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Homicide and Crack in New York City

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According to many newspaper accounts, the widespread distribution of crack is a "plague" wreaking havoc on our society. This drug, a cocaine derivative ingested by smoking, is believed to be responsible for, among other things, an unprecedented surge in violence. Many policymakers believe that public policy must address itself to this "scourge" and that vast expenditures of public funds are necessary to make our country safe from further destruction. Although there is considerable debate about which policies will be most effective in reducing the devastating impact of this "epidemic," most people believe that there is great urgency in finding solutions.

Before addressing the policy issues, however, it is prudent to examine these claims in a more systematic and objective fashion. Decisions regarding the speed and intensity of public policy should follow an assessment of the severity of the problem. The purpose of this paper is to add to the public policy debate, by providing a statistical assessment of one of the most potentially serious consequences of crack—homicides. Toward this end, we focus on one of the geographic areas believed to be most severely affected by crack—New York City.

Specifically, we examine the claim that the crack epidemic is responsible for

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an unprecedented surge in homicides in New York City. We use currently available data and statistical techniques to assess the magnitude and significance of the increase in homicides in New York City, following the introduction of crack. The importance of current increases in homicide rates can only be assessed through comparison with past levels and changes.

Relationship between Crack and Homicide

There are several reasons why drugs, in general, and crack, in particular, are believed to be related to increased levels of violence. Users are often earners of low wages who can only support their habits through illegal means. Further, the stronger the addiction and the greater the immediate need for drugs, the more risk the user will be willing to take to obtain money. This means that users will be more likely to resort to violence to obtain needed funds. If users are temporarily under the influence of drugs, or are experiencing withdrawal when engaging in crime, their judgment will be impaired and they will be more likely to react violently to an unexpected situation.

Some claim that the addiction changes the individual's valuation of time and risk. The addict is depicted as present-oriented and either indifferent to or favorably inclined toward risk. Since the cost of committing crimes is possible future incarceration, present-oriented, risk-preferring individuals are most likely to commit crimes, and most likely to resort to violence. Those who claim that the crack "epidemic" is worse than prior periods of drug use claim that the drug, itself, is different. Crack produces an immediate, intense high followed by a sharp crash, with a compelling drive to get high again. Crack is thus believed to be far more addictive than cocaine powder. It is also cheaper to obtain, opening the door to potential addiction for those who couldn't afford to even try cocaine. Unlike both cocaine powder and heroin, crack is believed to cause greater aggression in users. Unlike the availability of methadone for treating heroin withdrawal, there is no treatment to alleviate symptoms of withdrawal from cocaine or its derivative, crack.

Many believe that violence associated with drugs is primarily due to the illegality of the market. Drug producers and sellers have no other recourse to settling disputes and force is a typical method in obtaining market power. Some claim that individuals involved in crack production and distribution are a younger, tougher breed of drug marketeers, more violent and more indifferent to human life than in prior generations. For all of these reasons, we would expect the crack "epidemic" to be related to significantly elevated levels of homicide.

All the above arguments have a common but potentially erroneous premise: that the close association between drug use and crime reflects causation. That is, the drugs "cause" all the negative outcomes, which implies that by eliminating the drugs, or their illegal status, all the negative outcomes associated with drug use will be eliminated. Consider, for example, the argument that drug users commit crimes to support their habits. The implication is that if these individuals were not using drugs, they would not commit crimes. Researchers, however, find that many drug-using criminals began their criminal activities before they began using drugs.[1] The same characteristics believed to lead individuals to commit crimes—low wages in the legal sector, high rate of preference for the present compared to the future, high tolerance for risk, willingness to participate in activities thought to be illegal by many citizens—may also lead the same individuals to use and become addicted to drugs. It may be that the same individuals who commit violent acts also use drugs, but by eliminating drugs, we may not have as much impact on crime as suggested by newspaper accounts that criminals were on drugs.

The same causality issue applies to the supply side of the drug market. Although it may be true that illegal markets tend to be violent, it may also be true that individuals with a high tolerance for risk and violence are attracted to these industries. If all drug markets were legalized, these individuals might find other illegal or legal industries where they could apply their skills.

It is possible, then, that illegal drugs do not cause otherwise peaceful, law-abiding citizens to become murderers. Rather, it is possible that some individuals who either use or sell drugs would be criminals and violent in the absence of such drugs. Introduction of a new, highly addictive drug such as crack may not, necessarily, cause soaring murder rates, even if a high fraction of murders is committed by crack sellers and users. It becomes an empirical question. Was the introduction of crack associated with statistically significant increases in murders in New York City? If the answer to this question is no, then policymakers need to reexamine the causes and potential solutions to crime and other problems believed to be caused by drug use.

Empirical Implementation

Data

The monthly data on murders from January 1967 through March 1990 were obtained from monthly statistical reports from the Crime Analysis Unit of the New York City Police Department. The monthly numbers represent complaints (offenses known to have occurred) in the categories of murder and nonnegligent manslaughter. These categories conform to the guidelines issued by the Uniform Crime Reporting Committee of the United States Federal Bureau of Investigation. Annual figures dating from 1930 were obtained from a special report of the Crime

Analysis Unit of the New York City Police Department. In both cases, we began with the data from the first available date. We excluded the March 1990 Bronx social club fire, which resulted in 87 deaths, from the analysis.

Monthly population figures pertain to New York City residents 16 years and older and are from the U.S. Bureau of Labor Statistics' Current Population Survey beginning in January 1970. Because of the small sample size, race, sex, and age breakdowns are unavailable. Moreover, due to budget cuts at the Bureau of Labor Statistics, the number of households surveyed in New York City was reduced from 2,200 to 1,300 between March 1988 and October 1989. The population series was discontinued during this time but resumed in November 1989. The missing population figures were estimated by applying the compounded monthly rate of growth between February 1988 and November 1989 to the months with missing data.

