THE IMPACT OF ORDER-MAINTENANCE POLICING ON NEW YORK CITY HOMICIDE AND ROBBERY RATES: 1988-2001*

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Local officials and national observers have attributed the New York City drop in violent crime during the 1990s to the aggressive enforcement of public order, but relevant research is limited and yields contrasting conclusions regarding the effects of order-maintenance policing (OMP) on violent crime trends in New York City. The current study investigates the effects of order-maintenance arrests on precinct-level robbery and homicide trends in New York City with more reliable crime and arrest data, longer time series, and more extensive controls

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for other influences than used in prior research. We find statistically significant but small crime-reduction effects of OMP and conclude that the impact of aggressive order enforcement on the reduction in homicide and robbery rates in New York City during the 1990s was modest at best.

If there are 2,000 murders this year, get ready for 4,000. New York is dying.

Journalist Pete Hamill, 1990

We are the safest big city in America.

Mayor Michael Bloomberg, 2005[1]

Violent crime rates declined in most large U.S. cities during the 1990s, but nowhere was the crime drop more widely publicized or controversial than in New York City. Local officials and national observers attributed the New York City crime drop to law enforcement strategies that aggressively targeted low-level offenses as a way of averting more serious crimes. Many criminologists met these success claims with skepticism; yet little systematic evidence exists regarding the effects of order-maintenance policing (OMP) on New York City crime rates.

OMP was the engine driving the New York City "quality-of-life" policing initiative instituted in 1994. Under the initiative, police commanders are to give priority to reducing crime by aggressively targeting so-called quality-of-life offenses and arresting violators for vagrancy, loitering, prostitution, littering, graffiti, panhandling, public drunkenness, vandalism, minor drug use, excessive noise, public urination, and related breaches of public order. Police Commissioner William Bratton and other officials have credited the quality-of-life initiative as the primary reason for the New York City crime drop (Bratton, 1998; Bratton and Kelling, 2006; Joanes, 2000: 275–76; Karmen, 2004; Kelling and Bratton, 1998; Will, 2003).

The Wilson and Kelling (1982; Kelling and Coles, 1996) broken-windows thesis supplied the rationale for the quality-of-life initiative (Kelling and Bratton, 1998). Like fixing a broken window, arresting persons for committing minor infractions, according to this perspective, sends a message to community residents and outsiders that the police are paying attention and will enforce community standards. Failure to move aggressively against public disorder sends the opposite signal that the police are inattentive or indifferent, discourages residents from using public spaces, and "leads to the breakdown of community controls. . . . Such an area is vulnerable to criminal invasion" (Wilson and Kelling, 1982: 31–2).

1. Hamill quoted in Karmen (2000: 7). Bloomberg quoted in McIntire (2005).

Critics of the New York City version of OMP contend that it does not in fact reflect the Wilson and Kelling "social influence" model of crime deterrence. Rather, the police have used the broken-windows thesis as a cover for the mass surveillance of "disorderly" people, mainly young minority males (Harcourt, 2001; see, also, Fagan and Davies, 2000). A program of mass surveillance requires large numbers of police officers to carry it out. If the critics are correct, we should observe greater crime reductions in precincts with the largest increases in the number of officers, and little or no relationship between serious crime and arrests for minor offenses, with police size controlled. Of course, the two ideas—mass surveillance and broken-windows policing—are not mutually exclusive. Growth in the number of police officers and an order-maintenance arrest strategy may both reduce crime, and under the quality-of-life initiative, adding more police should increase the volume of arrests for minor offenses. We evaluate these hypotheses in the current research.

PRIOR RESEARCH ON THE NEW YORK CITY CRIME DROP

Prior research on the crime-reduction effects of the New York City policing changes consists primarily of city-wide studies that omit controls for other influences or omit direct measures of policing or comparisons with other places (see Eck and Maguire, 2006: 232–33). Several investigations conclude that the New York City post-1994 crime reductions, although sizable, are similar to those in other large cities that had not instituted comparable changes in policing (Eck and Maguire, 2006; Fagan, Zimring, and Kim, 1998; Joanes, 2000; Karmen, 2000). Analysts also have pointed out that the New York City homicide rate began to fall a few years before the quality-of-life initiative was introduced and that homicides committed indoors, which should be affected less by changes in enforcement patterns on the street, decreased at about the same rate as those committed outdoors (Karmen, 2000, 2004). These findings do not rule out the possibility that OMP contributed to the New York City crime decline, but they do suggest that other factors were involved.

The Corman and Mocan (2002) time-series analysis of city-wide monthly crime rates in New York City yields significant negative effects of misdemeanor arrests on robbery and motor-vehicle theft, but not on other crimes, controlling for imprisonment, police size, unemployment, real minimum wages, and age composition. This study has been criticized for omitting comparisons with other cities (Harcourt and Ludwig, 2006). Rosenfeld, Fornango, and Baumer (2005) compared pre- and post-1994 New York City homicide trends with those of the 95 largest U.S. cities. They found no significant difference in homicide trends between New

York City and other cities when controls for police size, imprisonment, and other covariates were included in the estimation. Their study, however, contains no direct measure of policing.

Only two published investigations have examined the relationship between OMP and violent crime trends across areas within New York City during the 1990s. Kelling and Sousa (2001) found a strong negative relationship between changes in violent crime rates and misdemeanor arrests, controlling for borough-level unemployment, age composition, and a measure of drug involvement, and they found no effects of these covariates on violent crime. They interpret their results as supporting broken-windows policing and as disconfirming explanations that emphasize poverty, racial disadvantage, and other "root causes" of crime. In a replication of the Kelling and Sousa (2001) study, Harcourt and Ludwig (2006) found no significant association between misdemeanor arrests and the New York City violent crime trend over the following decade. They conclude that Kelling and Sousa had mistakenly attributed decreases in violent crime to OMP when in fact they represent reversion to the mean from the high levels of criminal violence brought on by the crack-cocaine epidemic of the mid-to-late 1980s.

As a replication exercise, the Harcourt and Ludwig (2006) analysis understandably shares several limitations with the Kelling and Sousa (2001) research, but these limitations preclude drawing strong conclusions from either study. Both studies use the aggregate violent crime index as the outcome measure. The violent crime index combines the rates of homicide, felonious assault, rape, and robbery. Neither study, therefore, can investigate the differences across crime types in the effect of OMP revealed in prior research (Corman and Mocan, 2002). In addition, the violent crime index includes offenses subject to substantial measurement error. Rapes are notoriously underreported to the police, and recent evidence suggests that police have changed the recording of assaults over time, which has resulted in more events classified as felonies, independent of changes in victimization rates (Rosenfeld, 2007).

A second limitation of both studies is the omission of ordinance-violation arrests from the measure of OMP. Many breaches of public order targeted by the police under an aggressive order-maintenance policy (e.g., littering, excessive noise, graffiti, and teenagers congregating on street corners) do not qualify as criminal misdemeanors but are violations of city ordinance codes. Because the police traditionally have had considerable discretion in how to respond to such cases short of making an arrest, increases in ordinance-violation arrests should be an especially sensitive indicator of stepped-up enforcement of minor offending.

