
	(0.111)	(0.112)	(0.403)	(0.406)
Δ Prison releases per crime (− 2)	0.289	0.278	− 0.521	− 0.672
	(0.106)	(0.106)	(0.347)	(0.372)
Unemployment rate	0.007	0.004	− 0.114	− 0.290
	(0.019)	(0.034)	(0.055)	(0.042)
Median family income $* 10^{-5}$	0.000	0.004	0.003	0.009
	(0.006)	(0.002)	(0.003)	(0.004)
% black	0.003	0.019	− 0.030	0.059
	(0.001)	(0.017)	(0.007)	(0.061)
% aged 0–17	− 0.004	− 0.005	− 0.225	− 0.630
	(0.017)	(0.080)	(0.102)	(0.212)
% aged 18–24	− 0.073	− 0.153	0.510	− 0.533
	(0.052)	(0.147)	(0.225)	(0.370)
% aged 25–44	− 0.021	− 0.017	− 0.105	− 0.684
	(0.014)	(0.108)	(0.066)	(0.298)
% aged 45–64	− 0.020	0.024	− 0.105	− 0.601
	(0.043)	(0.108)	(0.190)	(0.320)
City fixed effects?	No	Yes	No	Yes
F-stat: instruments	6.53	5.90	1.00	1.60
R^2	0.277	0.290	0.247	0.327

Notes: Dependent variables are changes in per capita city crime in columns 1 and 2, and Δln (changes in city population) in columns 3 and 4. The sample is composed of annual observations from 1976 to 1993 for 127 U.S. central cities with populations greater than 100,000 in 1970. Year dummies are included in all specifications. Region dummies are included when city-fixed effects are omitted. Due to missing data, the number of observations is equal to 2,044 in all columns. Prison commitment and release data are defined at the state level and are changes in rates per reported crime. All variables are available annually, except for % black, which is linearly interpolated between decennial census years, and median family income, which is adjusted as described in the data appendix. Control variables are once-lagged to minimize endogeneity. The method of estimation is weighted least squares with the weights proportional to city population. Standard errors, in parentheses, have been adjusted using White's generalized method to take into account the fact that the prison variables are defined at the state level. The bottom row of the table gives the ***F***-value of the joint significance of the four prison variables.