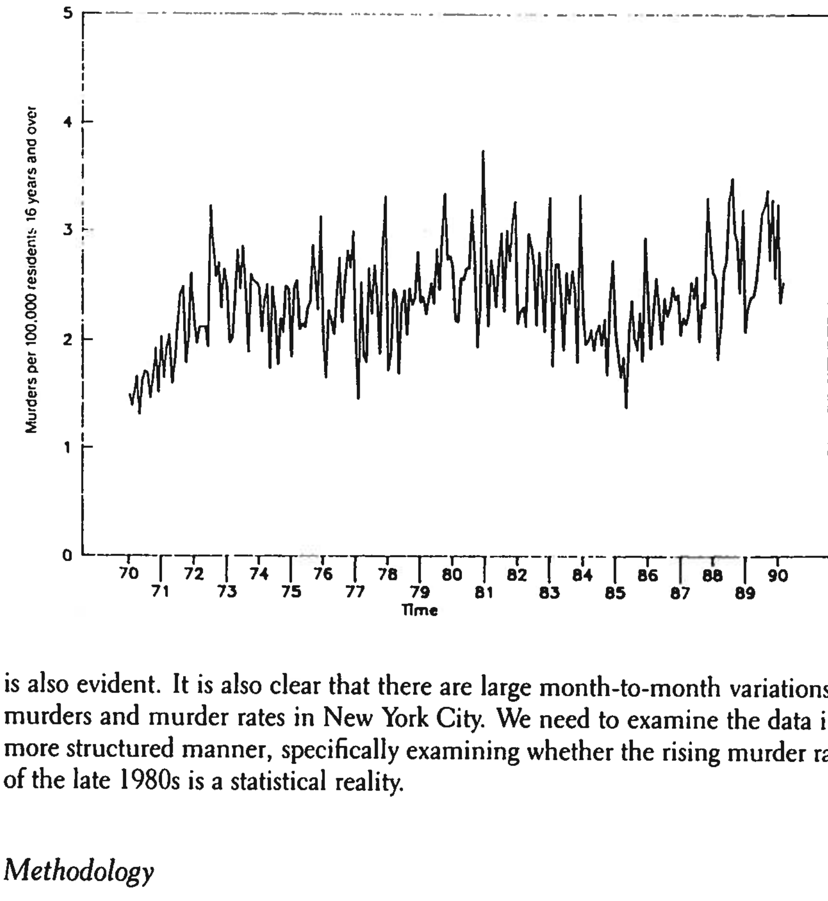
Annual population figures for New York City residents of all ages are based on the census. Intercensal years represent the annually compounded rate of growth between the census years. Annual population figures for 1981 through 1989 apply the annual rate of growth (from April to April) in the population 16 years and over from the Current Population Survey measured to the 1980 census.

There is considerable controversy about the growth or decline of the population of New York City between 1980 and 1990. It may take years to have an accurate assessment of New York City's 1990 population. Our methodology results in a modest increase in the city's population over the second decade of our study. To increase the validity of our results, however, we employ not only murder rates per 100,000 population aged 16 and above, but we also employ the actual number of murders. It should be noted that no matter whose population estimates are used, the city's population was relatively stable over the two decades of our analysis.

Figures 7.1a through 7.1c plot the annual number of murders, murder rates per 100,000 residents, and murder rates per 100,000 males aged 15 to 29 in New York City between 1930 and 1990. Several trends are apparent. First, murders increased approximately fourfold in the decade of the 1960s through the early 1970s. Second, there has been a sharp increase in murders and murder rates from approximately 1986, but this was preceded by a sharp decrease from 1982 to 1986. These trends are irrespective of whether murders or murder rates per resident or murder rates per young male are examined. Even though we cannot distinguish population subgroups in our monthly estimates, it is helpful to know that, on an annual basis, neither the large increase in the young male adult population in the 1960s nor the decline in the young male adult population in the 1980s can account for the trends in murders observed during these decades.

Figures 7.2a and 7.2b plot monthly murders and murder rates, respectively. The (latter part of the) upward trend from the early 1960s to the early 1979s is, again, apparent. The decline from 1981 to 1985, followed by the rise from 1985,

FIGURE 7.1A. NUMBER OF MURDERS, 1930–1989.



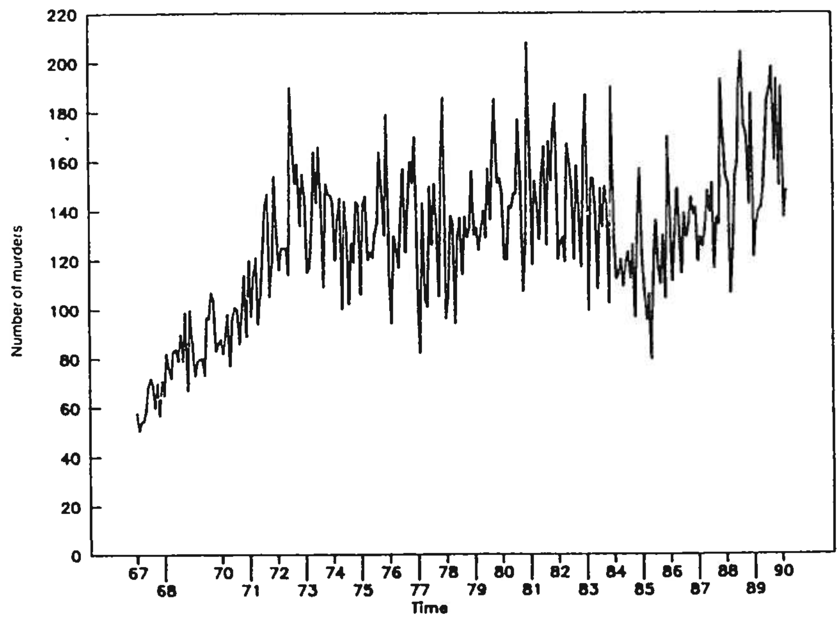
is also evident. It is also clear that there are large month-to-month variations in murders and murder rates in New York City. We need to examine the data in a more structured manner, specifically examining whether the rising murder rates of the late 1980s is a statistical reality.

Methodology

We address two questions: First, does the upturn in murders and in the murder rate in or about 1985 in New York City represent a statistically significant shift in the series given the previous 23 years? If yes, is it reasonable to link the rise to the introduction and spread of crack in New York City?

Given the seasonality in the murder series and its inherent variability, it is difficult to pinpoint a turning point. According to Figures 7.2a and 7.2b, a rough estimate would be mid-1985. Similarly, there is no exact date that defines the introduction of crack into the New York City drug market. The best guess is that crack became a factor sometime between 1984 and 1985; the Public Affairs Office of the U.S. Drug Enforcement Agency reports that crack was a "serious problem" in New York City by the beginning of 1986. Consequently, any attempt to establish a turning point in murders and to link it to the introduction of crack

FIGURE 7.1B. NUMBER OF MURDERS PER 100,000 RESIDENTS, 1930–1989

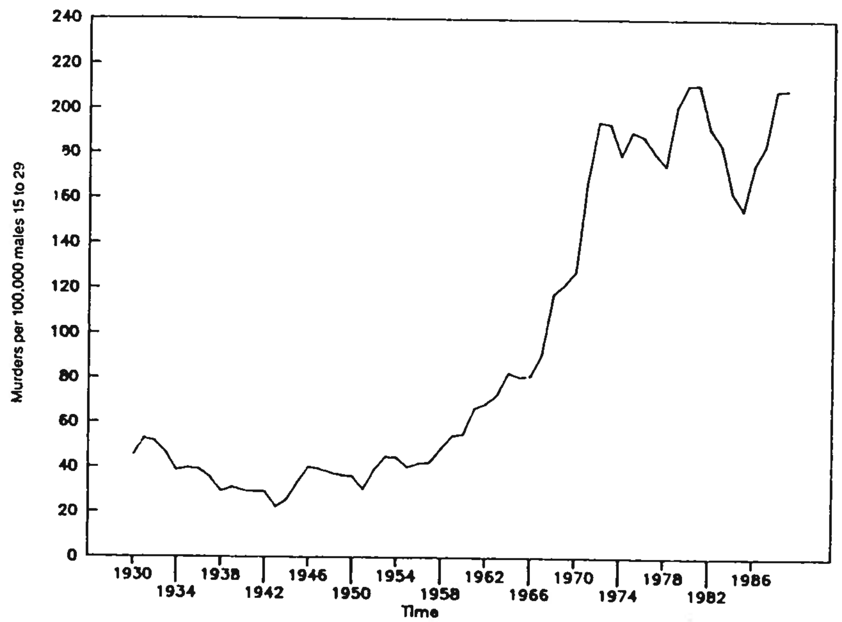


must be considered exploratory. As a result, we have approached the problem in several ways.