Third, by omitting *complaints* of disorder by residents, prior research has failed to consider how the volume of disorder may affect serious crime and police response. The central proposition of the broken-windows thesis is that disorder leads to crime. Citizen complaints reflect, perhaps imperfectly, the prevalence of disorder in a community. As such, citizen complaints of disorder determine "demand" for OMP and should be included in analyses of the effects of order-maintenance arrests on crime.

Fourth, neither the Kelling and Sousa (2001) nor the Harcourt and Ludwig (2006) study accounts for possible simultaneity in the relationship between OMP and the incidence of serious crimes. As felonies decrease over time, police resources are freed up to address less serious offenses, which results in more arrests for misdemeanors and violations of city ordinances. One way of dealing with this possibility is to include felony arrests in the estimation of violent crime trends to capture changes in police resources devoted to serious crimes. The inclusion of felony arrests also reduces the chances of misattributing crime-reduction effects to OMP when they actually may result from arrests for serious crimes.

A fifth and related issue neglected in prior research concerns the possible indirect effects of several variables on violent crime trends through their influence on OMP. The production of order-maintenance arrests should be affected by both supply factors and demand factors. On the supply side, the greater the number of police officers and the less time they spend on felony enforcement, the more time and resources that are available to devote to misdemeanor and ordinance enforcement. We should therefore expect to observe, all else equal, increases in misdemeanor and ordinance violation arrests in precincts where the number of officers is increasing and the number of felony arrests is declining. The level of disorder in a precinct determines the demand for order-maintenance arrests. When and where more complaints of disorder occur, as indicated earlier, more enforcement opportunities exist. Therefore, the number of police officers, the rate of felony arrests, and the volume of misdemeanor and ordinance violation complaints should affect *both* the rate of misdemeanor and ordinance violation arrests and the rate of serious crime in a precinct. It follows that these variables could have two different effects on serious crime, one direct and the other indirect through their effect on order-maintenance arrests.

As Harcourt and Ludwig (2006) point out, the Kelling and Sousa analysis (2001) incorporates controls for only a few other factors that may have contributed to the New York City crime reductions, and they are measured at the borough level, thereby concealing heterogeneity across precincts within boroughs.[2] Although Harcourt and Ludwig (2006) include additional covariates measured at the census tract level and aggregated to

2. The 76 precincts of New York City are distributed across the five boroughs (Manhattan, Brooklyn, Queens, Staten Island, and the Bronx).

police precincts, their study also omits potentially important influences on violent crime trends, notably the imprisonment rate. Prison populations grew substantially during the 1990s, and several studies attribute crime declines to prison expansion (Levitt, 2002; Marvell and Moody, 1997; Spelman, 2000). Although broad sentencing policies are set at the state level and do not vary across police precincts, the incarceration rate does vary by precinct and over time, and prior research suggests that the incarceration rate should be negatively associated with crime rates.

Finally, neither study controls for spatial autocorrelation in the data. Increased enforcement in one area may produce displacement effects in neighboring precincts, and crime may spill over or diffuse across spatial boundaries for several reasons (Baller et al., 2001; Cohen and Tita, 1999; Messner et al., 1999). Failure to account for spatial autocorrelation could lead to biased estimates of the effect of OMP on precinct-level violent crime trends.

The current study addresses each of these limitations of prior research on the New York City crime drop. We estimate the effects of both misdemeanor and ordinance-violation arrests separately for New York City homicide and robbery trends between 1988 and 2001, which is a longer time period than used in prior research. Our arrest measures are based on misdemeanor and ordinance-violation arrests, and our crime models incorporate controls for citizen complaints of disorder, felony arrests, imprisonment rates, a measure of drug involvement, police size, initial crime rates (to capture possible mean reversion), and levels and changes in a broad range of demographic, social, and economic conditions. We estimate the direct effects of these factors on homicide and robbery trends and the indirect effects of several of them through their effects on OMP. Finally, our models include controls for spatial autocorrelation in both the crime and the arrest data.

DATA AND METHODS

The crime, arrest, and criminal complaint data used in this study are from precinct-level annual reports produced by the New York City Police Department and stored at the Lloyd Sealy Library of the John Jay College of Criminal Justice, City University of New York. The annual number of police officers per precinct was obtained from the New York City Civilian Complaint Review Board. The New York State Division of Criminal Justice Services provided data on the number of persons sentenced to prison from each precinct. Sandro Galea, a researcher formerly with the New York State Academy of Medicine, furnished medical examiner data on the annual number of cocaine overdose deaths in each precinct. Finally, the census data used in the analysis are from the Geolytics Neighborhood

Change Database 1970–2000 (Tatian, 2003). Descriptions, means, and standard deviations for all variables are presented in appendix A.

The unit of analysis is the New York City police precinct. Precincts represent the smallest level of aggregation for which yearly crime and arrest data are available over the 1988–2001 period under investigation. The average residential population of the 76 precincts in New York City in 2000 was 105,204 (SD = 51,300).[3] Because precincts do not correspond directly with any census-defined geography, a cross-walk file was created in a Geographic Information System environment to allocate census tract data from 1990 and 2000 to the appropriate police precincts. The 1990 census tract data were normalized to the 2000 census tract boundaries (see Tatian, 2003, for a description of the normalization method).

The dependent variables in the analysis are the *homicide rates* and *robbery rates* per 10,000 precinct residents. The key explanatory construct is OMP, which we operationalized as the annual number of misdemeanor and ordinance violation arrests per 10,000 precinct residents. We include the number of citizen complaints of misdemeanor and ordinance violations per 10,000 residents as a measure of *disorder* in our homicide, robbery, and OMP models.

We also include the number of felony arrests per 10,000 felony complaints (*felony arrest-complaint ratio*) in our OMP model as a control for police resources devoted to addressing serious crimes. We included this measure in preliminary models of robbery and homicide trends as a check for simultaneity in the relationship between OMP and violent crime (declining felony arrests free resources for OMP) and to account for spuriousness (the effects of OMP simply reflect those of the arrest process generally or of arrests for serious crimes). But the strong association between felony arrests and prison admissions resulted in inefficient estimates of the two variables. We therefore combined them in a single measure of prison admissions per 1,000 felony arrests (*imprisonment–felony arrest ratio*).

Our models also incorporate measures of several other conditions shown in prior research to influence violent crime rates (Levitt, 2004; Rosenfeld, 2004): the annual rate of *police officers* per 10,000 precinct residents, an indicator of *drug markets* consisting of the rate of cocaine overdose deaths per 10,000 residents,[4] and as mentioned, the imprisonment–felony ratio. The measures of crime, arrests, citizen complaints,

3. Two precincts were omitted from the analysis. Precinct 22 (Central Park) was excluded because it has no permanent resident population on which crime rates can be calculated. Precinct 33 (Washington Heights) did not exist as a separate precinct before 1995, when it was split off from precinct 34. The 1995–2001 data for this precinct were added to precinct 34.

4. The available cocaine overdose death data are for the years 1990–2001. We fit a

police size, felony arrests, imprisonment, and drug markets are log transformed (base e) to correct for positive skew. The resulting coefficients represent elasticities or the percentage change in the outcome associated with a 1 percent change in the predictor.

We also include measures of socioeconomic *disadvantage*, residential *instability*, and *immigration* in the analysis. These variables represent the classic dimensions of social disorganization that have been tied to diminished social control and increased rates of crime across urban neighborhoods (Bursik and Grasmick, 1993; Sampson, Raudenbush, and Earls, 1997). We derived the three measures empirically from a principal components factor analysis (with varimax rotation) of multiple census indicators aggregated to the 74 police precincts. The three underlying dimensions identified in the analysis account for 75.8 percent of the variation in the indicators. *Disadvantage* is composed (factor loadings in parentheses) of the percent Hispanic (.773), female headed-households with children under age 18 (.953), percent living in Puerto Rico 5 years before (.766), male unemployment rate (.908), poverty rate (.958), percent of households receiving public assistance (.978), median family income (–.864), and percent of the population aged 15–24 years (.757). *Instability* is composed of the divorce rate (.866), percent of the population living in the same house 5 years before (–.638), percent vacant housing units (.707), percent owner-occupied housing (–.589), and population density (.645). *Immigration* is composed of the percent of the population living outside the United States and Puerto Rico 5 years before (.958) and percent foreign born (.949). The percent non-Hispanic black was included in the analysis as an additional measure of population heterogeneity, but results indicated that this measure does not share common variance with the other indicators. It was therefore entered into the models as a separate indicator along with the three retained factors (*percent black*).

To capture possible mean reversion in crime rates as described by Harcourt and Ludwig (2006), we include the initial (1988) robbery or homicide rate in our models. The two crime rates are combined into a single measure of *violent crime* in the model estimating OMP. We also incorporate controls for spatial autocorrelation in both the crime and the arrest data. We checked for spatial autocorrelation using the Moran's I (see Baller et al., 2001, for a similar application).[5] Given the size of New York City and its island topography, we created the spatial weights using the 10 nearest

quadratic model to the available data (the best-fitting polynomial function) and obtained estimated values for 1988 and 1989 from this regression.

5. Spatial analysis was conducted using the GeoDa statistical software (Anselin, 2002).

neighbors rather than simple contiguity or inverse distance weights.[6] Spatial lags were computed from these analyses and entered into our models.

ESTIMATION STRATEGY

To assess the within-precinct effects of OMP conditional on other within- and between-precinct differences, we estimate a two-level hierarchical linear model (HLM). The HLM is preferred over alternative estimators such as fixed- and random-effects panel models because of its flexibility in estimating precinct differences in both the levels and the trends in crime rates. Fixed-effects models estimate differences across precincts in the average crime rate using a unit-specific intercept. However, linear slope coefficients are assumed to be equal across precincts unless unit–time interaction terms are included in the model, which requires the use of a large number of degrees of freedom, thereby greatly reducing the power of the model. Fixed-effects models suffer from the additional drawback that they cannot produce coefficient estimates for time-stable covariates. Random-effects models can accommodate time-stable covariates, but they also require the assumption that coefficient estimates are constant across units. As a random coefficient model, the HLM resolves both of these issues by estimating the intercept and linear trend as coefficients allowed to vary across units and by permitting the inclusion of time-stable factors as independent variables to explain that variation (Raudenbush and Bryk, 2002; see also Sayrs, 1989).

The HLM consists of a two-level model in which level 1 estimates individual precinct trends in violent crime rates from the following equation:

$$VC_{ti} = \beta_{0i} + \beta_{1i}T_{ti} + \beta_{2i}X_{ti} + e_{ti} \qquad (1)$$

where VC_{ti} is the log violent crime rate at time t for precinct i, β_{0i} is the log violent crime rate in 1988 for precinct i,[7] β_{1i} is the average linear change in violent crime rates between 1988 and 2001 for precinct i, T_{ti} is a linear time trend with 1988 equal to 0, β_{2i} is the average effect estimate of a mean-centered, time-varying covariate X_{ti} for precinct i, and e_{ti} is the level 1 error term at time t for precinct i. With this specification, the annual violent crime rate is modeled as a function of both a linear time trend and precinct-specific circumstances that fluctuate from year to year.

6. Nearest neighbors are defined by the distance between precinct centroids. Additional analyses were conducted using five nearest neighbors with no substantive change in results.
7. The level 1 intercept β_{0i} represents the average violent crime rate across precincts when all other covariates are set to 0. With time coded as equal to 0 in 1988 and all other covariates mean-centered within precincts, β_{0i} represents the violent crime rate in 1988, conditional on the average level of other conditions.

At level 2, HLM models the between-precinct heterogeneity in level 1 parameter estimates using the following equations:

$$\beta_{0i} = \gamma_{00} + \gamma_{01}W_i + u_{0i} \tag{2}$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11}W_i + u_{1i} \tag{3}$$

$$\beta_{2i} = \gamma_{20} \tag{4}$$

In equation 2, γ_{00} represents the average violent crime rate in 1988 across precincts, γ_{01} is the effect of a precinct-specific, time-stable covariate W_i on the initial violent crime rate, and u_{0i} is the residual, or random-effect, for precinct *i*. Equation 3 is similar in that γ_{10} represents the average linear trend in violent crime rates between 1988 and 2001 across precincts, γ_{11} is the effect of a precinct-specific, time-stable covariate W_i on the linear trend in violent crime, and u_{1i} is the random effect on the trend for precinct *i*. Finally, in equation 4, the within-precinct average effect of a time-varying covariate β_{2i} is estimated as γ_{20}, the average across all precincts. Nesting equations 2 through 4 within equation 1, the full random coefficient model is

$$VC_{ti} = \gamma_{00} + \gamma_{01}W_i + \gamma_{10}T_{ti} + \gamma_{11}W_iT_{ti} + \gamma_{20}X_{ti} + (e_{ti} + u_{0i} + u_{1i}T_{ti}) \tag{5}$$

which illustrates the decomposition of annual violent crime rates into within- and between-precinct components. The same approach is used to model within- and between-precinct variation in OMP, with misdemeanor and ordinance-violation arrests per 10,000 residents substituted on the left-hand side.

The time-varying covariates at level 1 of the homicide and robbery models include *OMP*, *disorder*, *police officers*, *imprisonment–felony ratio*, and *drug markets*, as defined above. The level 1 covariates are group-mean-centered, which allows us to disentangle the effects on the outcome of within-precinct changes in the level 1 covariates from their average differences across precincts. Chi-square tests of the residual variance of the level 1 parameters indicate that only the intercept and linear time trend exhibit significant variability across precincts. Therefore, the level 1 coefficients for *OMP*, *disorder*, *police officers*, the *imprisonment–felony ratio*, and *drug markets* are estimated as fixed parameters.

Given their brevity and dominance of the linear component in the time series, we estimate a linear trend for the robbery and homicide data. The resulting coefficients for the remaining level 1 covariates (the *Xs*) represent their association with the crime trends. At level 2, the explanatory variables (the *Ws*) serve to explain the variation in initial crime rates and the trends not explained by changes in the level 1 covariates. These coefficients represent the increment or decrement to the base rate and linear trend across precincts, given a unit change in the indicator. The level 2 time-stable covariates include the *disadvantage*, *instability*, and *immigration* factor scores and *percent black*. Each time-stable variable is measured in 1988, the first time point in the study. In addition, we incorporate at level 2 residual change scores for each of these variables to capture their possible time-varying effects on the robbery and homicide trends (*disadvantage* Δ, *instability* Δ, *immigration* Δ, and *percent black* Δ, respectively).[8] The 1988 levels of robbery and homicide and spatial lags for robbery, homicide, and OMP also are included at level 2 of the crime models.