First, we fit univariate time-series models to murders and murder rates up until a hypothetical turning point.[2] We then project the series forward from that point and assess how well the actual data compare to the forecasts. If a true turning point occurred at the proposed date, then the forecasts should be poor compared with the actual data. One indicator of poor forecasts would be if the actual data were consistently above the 95-percent confidence interval for the forecasts. A second indicator would be whether the mean of the forecast errors is large in absolute value relative to the standard deviation. If we have specified the true underlying process correctly, and if there has been no important shift in the series, then the forecast errors T-periods ahead should be distributed symmetrically around zero. If the mean of the forecast errors divided by its standard deviation were positive and greater than 2, then this would be evidence that an unanticipated upturn in murders or murder rates may have occurred.

In the second approach we build an intervention model for the entire series by adding a dummy variable to the autoregressive integrated moving-average (ARIMA) specification. The dummy variable equals zero prior to the hypothesized turning point and one thereafter. A positive and statistically significant

FIGURE 7.1C. NUMBER OF MURDERS PER 100,000 MALES AGED 15 TO 29, 1930–1989



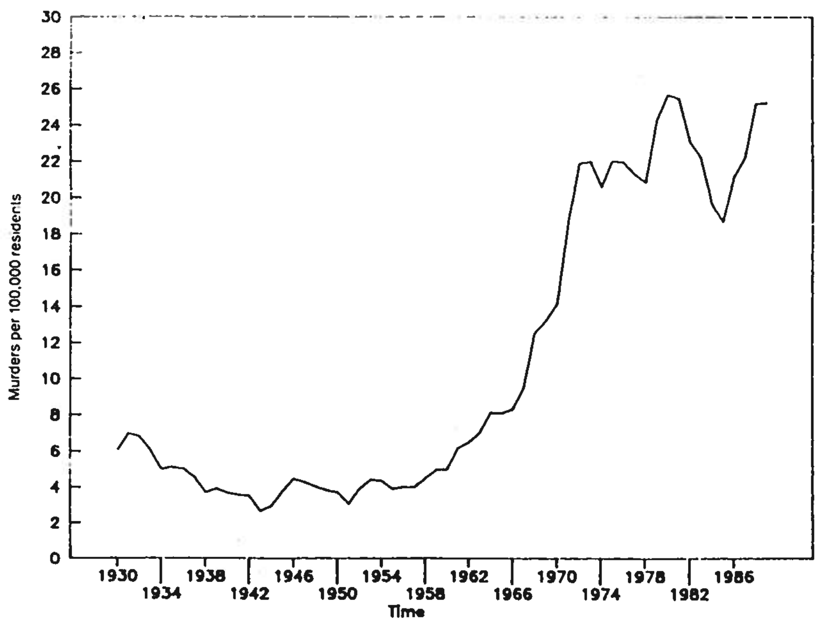
coefficient on the dummy variable would be evidence of a potentially important upward shift in murders.

The drawback to the intervention analysis is the uncertain timing of the introduction of crack into New York City. It would be possible to find one statistically significant intervention date in the 24-month span between 1984 and 1986 when in fact no true intervention occurred. The reverse is also possible. Multicollinearity among the parameters as well as a lack of sufficient postintervention data points could prevent us from finding a statistically meaningful change in the series.

Because of these drawbacks, we also employ a third approach to test whether there was a significant increase in murders coincident with the crack epidemic. Our third approach uses the intervention models from our second approach to forecast murders from January 1987 through March 1990. We compare these forecasts to the forecasts obtained in models that exclude the intervention components. If by modeling an intervention we can improve our forecasts over a period in which crack is well established, then we would accept such a result as evidence that a potentially meaningful upward shift in murders took place at or around the hypothesized date.

The most convincing evidence of a significant upturn in murders coincident

FIGURE 7.2A. NUMBER OF MURDERS 1967–1990 (MONTHLY)



with the introduction of crack in New York City would be agreement across the three approaches for at least one of the hypothesized intervention dates between January 1984 and January 1986. Similarly, forecast errors that were no different from zero, forecasts that were within the confidence intervals, intervention components that were statistically insignificant, and forecasts that were not improved by modeling the intervention would suggest that although murders have risen since 1985, the shift is not inconsistent with past movements in the series.

RESULTS

Figures 7.3 through 7.7 compare the projected number of murders to the actual number over a 24-month horizon. The forecasts are based on data up until the hypothesized introduction of crack to the New York City market. We use January 1984, July 1984, January 1985, July 1985, and January 1986 as possible dates associated with the introduction of crack. Figures 7.8 and 7.12 make the same comparisons for murder rates per 100,000 residents aged 16 and above. We include only the upper 95-percent confidence interval because we are most interested in whether actual murders exceed predicted murders. Table 7.1

FIGURE 7.2B. MURDER RATES 1970–1990 (MONTHLY)

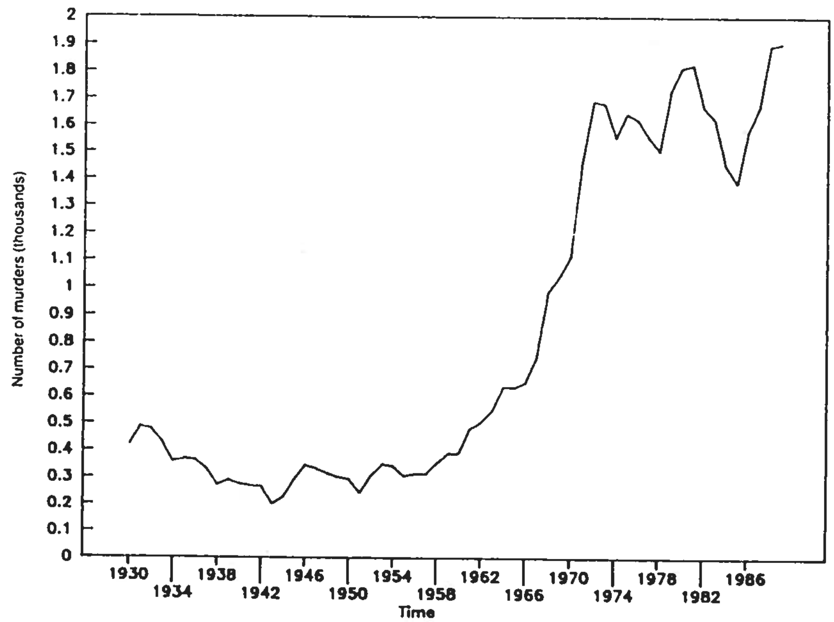


TABLE 7.1. THE MEAN AND THE STANDARD DEVIATION OF THE MEAN (IN PARENTHESES) FOR FORECAST ERRORS OVER A 24-MONTH HORIZON

January 1984	*July 1984*	*January 1985*	*July 1985*	*January 1986*
		Murders		
−20.2	−5.0	4.9	23.0	21.7
(2.9)	(3.3)	(3.4)	(3.1)	(3.6)
		Murder rates		
−3.3	.3	3.0	5.9	4.9
(.6)	(.7)	(.8)	(.7)	(.8)