We also estimate a linear trend for the OMP time series. The measures of felony arrests, police size, citizen complaints of disorder, and drug markets are included at level 1 of the order-maintenance arrest model and, as with the robbery and homicide models, are treated as fixed effects. Order-maintenance arrests should be unaffected by prison admissions, which are excluded from the model. In light of charges that the quality-of-life initiative targeted disadvantaged minority communities, the levels of and changes in disadvantage, instability, immigration, and racial composition are included at level 2 of the model. Level 2 of the order-maintenance model also incorporates a spatial lag for the order-maintenance indicator and the combined 1988 rates of homicide and robbery.

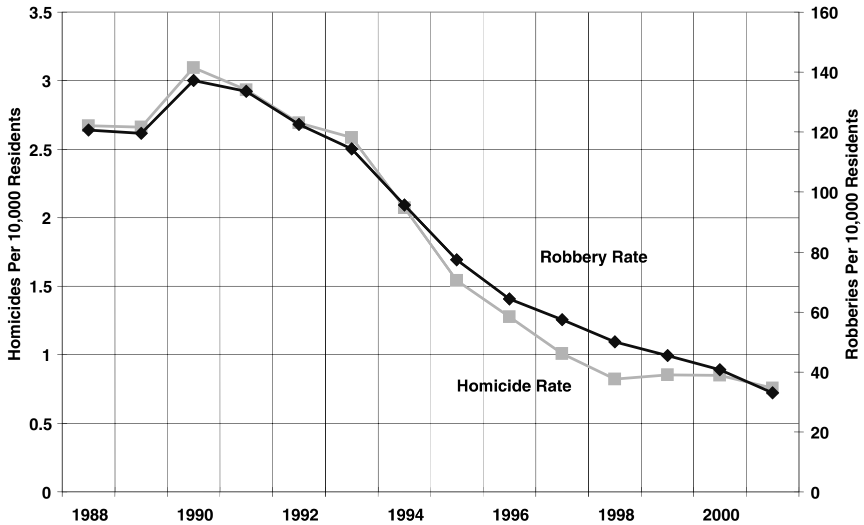
RESULTS

After rising to peak levels in 1990, the New York City homicide and robbery rates declined by nearly 76 percent through 2001. Although they had been decreasing before implementation of the quality-of-life initiative, the rate of decline in homicide and robbery accelerated in 1994 (see figure 1). After declining for several years, the rate of misdemeanor and ordinance-violation arrests in New York City rose slightly in 1993, sharply in 1994, and flattened after 1997 (see figure 2). The juxtaposition of declining rates of serious crime and rising arrest rates for minor crimes in New York City is the principle evidence used by broken-windows proponents for the efficacy of OMP (Bratton and Kelling, 2006; Kelling and Sousa, 2001). The threshold question is whether this relationship withstands controls for the many other factors that may have contributed to both the New York City declining crime rates and rising order-maintenance arrests.

Table 1 presents the results of our assessment of the New York City

8. The change measures were created by regressing their values from the 2000 census on their values from the 1990 census. Ideally, these factors should be entered as time-varying covariates at level 1. But basing their time-varying counterparts on linear interpolation from only two independent data points (the 1990 and 2000 decennial census years) results in unacceptable levels of multicollinearity when they are entered together.

Figure 1. New York City Homicide and Robbery Trends, 1988–2001



precinct-level trends in robbery and homicide. The table is lengthy, and so we move immediately to the results of central concern, the effect of OMP on the robbery and homicide trends.

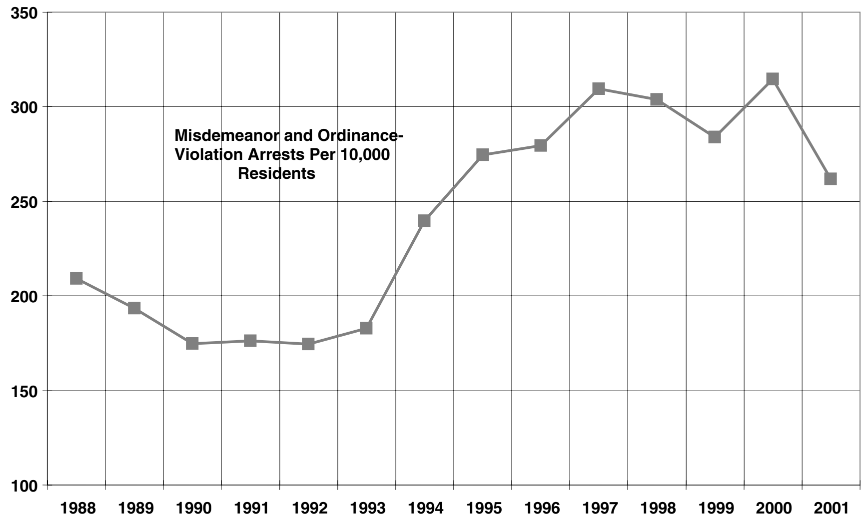
OMP, THE PREVALENCE OF DISORDER, ROBBERY, AND HOMICIDE

OMP had a significant, negative effect on trends in robbery and homicide within New York City precincts between 1988 and 2001.[9] Precincts in which arrests for misdemeanors and ordinance violations grew most rapidly experienced the greatest declines in these offenses. The coefficients on the measure of OMP (β_{20} = –.113 for robbery and –.285 for homicide) imply that a 1 percent increase in the rate of misdemeanor and ordinance-violation arrests produces a .11 percent reduction in the robbery rate and a .28 percent reduction in the robbery rate. In other words, a doubling of the rate of order-maintenance arrests on average would produce about an 11 percent reduction in robbery and a 28 percent reduction in homicide. These results are consistent with claims by broken-windows proponents that the strategy of aggressively targeting so-called quality-of-life offenses in New York City contributed to declines in more serious crimes.

The results shown in table 1 also reveal a significant and sizable effect of

9. Given the brevity of the time series, we present robust standard errors in table 1, which are adjusted for degrees of freedom used in the estimates.

Figure 2. New York City Order-Maintenance Arrest Trend, 1988–2001



the prevalence of disorder in a precinct, as indicated by the volume of citizen complaints of misdemeanor and ordinance violations, on robbery and homicide trends (β_{30} = .477 and .504, respectively). Precincts in which the level of disorder decreased the most also experienced the greatest declines in robbery and homicide. This finding supports the broken-windows hypothesis that disorder and crime are directly related and runs counter to prior research showing little or no relationship between disorder and more serious crime in other cities, once conditions affecting both are controlled (Sampson and Raudenbush, 1999, 2001; Taylor, 2001).

OTHER INFLUENCES ON ROBBERY AND HOMICIDE

The remainder of the results shown in table 1 concern other time-varying and time-invariant influences on precinct-level robbery and homicide rates in New York City. The intercept (β_{00}) models describe between-precinct differences in 1988 levels of robbery and homicide controlling for these other factors. The trend (β_{10}) models show the effects of these conditions on the 1988–2001 within-precinct robbery and homicide trends.

The base rate of robbery is positively associated with the prevalence of disorder, whereas the homicide base rate is unrelated to the extent of disorder. This finding is consistent with prior research showing a connection between disorder and robbery but not other serious crimes (Corman and Mocan, 2002; Sampson and Raudenbush, 1999). The two offense types

Table 1. Hierarchical Linear Model Results for Robbery and Homicide in New York City Police Precincts, 1988–2001

Fixed Effects	Robbery Rate	Homicide Rate
Level 1 Time-Varying Effects (*N* = 1,036)		
OMP $ß_{20}$	–.113 (.026)***	–.285 (.045)***
Disorder $ß_{30}$	.477 (.078)***	.504 (.126)***
Police officers $ß_{40}$	–.436 (.086)***	–.181 (.136)
Drug markets $ß_{50}$	.024 (.009)*	.040 (.019)*
Imprisonment–felony ratio $ß_{60}$	.033 (.029)	–.071 (.055)
Level 2 Time-Invariant Effects (*N* = 74)		
Intercept β_{00}	–.517 (.384)	–.801 (.423)
Mean OMP γ_{01}	–.028 (.051)	.170 (.059)**
Mean disorder γ_{02}	.330 (.080)***	.033 (.107)
Mean police officers γ_{03}	–.216 (.067)**	–.013 (.063)
Mean drug markets γ_{04}	.038 (.053)	.090 (.056)
Mean imprisonment–felony ratio γ_{05}	.028 (.037)	–.066 (.045)
Percent black γ_{06}	–.001 (.001)	.004 (.002)*
Disadvantage γ_{07}	–.017 (.029)	.179 (.060)**
Instability γ_{08}	–.036 (.035)	–.017 (.041)
Immigration γ_{09}	.077 (.020)***	.080 (.028)**
Percent black Δ γ_{010}	.002 (.002)	–.004 (.003)
Disadvantage Δ γ_{011}	–.051 (.078)	–.127 (.115)
Instability Δ γ_{012}	.050 (.058)	.057 (.089)
Immigration Δ γ_{013}	.087 (.056)	–.075 (.081)
1988 robbery (homicide) rate γ_{014}	.898 (.060)***	.481 (.101)***
Spatial lag—Robbery (homicide) rate γ_{015}	.187 (.084)*	.216 (.108)*
Spatial lag—OMP γ_{016}	–.132 (.069)	–.129 (.092)
Trend $\boldsymbol{\beta_{10}}$	–.027 (.022)	–.030 (.012)*
Percent black γ_{11}	.0003(.0001)**	.0002(.0002)
Disadvantage γ_{12}	.001 (.004)	–.006 (.006)
Instability γ_{13}	–.008 (.004)*	–.002 (.005)
Immigration γ_{14}	.001 (.002)	–.006 (.003)*
Percent black Δ γ_{15}	.0003(.0002)	.0005(.0003)
Disadvantage Δ γ_{16}	.001 (.010)	.023 (.012)*
Instability Δ γ_{17}	–.008 (.007)	.005 (.012)
Immigration Δ γ_{18}	.007 (.008)	.012 (.010)
1988 Robbery (homicide) rate γ_{19}	–.017 (.005)**	–.031 (.012)**
Spatial lag—Robbery (homicide) rate γ_{110}	–.004 (.010)	–.005 (.012)
Spatial lag—OMP γ_{111}	.005 (.010)	–.007 (.012)
Random Effects	**Variance**	**Variance**
Intercept r_0	.0102***	.0133**
Year r_1	.0002***	.0002**
Level 1 error	.0156	.0641
Deviance	–634.505	349.87
df	4	4

*p < .05; **p < .01; ***p < .001.
Robust standard errors in parentheses.

also differ with respect to the effects of mean levels of OMP and police size in the intercept model. We find a positive association between OMP and the base rate of homicide but no relationship between OMP and the base rate of robbery. On the other hand, precincts with more police per capita have lower base rates of robbery but do not differ significantly in their base rates of homicide. Neither the average level of drug market activity nor imprisonments per felony arrests are significantly associated with robbery or homicide in the intercept model.

The area characteristics featured in classic social disorganization explanations of crime also have somewhat different effects on the two offense types. Table 1 shows the effects of both the levels and the residual changes in these characteristics. Levels of and changes in residential instability are unrelated to the base rates of robbery and homicide. The level of immigration is positively associated with both offense types. The base rates of robbery and homicide, in other words, are higher in precincts with greater immigrant concentrations. The homicide base rates are also higher in more disadvantaged areas and those with larger proportions of black residents. Robbery rates are unrelated to precinct disadvantage and racial composition. Finally, base rates of robbery and homicide are greater in precincts near areas with high robbery and homicide rates.

Turning now to the trend models, we find that homicide declines were greater than average in areas with larger proportions of recent immigrants and foreign-born residents, lower than average in areas with increasing disadvantage, and greater in those with high initial homicide rates. Areas with high initial robbery rates also experienced greater-than-average declines in robbery. The latter findings are consistent with the hypothesis of mean reversion, such that areas with higher initial crime rates will experience larger crime declines (Harcourt and Ludwig, 2006). Robbery trends were unrelated to area disadvantage and immigration. We observe smaller-than-average robbery decreases in precincts with larger proportions of black residents and larger decreases in less stable areas. Robbery but not homicide declines were greater in precincts that added more police per capita. Finally, precincts in which the rate of cocaine-overdose deaths declined the most experienced significantly greater reductions in both robbery and homicide rates between 1988 and 2001. Taken together, these results contradict the strong version of the broken-windows thesis, which suggests that *only* aggressive quality-of-life enforcement was responsible for the New York City crime drop (Kelling and Sousa, 2001).

DETERMINANTS OF OMP

A comprehensive assessment of the impact of OMP on the New York City crime drop should take account of the possibility that many factors considered thus far are related to OMP and not simply to differences in crime levels and trends across New York City police precincts. Conditions that do not affect crime rates directly may nonetheless influence crime rates through their relationship with OMP. Failure to account for such indirect effects could result in overestimates of the contribution of the order-maintenance strategy to crime reduction and underestimates of the importance of other factors for explaining variation in both OMP and crime. Furthermore, a systematic appraisal of the determinants of OMP in New York City allows us to evaluate the charge of critics that police pursued particularly aggressive arrest strategies in disadvantaged minority communities.

The results for OMP are presented in table 2. We observe, first, that precincts with more disorder or greater-than-average growth in disorder also engaged in more OMP. Precincts with more police per capita and drug market activity did not exhibit higher base levels of OMP; however, growth in police size and drug markets is significantly associated with growth in OMP.

Contrary to expectations, we observe a strong, *positive* association between OMP and the ratio of felony arrests to felony complaints. Both the base level and the growth rate in OMP were greater in precincts with higher base levels and growth in the felony arrest–complaint ratio.[10] We hypothesized that this relationship would be negative, in other words, that precincts with fewer felony arrests would produce more order-maintenance arrests, assuming a trade-off in resources devoted to enforcing order and pursuing more serious crime. The results suggest that such trade-offs are minimal or that mass arrests for minor offenses on occasion net bigger fish, such as persons possessing firearms or large quantities of illicit drugs or who are wanted on felony warrants.

Did the New York City order-maintenance strategy target disadvantaged and minority communities? The results offer some support for the claims of critics (Greene, 1999; Harcourt, 2001; Karmen, 2004; McArdle and Erzen, 2001). The base level of OMP actually was lower in more disadvantaged areas, areas with greater-than-average increases in disadvantage, and those with a larger proportion of black residents. But *growth* in arrest rates for misdemeanors and violations of city ordinances was greater than elsewhere in more disadvantaged areas and those with larger proportions of blacks, even with initial violent crime rates, growth in disorder, and growth in drug markets controlled. These results suggest that the spike in OMP during the early 1990s was greater in New York City disadvantaged minority communities.