Figure 7.3. Actual vs. forecasted murders January 1984–March 1990 (intervention date: January 1984)

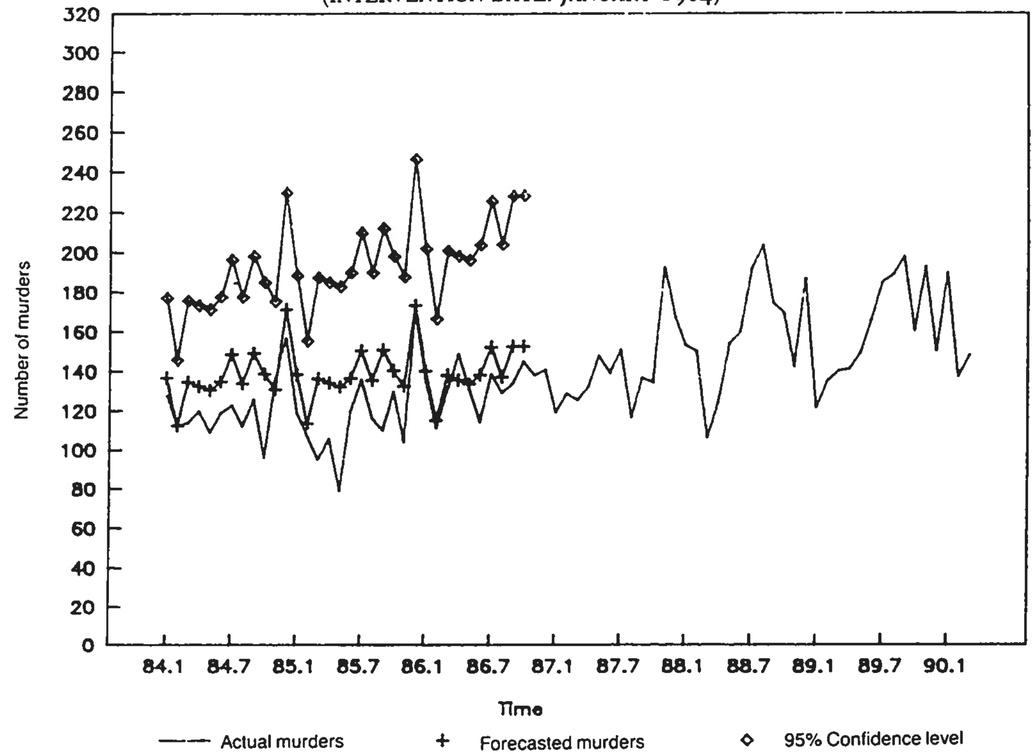


FIGURE 7.4. ACTUAL VS. FORECASTED MURDERS JANUARY 1984–MARCH 1990 (INTERVENTION DATE: JULY 1984)

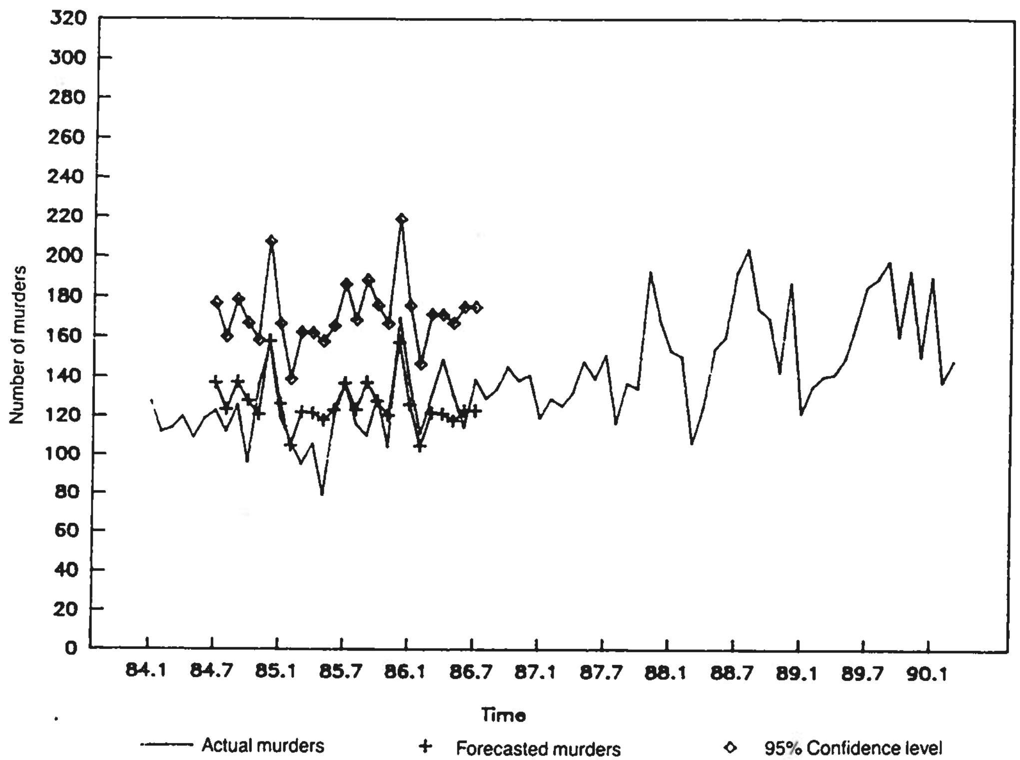


Figure 7.5. Actual vs. forecasted murders January 1984–March 1990 (intervention date: January 1985)