10. The results are the same when the rate of felony arrests per 10,000 precinct residents is substituted for the ratio of felony arrests to complaints.

Table 2. Hierarchical Linear Model Results for Order-Maintenance Policing in New York City Police Precincts

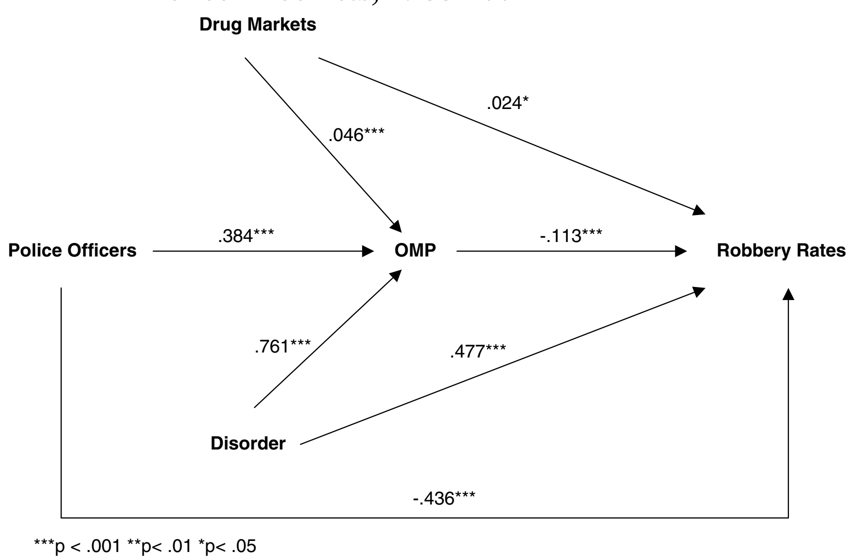
Fixed Effects	**OMP**	
Level 1 Time-Varying Effects (*N* = 1,036)		
Disorder β_{20}	.761	(.112)***
Police officers β_{30}	.384	(.102)***
Drug markets β_{40}	.046	(.012)***
Felony arrest–complaint ratio β_{50}	.740	(.066)***
Level 2 Time-Invariant Effects (*N* = 74)		
Intercept β_{00}	–3.730	(.582)***
Mean disorder γ_{01}	1.366	(.125)***
Mean police officers γ_{02}	–.100	(.094)
Mean drug markets γ_{03}	–.088	(.090)
Mean felony arrest–complaint ratio γ_{04}	.601	(.073)***
Percent black γ_{05}	–.007	(.002)**
Disadvantage γ_{06}	–.136	(.061)*
Instability γ_{07}	.063	(.067)
Immigration γ_{08}	.011	(.046)
Percent black Δ γ_{09}	.001	(.003)
Disadvantage Δ γ_{010}	–.383	(.176)*
Instability Δ γ_{011}	–.134	(.144)
Immigration Δ γ_{012}	–.063	(.101)
1988 homicide-robbery rate γ_{013}	.182	(.102)
Spatial lag—OMP γ_{014}	.076	(.085)
Trend $\boldsymbol{\beta_{10}}$	.092	(.032)**
Percent black γ_{11}	.0006	(.0002)**
Disadvantage γ_{12}	.012	(.004)**
Instability γ_{13}	.0005	(.006)
Immigration γ_{14}	.005	(.004)
Percent black Δ γ_{15}	.00004	(.0004)
Disadvantage Δ γ_{16}	.011	(.014)
Instability Δ γ_{17}	.005	(.012)
Immigration Δ γ_{18}	.009	(.008)
1988 homicide-robbery rate γ_{19}	–.013	(.007)
Spatial lag—OMP γ_{110}	–.005	(.010)
Random Effects	**Variance**	
Intercept r_0	.0651	***
Year r_1	.0005	***
Level 1 error	.0268	
Deviance	–181.962	
df	4	

*$p < .05$; **$p < .01$; ***$p < .001$.
Robust standard errors in parentheses.

DIRECT AND INDIRECT EFFECTS

Several time-varying covariates had significant effects on the OMP trends and, therefore, contributed indirectly to the New York City robbery and homicide reductions. These results are summarized in figures 3 and 4. As shown in the figures, growth in drug market activity, police size, and disorder contributed to increases in OMP, which is significantly related to declines in robbery and homicide rates.[11] Growth in drug markets contributed directly to the within-precinct trends in both offenses. Growth in police per capita had a direct effect on robbery trends but not on homicide trends. Prior research has shown that increases in police officers are associated with crime reductions, but the mechanisms linking more police and less crime remain unclear (Levitt, 2002, 2004). Our results suggest that OMP may be one such mechanism.

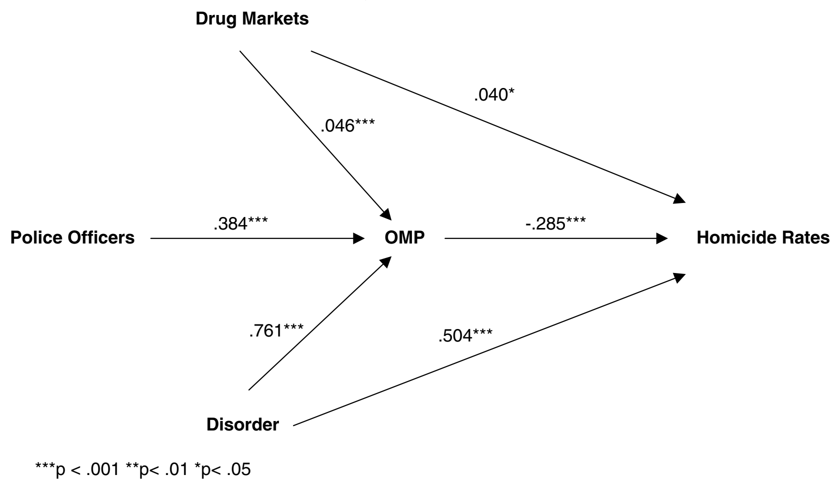
Figure 3. Direct and Indirect Effects of Disorder, Police Size, Drug Markets, and Order-Maintenance Policing on Robbery Rates in New York City Police Precincts, 1988-2001



The results summarized in figures 3 and 4 also confirm the importance of including an indicator of the prevalence of disorder in assessments of the impact of OMP on crime. Precincts with more disorder engage in more

11. Because its causal direction is uncertain, the significant association between order-maintenance policing and the felony arrest–complaint ratio is not shown.

Figure 4. Direct and Indirect Effects of Disorder, Police Size, Drug Markets, and Order-Maintenance Policing on Homicide Rates in New York City Police Precincts, 1988-2001



OMP, and even though OMP seems to reduce robbery and homicide, disorder has a large residual effect on the crime trends. Unless disorder is badly mismeasured on the basis of complaints to the police by residents, these results support the broken-windows thesis that disorder and crime are connected. But they also imply that arresting people for minor offenses may not be sufficient to sever the connection.

MODEL FIT AND SENSITIVITY TESTS

Our estimates of the impact of OMP on the New York City crime drop are only as reliable as the models used to produce them. It is important, therefore, to determine how well the models fit the data and to gauge the robustness of the results across differing model specifications. An indication of model fit can be gained by examining the reduction in the pooled error variance at level 1 between the unconditional models (not shown) containing only the time parameters and the full models reported in tables 1 and 2. The percentage reduction in level 1 error between the unconditional and full robbery models is 53.3 percent. The percentage reduction in level 1 error between the two homicide models is 15.5 percent. The full model for OMP produces a reduction in level 1 error of 45.6 percent over the unconditional model. These results inspire somewhat greater confidence in the estimated effects of OMP on the robbery trends than the homicide trends.

To test the sensitivity of our results to differing model specifications, we first trimmed the robbery and homicide models of all variables with *p*-values above the marginal statistical significance threshold of $p = .10$, based on the robust standard errors reported in tables 1 and 2. We reestimated the trimmed models and obtained the revised coefficients for the measure of OMP. The revised coefficients do not differ greatly from those in the original models. The OMP coefficient in the trimmed robbery model is –.108 ($p < .001$), compared with –.113 in the full model. The OMP coefficients in the trimmed and full homicide models are –.270 ($p < .001$) and –.285, respectively.[12]

Although our models contain a measure of drug activity and the initial (1988) robbery or homicide rate, it is possible that these variables do not fully capture the initial crime increase and subsequent mean reversion in the precincts hardest hit by the violence associated with the crack markets.[13] The beginning of the New York City crack epidemic has been traced to the early-to-mid 1980s (Goldstein, 1985; Golub and Johnson, 1994). Therefore, as a second sensitivity test, we obtained precinct-level robbery and homicide data for 1984 and modeled the increase in robbery and homicide rates from their 1984 levels to their respective peak rates on the assumption that precincts exhibiting the largest crime increases associated with the crack epidemic of the 1980s would also show the sharpest post-epidemic declines (Harcourt and Ludwig, 2006). We measured the crime increase in two ways, by including the percentage change in robbery and homicide rates from 1984 to their precinct-specific peaks and the percentage change to their city-wide peaks in 1990. Neither modification produced important changes in the results.[14]

It is also important to determine the sensitivity of the estimated effect of OMP on crime rates to possible measurement error in the indicator of disorder. If citizen complaints of disorder increase in response to greater police attention to disorder, they may spur even more misdemeanor and ordinance-violation arrests and, in turn, more citizen complaints, regardless of changes in the level of disorder in the precinct. On the other hand, omitted variable bias will result from excluding a measure of disorder

12. We also reestimated the OMP model trimmed of nonsignificant variables. The resulting coefficient for police officers is .378 ($p < .001$), which is nearly identical to the coefficient in the original model (see table 2).
13. We thank an anonymous reviewer for pointing this out and Jens Ludwig for providing the 1984 precinct-level homicide and robbery data.
14. When the percentage change to the precinct-specific rate is added, the resulting OMP coefficient for homicide is –.280 ($p < .001$), compared with –.285 in the original model, and –.118 ($p < .001$) for robbery, compared with –.113 in the original robbery model. When the city-wide peak rates are used, the resulting coefficients for homicide and robbery are –.276 and –.116, respectively (both significant at $p < .001$).

from our models if, in fact, disorder is a significant determinant of police arrest practices or serious crime, as the broken-windows thesis holds.

Although we cannot resolve this issue with the available data, we can determine the extent to which the disorder indicator affects the coefficient on the OMP measure by comparing the results of models from which the disorder variable has been dropped with those from the full models. The coefficient in the robbery model from which the complaints measure was dropped (not shown) is –.066 ($p < .05$), compared with –.113 in the full model. The coefficient in the revised homicide model is –.239 ($p < .001$), compared with –.285 in the full model. Although the effect sizes are somewhat smaller when the disorder measure is removed, we find significant effects of OMP on robbery and homicide trends in models with and without this covariate.

The results presented thus far suggest that OMP had nonzero effects on robbery and homicide trends, but the final question remains: How much of the robbery and homicide reduction in New York City can be attributed to OMP? The coefficients from our models can be used to obtain broad estimates of the percentage of the reduction in robbery and homicide rates that is attributable to the order-maintenance strategy.

THE MAGNITUDE OF THE OMP EFFECTS

The contribution of OMP to the New York City robbery and homicide reductions is a function of three values, two observed and one estimated: the average rate of change in misdemeanor and ordinance-violation arrests, the average rate of change in robbery and homicide, and the estimated conditional effects of OMP on the homicide and robbery trends. Order-maintenance arrest rates grew at an average annual rate of 1.79 percent over the 14-year period under investigation, from 209.2 misdemeanor and ordinance violation arrests per 100,000 residents in 1988 to a rate of 261.8 arrests per 100,000 in 2001 (see figure 2). Robbery rates declined at an average annual rate of 5.19 percent, with 120.7 robberies per 100,000 New York City residents in 1988 decreasing to 33.1 per 100,000 in 2001. Homicide rates decreased at an annual rate of 5.12 percent, with 26.7 homicides per 100,000 in 1988 decreasing to 7.56 per 100,000 in 2001 (see figure 1). The coefficients on the measure of OMP yield an annual percentage change in the New York City robbery rate of –.113 percent for every 1 percent change in OMP and an annual percentage change of –.285 percent in the homicide rate for every 1 percent change in OMP (see table 1). These results imply that about 4 percent of the New York City annual reduction in robbery rates and 10 percent of the reduction in homicide rates are attributable to the observed growth in OMP.[15]

15. Given yearly growth rates of –5.19 percent and –5.12 percent and elasticities of

Caution should be exercised in interpreting these point estimates. The precision of the OMP effects is subject to sampling error. The actual percentage reduction in the robbery rate for every 1 percent increase in the rate of OMP is anywhere between .09 percent and .14 percent at the 95 percent confidence level. The comparable reduction in the homicide rate is between .24 percent and .33 percent (see table 1). In addition, the results represent average changes across precincts and over time. The effects of OMP on the crime trends likely differed when it was growing rapidly between 1993 and 1997 and when it was roughly stationary in the preceding and subsequent years under consideration (see figure 2). Finally, the estimated effects will be biased to the extent that the models are misspecified. Although the sensitivity tests suggest that the OMP effects are reasonably stable across differing model specifications, they are somewhat larger in models containing the measure of disorder than in those without it. Because plausible grounds exist for including or excluding this measure, and the available data cannot be used to choose between them, the safest course is to bound our estimates of the impact of OMP on the New York City robbery and homicide trends with the coefficients from the alternative model specifications. The standard errors of the estimates also can be used to create upper and lower bounds on the reduction in robbery and homicide rates attributable to OMP.

Table 3. Estimated Percentage of New York's Robbery and Homicide Declines Attributable to Growth in Order-Maintenance Policing, 1988–2001

	Robbery	**Homicide**
High estimate[a]	4.79	11.54
Low estimate[b]	1.30	6.82

[a]OMP estimate plus standard error from models including disorder.
[b]OMP estimate minus standard error from models without disorder.