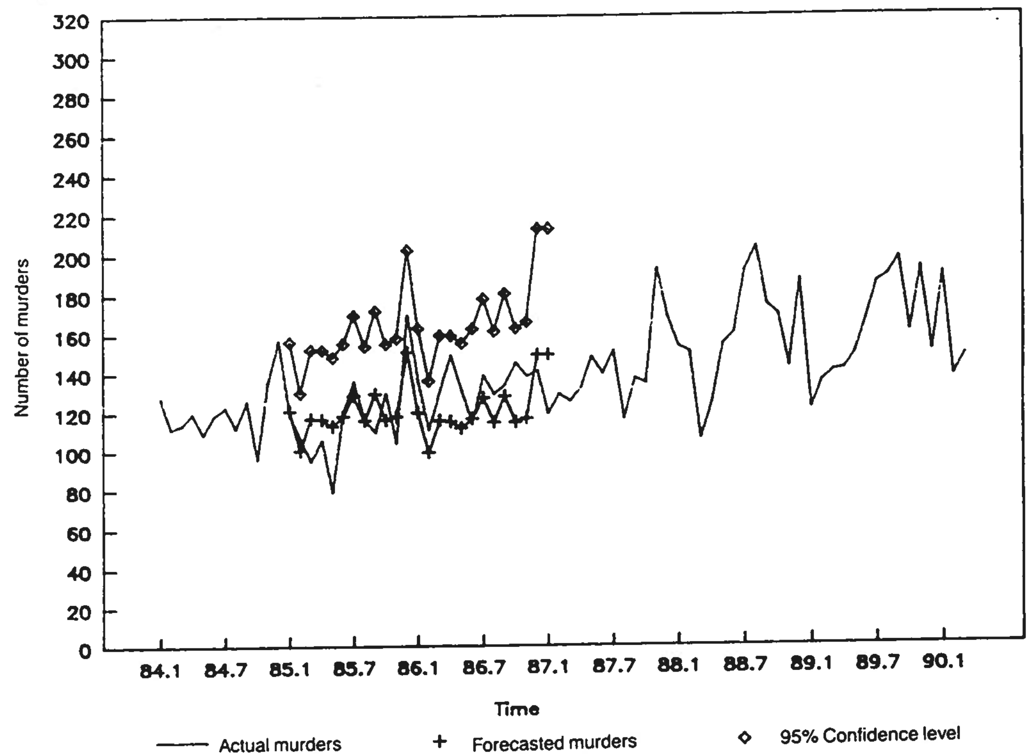


Figure 7.6. Actual vs. forecasted murders January 1984–March 1990 (intervention date: July 1985)

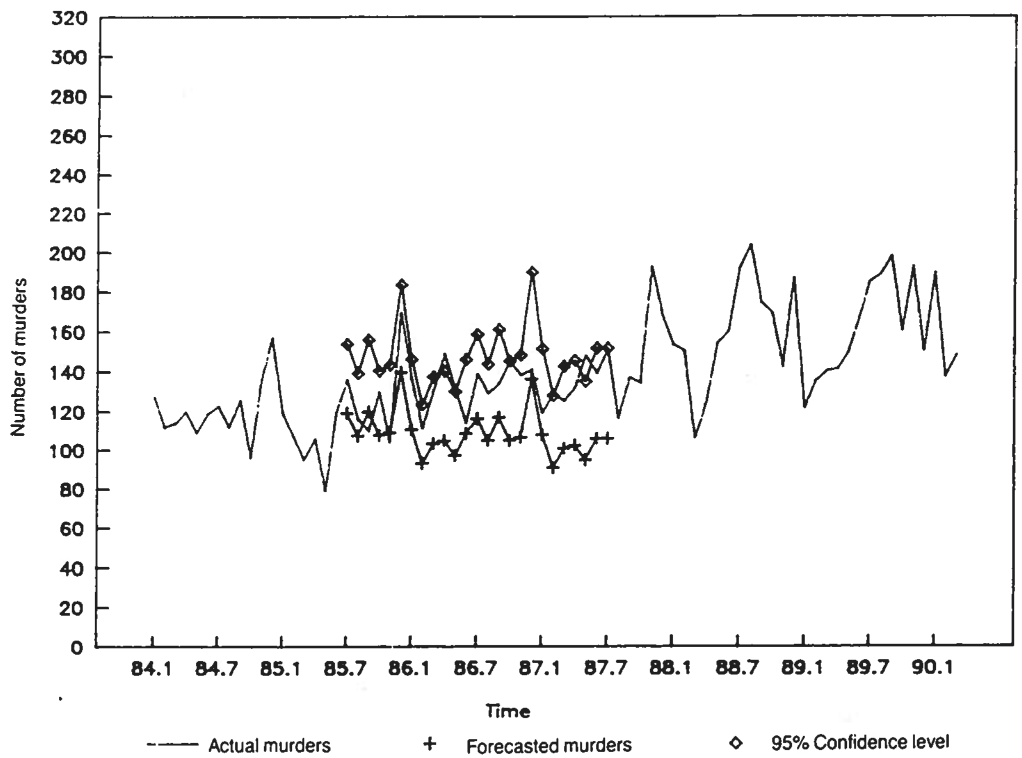


FIGURE 7.7. ACTUAL VS. FORECASTED MURDERS JANUARY 1984–MARCH 1990 (INTERVENTION DATE: JANUARY 1986)

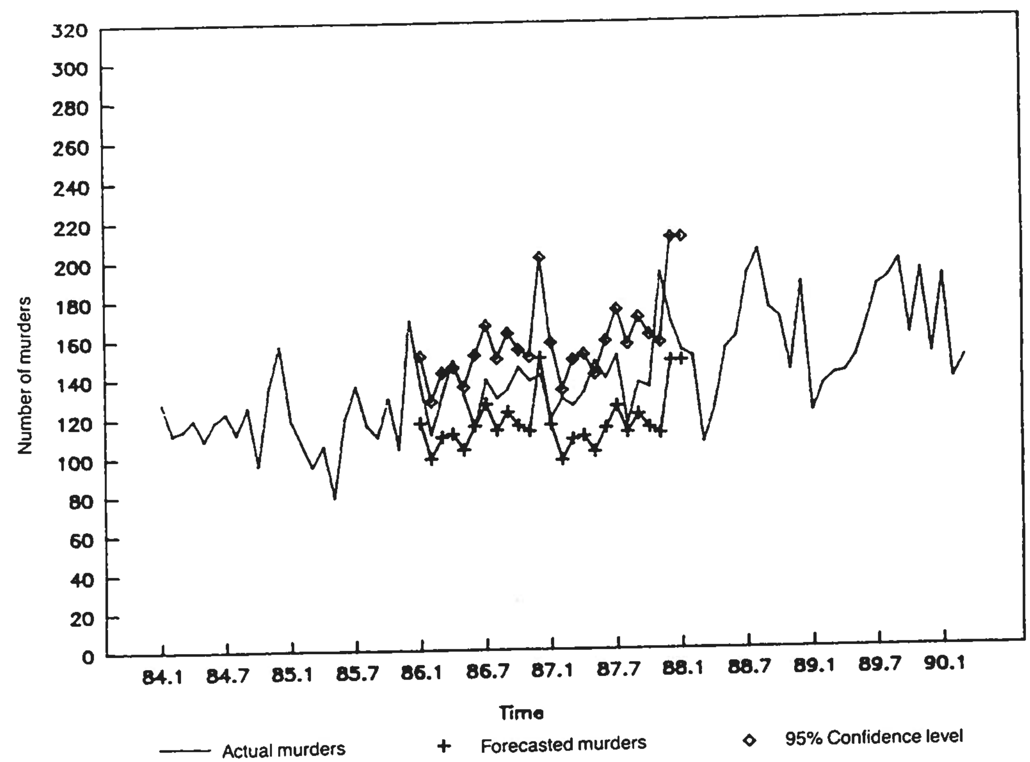


FIGURE 7.8. ACTUAL VS. FORECASTED MURDER RATES JANUARY 1984–MARCH 1990 (INTERVENTION DATE: JANUARY 1984)