Table 3 presents upper- and lower-bound estimates of the percentage of the New York City robbery and homicide declines associated with growth

–.113 percent and –.285 percent for robbery and homicide, respectively, the observed 1.79 percent yearly growth in OMP produced an estimated –.202 percent yearly change in robbery rates (1.79 × –.113) and –.510 percent yearly change in homicide rates (1.79 × –.285). The estimated yearly reduction in robbery attributable to OMP growth accounts for 3.89 percent of the observed reduction ((–.202 / –5.19) × 100). The comparable estimated reduction in homicide accounts for 9.96 percent of the observed reduction ((–.510 / –5.12) × 100).

in misdemeanor and ordinance-violation arrest rates between 1988 and 2001. The upper-bound estimates were calculated by adding the standard error to the OMP coefficient in the models containing the disorder covariate. The lower-bound estimates were calculated by subtracting the standard error from the coefficients in the models omitting the disorder indicator (computational procedures are in footnote 15). Growth in OMP accounts for roughly 1–5 percent of the robbery decline and 7–12 percent of the homicide decline. The results indicate modest impacts of OMP on New York City robbery and homicide trends during the 1990s.

DISCUSSION

Criminologists and policy analysts have debated the causes of the New York City dramatic crime decline, particularly the contribution of "quality-of-life" policing strategies introduced in 1994. Prior research is limited and offers widely differing assessments of the impact of OMP on the New York City crime reductions. Building on these investigations, the current study finds that OMP did contribute to New York City robbery and homicide declines. The impact was modest, however, and we conclude that substantial crime reductions likely would have occurred even without the growth in OMP.

Harcourt (2001) and other critics have challenged the role of the police in the New York City crime drop, arguing that their influence may have had less to do with restoring order than with mass surveillance of poor minority communities. Although the distinction he draws is subtle, it implies that the sheer number of police officers should have a greater effect than policing disorder on rates of serious crime. Contrary to the Harcourt (2001) contention, our findings suggest that the primary impact of more police officers on the New York City homicide decline was to enable the police to engage in more OMP. The results for robbery offer more support for the empirical expectation derived from the Harcourt (2001) argument.

Our results do indicate that precincts with larger proportions of black and disadvantaged residents experienced increased growth in misdemeanor and ordinance violation arrests, controlling for growth in drug activity and disorder and initial levels of robbery and homicide. These findings suggest that the police may have targeted such communities; however, we do not know how much of the increase in order enforcement may have been elicited by residents of those communities in response to greater police attention. Nor do the results reveal whether police misconduct increased along with order enforcement. In light of other research showing that police misconduct is related to higher levels of violent crime in disadvantaged New York City communities (Kane, 2005), whether the crime-reduction effects of OMP are diminished when citizens believe their rights are violated is a critical issue for research on order enforcement and police–citizen relationships.

Several factors in addition to OMP are associated with New York City robbery and homicide declines. Contrary to the Kelling and Sousa (2001) assertion that the so-called root causes of crime played no role in the New York City violent crime drop, we find significant effects of socioeconomic disadvantage, racial composition, and immigrant concentration on robbery and homicide levels and trends. We also find some evidence of mean reversion in the data: Areas with greater initial crime levels experienced significantly larger crime decreases. But controlling for mean reversion does not wipe away the effect of order-maintenance arrests on the crime trends. The order-maintenance effects persist even when we control for robbery and homicide increases since 1984 at the beginning of the New York City crack epidemic. The growth in OMP was *not* significantly greater in precincts with higher initial levels or growth in robbery and homicide. As we have observed, it was concentrated in more disadvantaged areas with larger black populations, as charged by New York City policing critics. In other words, the effects of mean reversion on the crime trends and order-maintenance arrests are largely independent of one another.

Several reasons for caution exist in interpreting our results. We do not have precinct-level data on other policing changes tied to the New York City policing reforms beyond arrests for misdemeanor and ordinance violations. Conceivably, precincts that faithfully implemented the order-maintenance strategy also kept better or timelier crime records, engaged in more "hot spot" policing, or took other actions that reduced crime, and the effects of OMP could be confounded with such unmeasured influences. In addition, heightened arrest activity is only one of several possible means of implementing the quality-of-life initiative. Because we have no systematic data on other police tactics, our investigation, like those of Kelling and Sousa (2001) and Harcourt and Ludwig (2006), is limited to the crime-reduction effects of order-maintenance *arrests*. Researchers may need to combine quantitative and qualitative data for insights about the effects of the full range of New York City policing reforms (see Kelling and Sousa, 2001, for an example).

Our homicide results invite special caution given the large residual error in the homicide model. This limitation may be remedied in future research through the addition of relevant covariates (e.g., firearm availability) and the use of more refined data that partitions the incidents by weapon type, location (indoors vs. outdoors), circumstance, and victim–offender relationship.

The most important reason for caution regarding our results, as well as those of nearly all prior studies of policing effects on crime, is that they are based on observational data and methods permitting no experimental manipulation of the “treatment” of interest. An ideal study design would allow the investigator to randomly allocate police precincts to “high” and “low” order-maintenance arrest conditions. That level of investigator control over research conditions was not possible in the current study and is likely to remain a rarity in criminal justice research for some time. Meanwhile, the widespread adoption across the United States of OMP and other innovations modeled on the New York City *Compstat* initiative (Kilzer, 2006; Weisburd et al., 2003) lends renewed significance to studies of the effects of policing on crime. As we await the results of studies based on new data and diverse methods, we conclude that OMP had a discernible but small impact on robbery and homicide trends in New York City during the 1990s.

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Appendix A. Variable Definitions and Descriptive Statistics

Variable	Description	Mean	SD
Level 1: Time-varying (N = 1,036)[a]			
Homicide Rate	Homicide rate per 10,000 residents	2.14	2.34
Robbery Rate	Robbery rate per 10,000 residents	108.95	135.99
OMP	Misdemeanor and ordinance violation arrests per 10,000 residents	364.79	728.49
Disorder	Misdemeanor and ordinance violation complaints per 10,000 residents	882.57	933.35
Imprisonment–Felony Ratio	Prison admissions per 1,000 felony arrests	102.94	43.67
Felony Arrest–Complaint Ratio	Felony arrests per 10,000 felony complaints	.38	.23
Police Officers	Uniformed patrol officers per 10,000 residents	27.88	19.94
Drug Markets	Cocaine overdose deaths per 10,000 residents	.76	.75
Level 2: Time-stable (N = 74)			
Disadvantage	Principal components factor score representing socioeconomic disadvantage	.00	1.00
Instability	Principal components factor score representing population instability/mobility	.00	1.00
Immigration	Principal components factor score representing population immigration	.00	1.00
Percent Black	Non-Hispanic black percentage of population	27.19	27.86
1988 Homicide Rate	1988 Homicide rate per 10,000 residents	3.15	2.64
1988 Robbery Rate	1988 Robbery rate per 10,000 residents	161.24	209.11
Spatial Lag—Homicide	Spatial lag of 10 nearest neighbors homicide rates per 10,000 residents	.12	.52
Spatial Lag—Robbery	Spatial lag of 10 nearest neighbors robbery rates per 10,000 residents	.16	.47
Spatial Lag—OMP	Spatial lag of 10 nearest neighbors OMP arrest rates per 10,000 residents	.07	.60
Disadvantage Δ	1990–2000 residual change score for Disadvantage	.00	.23
Instability Δ	1990–2000 residual change score for Instability	.00	.24
Immigration Δ	1990–2000 residual change score for Immigration	.00	.37
Percent Black Δ	1990–2000 residual change score for Percent Black	.00	7.19

[a]Computed on pooled data.