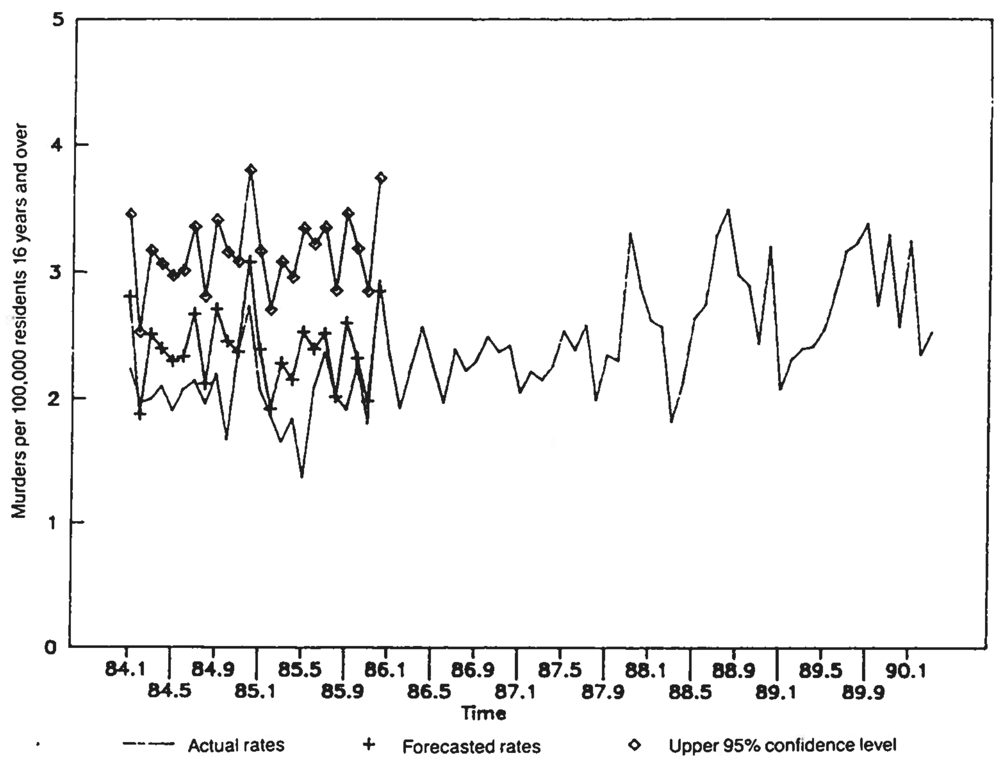


FIGURE 7.9. ACTUAL VS. FORECASTED MURDER RATES JANUARY 1984–MARCH 1990 (INTERVENTION DATE: JULY 1984)

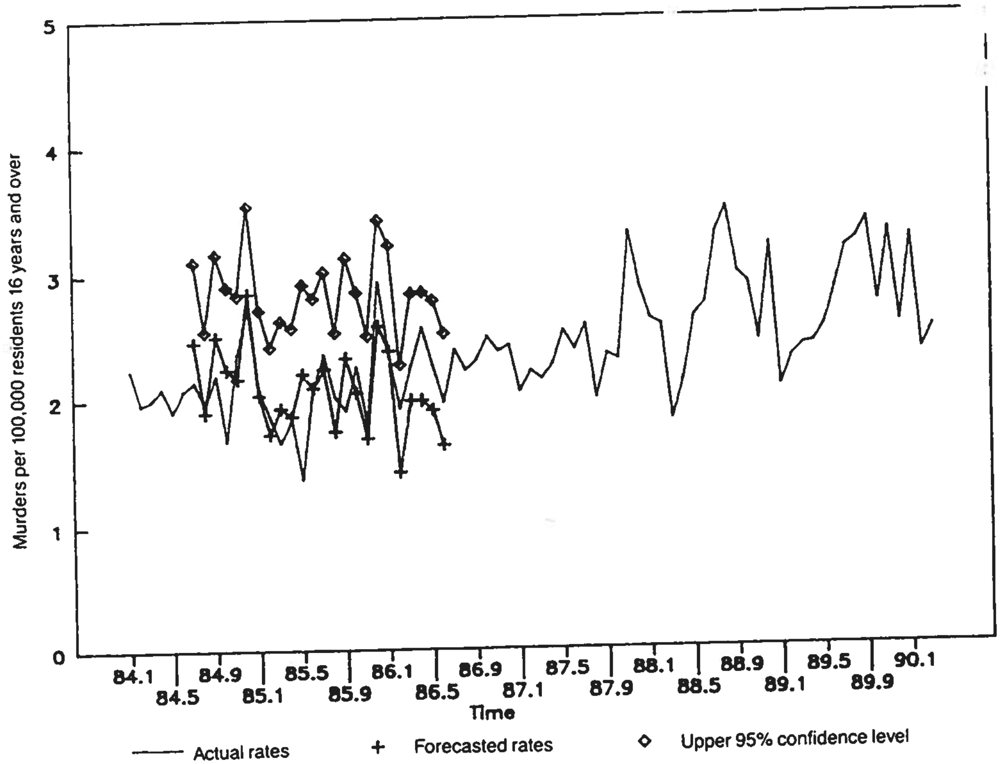


FIGURE 7.10. ACTUAL VS. FORECASTED MURDER RATES JANUARY 1984–MARCH 1990 (INTERVENTION DATE: JANUARY 1985)

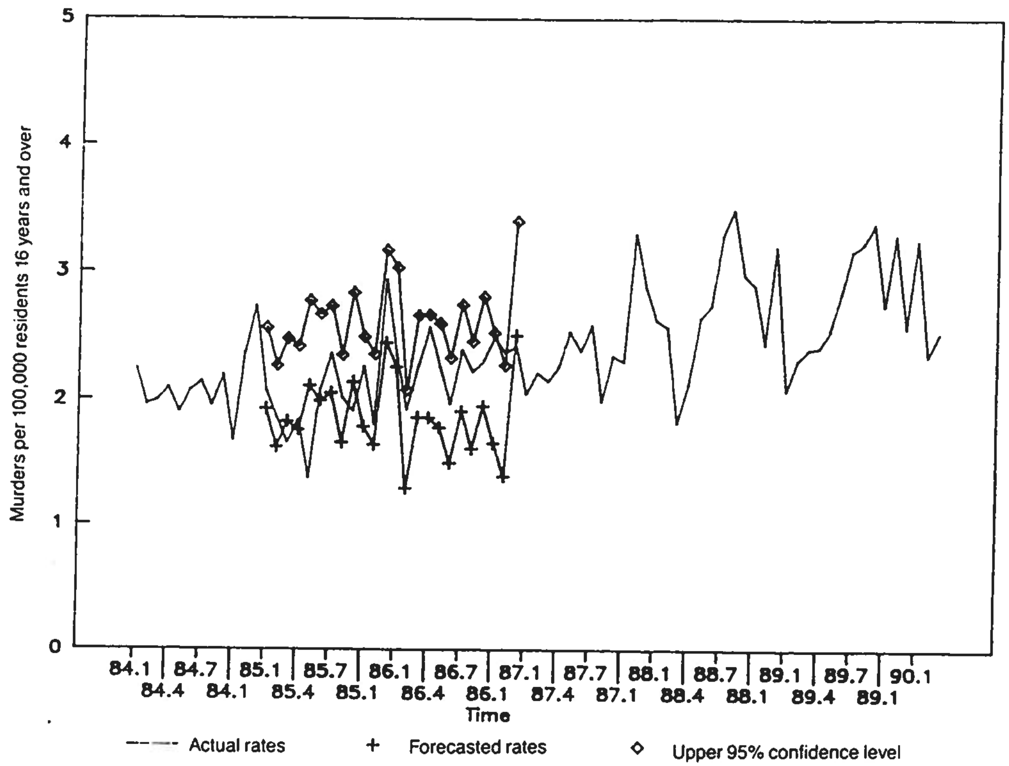


Figure 7.11. Actual vs. forecasted murder rates January 1984–March 1990 (intervention date: July 1985)

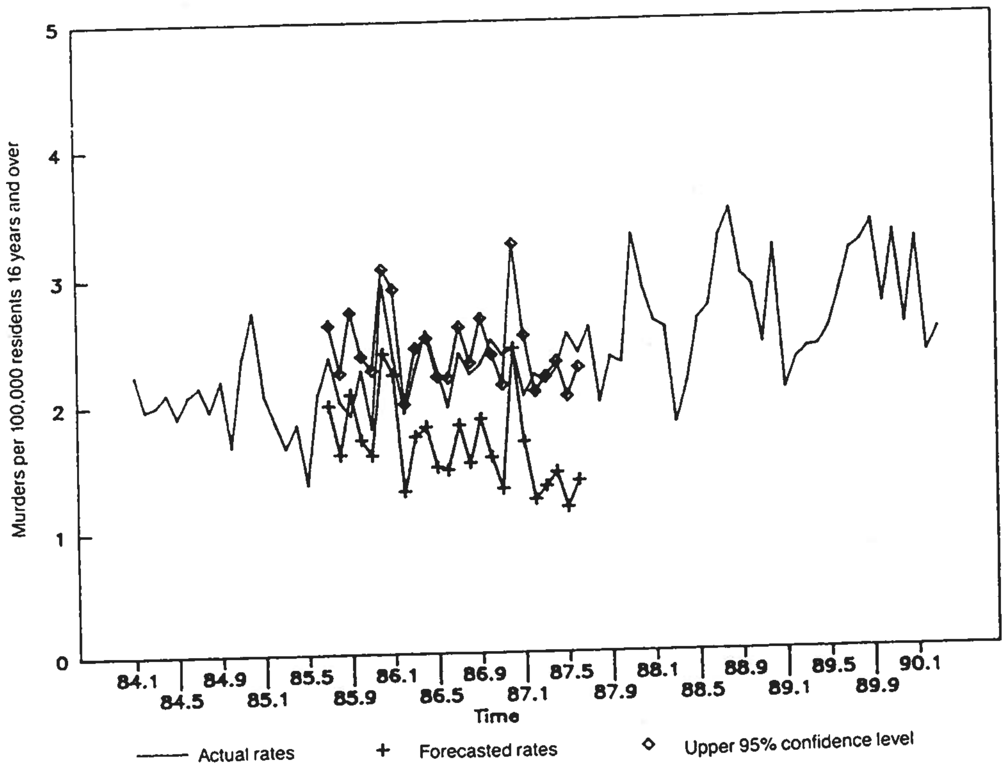
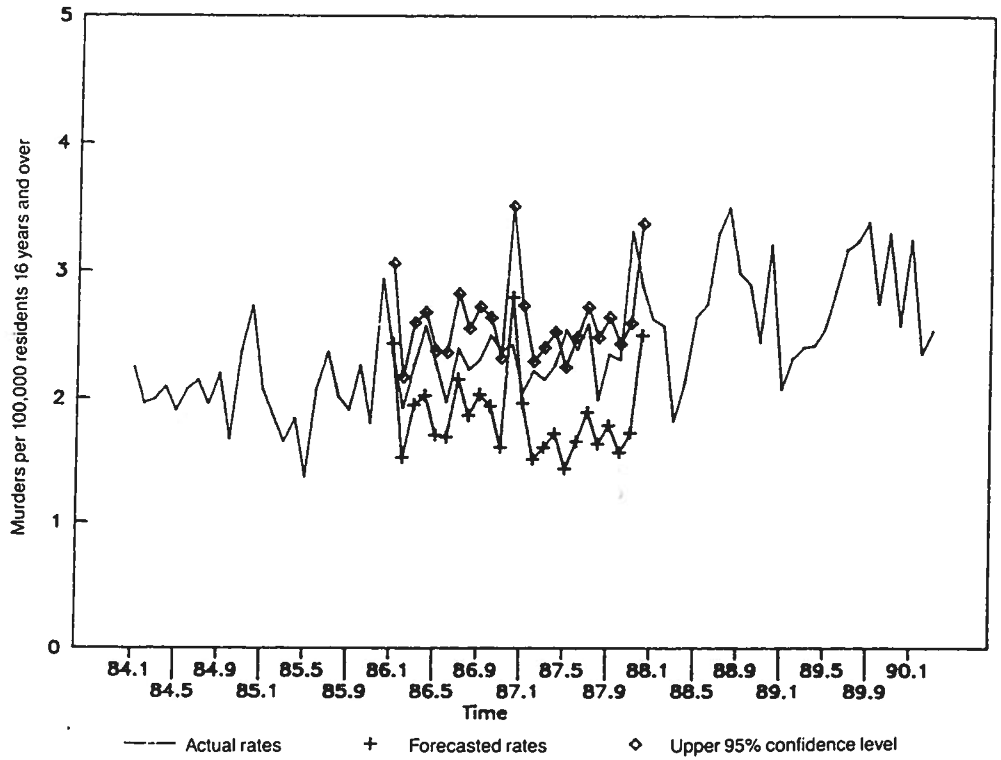


FIGURE 7.12. ACTUAL VS. FORECASTED MURDER RATES JANUARY 1984–MARCH 1990 (INTERVENTION DATE: JANUARY 1986)



presents the mean forecast errors for the 24-month horizon and the respective standard deviations.

Figures 7.3 through 7.12 indicate that the model's ability to forecast murders is rather poor. As shown in Figures 7.3 through 7.7, and Table 7.1, predicted murders at first exceed actual murders based on forecasts in January and July of 1984, but then the mean of the errors becomes positive and large relative to the standard deviation of the mean after July 1985. The same pattern occurs with murder rates, except that the mean of the errors becomes positive beginning with forecasts in July 1984. As can be seen from Figures 7.1 and 7.2, the steep decline in murders after 1981, coupled with an equally steep upturn in 1985, make this an especially difficult series to forecast.

Nevertheless, actual murders never exceed the 95-percent confidence interval for forecasts made in January 1985; they exceed it only four times for forecasts made in July 1985 and only three times for forecasts made in January 1986. The results for murder rates are the same except for forecasts made in July 1985 in which the actual exceeds the 95-percent confidence interval seven times. In short, the results are mixed. The nonsymmetrical errors imply weak forecasts, but the forecasts are not consistently outside their expected bounds.

The results from the intervention analysis are also ambiguous (Tables 7.2 and 7.3). We again specified January 1984, July 1984, January 1985, July 1985, and January 1986 as possible intervention dates and estimated a separate model for each date. We constructed an intervention component that allowed the data to dictate the rate at which the series reached a new level.[3] In none of the cases was the month-to-month change as measured by the numerator of the intervention component statistically significant. The denominators in the intervention components are large in absolute value, however, and often outside the bounds of stability.

In the case of murders with a January 1985 intervention date, the coefficient on the denominator is equal to one, which means the change in murders is nonstationary—in other words, it fails to level off. The same is true for murder rates with a July 1984 intervention date. The intervention models simply confirm what can be seen from Figures 7.1 and 7.2: The upturn in murders has failed to reach a new level. Taken at face value, the lack of statistical significance of the month-to-month change in murders and murder rates implies that even if the series had reached a new level, we would still reject the null hypothesis that an important intervention had occurred. One is cautioned from such an interpretation, given the instability of the parameters and the lack of precision; without more postintervention data, we cannot eliminate the possibility that a statistically significant intervention might have occurred. With the second approach, as with the first, we are left with uncertain results.[5]

The third approach used the intervention models to project murders and murder rates from January 1987 through March 1990. The projections were compared to similar ones made by models that excluded any intervention terms. In other words, we asked whether forecasts improve when the forecasting equation explicitly models a shift in the series.[6] The answer is yes. As displayed in Table 7.4, the mean squared error and the mean absolute percent error fall for interventions specified at January 1985 for murders and July 1984 for murder rates, relative to their respective naive models. Are the improvements substantial? Again, the answer is yes. For murders the mean absolute percentage error falls 3.9 points or 25 percent; in the case of murder rates, it falls 7.5 points or 38 percent. A comparison of mean squared error reveals similar improvements. Clearly, the intervention models yield gains that should not be ignored if one were attempting to forecast beyond March 1990.

As a final exercise, we use the "best" model for murders and murder rates to forecast each of the series through 1991. For murders, this is the intervention

TABLE 7.2. ARIMA INTERVENTION MODELS FOR MURDERS (IN LOGS) IN NEW YORK CITY: JANUARY 1970–MARCH 1990

Intervention dates and coefficients	*84:1*	*84:7*	*85:1*	*85:7*	*86:1*
θ_1	−.835	−.828	−.822	−.817	−.823
	(−24.3)	(−23.30)	(−23.29)	(−22.76)	(−23.12)
Θ_{12}	−.863	−.861	−.850	−.836	−.856
	(−26.4)	(−26.30)	(−23.75)	(−26.38)	(−35.47)
ω	−.055	−.144	−.007	−.007	−.176
	(−1.19)	(−.97)	(.82)	(.07)	(1.43)
δ	.769	−.095	.998	.938	−.468
	(3.49)	(−.09)	(−29.78)	(−.59)	(−.62)
Q-statistic	51.86	50.5	52.83	51.07	50.93
	(.32)	(.37)	(.29)	(.35)	(.36.3)

NOTE: The estimated model can be specified as follows:

$$LM_t = \frac{\omega}{1 - \delta B} I_t + \frac{(1 - \theta_1)(1 - \Theta)}{(1 - B)(1 - B_{12})} a_t$$

where LM_t is the natural log of murders, I_t is the intervention component that equals zero prior to the intervention date and 1 thereafter, and a_t is the residual. B is the backshift operator. Estimated t-statistics are in parentheses except for the Q-statistic, in which the marginal significance level is in parentheses. Note that the nonintervention ARIMA model is comprised of the second right-hand term.

TABLE 7.3. ARIMA INTERVENTION MODELS FOR MURDER RATES IN NEW YORK CITY: JANUARY 1970–MARCH 1990

Intervention dates and coefficients	*84:1*	*84:7*	*85:1*	*85:7*	*86:1*
θ_1	−.859	−.846	−.378	−.825	−.823
	(−22.94)	(−21.69)	(−4.91)	(−20.31)	(−24.15)
Θ_{12}	−.714	−.715	−.686	−.713	−.706
	(−11.39)	(−11.39)	(−11.17)	(−11.36)	(−11.36)
Θ_{24}	−.497	−.496	−.503	−.499	−.495
	(−7.61)	(−7.60)	(−7.97)	(−7.62)	(−7.66)
ω	−1.684	−.217	−.000	−.663	−.001
	(−1.27)	(−1.43)	(00)	(.32)	(1.11)
δ	.683	1.009	−1.155	.953	−1.221
	(2.52)	(76.63)	(−.02)	(−2.75)	(−5.45)
Q-statistic	36.69	36.27	67.10	38.00	40.46
	(.70)	(.72)	(.08)	(.65)	(.54)

NOTE: The estimated model can be specified as follows:

$$MR_t = \frac{\omega}{1 - \delta B} I_t + \frac{(1 - \theta_1)}{(1 - \Theta_{12} - \Theta_{24})(1 - B)(1 - B_{12})} a_t$$

where MR_t is the murder rate, I_t is the intervention component that equals zero prior to the intervention date and 1 thereafter, and a_t is the residual. B is the backshift operator. Estimated t-statistics are in parentheses except for the Q-statistic, in which the marginal significance level is in parentheses. Note that the nonintervention ARIMA model is comprised of the second right-hand term.

model with January 1985 as the intervention date. For the murder rate, it is the model with July 1984 as the intervention date. Figures 7.13 and 7.14 present the two projections. Although the forecasts rise, they begin to level off. The average monthly number of murders was 161 in 1989 and we estimate that it will be 169 in 1990 and 172 in 1991.[7] The same is true for murder rates. The average monthly rate was 27.5 in 1989, and is projected to be 29.8 in 1990, and 30.47 in 1991.

TABLE 7.4. SUMMARY STATISTICS OF WITHIN-SAMPLE FORECASTS OF MURDERS AND MURDER RATES FOR INTERVENTION MODELS AND A NAIVE MODEL

Interventions	*84:1*	*84:7*	*85:1*	*85:7*	*86:1*	
	Murder intervention models					*Naive*
Mean error	13.9	17.5	5.01	21.1	24.9	21.2
Mean squared error	708.0	832.1	535.9	1002.6	1211.7	1007.9
Mean absolute percent error	12.8	14.1	11.6	15.4	16.9	15.5
	Murder rate intervention models					*Naive*
Mean error	1.9	2.0	4.6	5.2	5.3	5.4
Mean squared error	18.1	18.4	36.8	43.7	44.4	46.3
Mean absolute percent error	11.8	12.1	16.4	19.1	19.1	19.6

NOTE: The forecast period is January 1987–March 1990. The summary statistics are based on projections made from the estimated intervention models in Tables 7.2 and 7.3. The naive model has the same ARIMA specification as the intervention models less the intervention term.

DISCUSSION

We began this analysis by stating that public-policy response should be commensurate with the importance and severity of the problem. Since many claim that crack is responsible for a surge in murders, and that this is an extremely important problem, we examined the increase in murder rates since the introduction of crack into New York City. We found only weak evidence of any significant upturn in murders and murder rates. Murders increased from 151 per month in 1980 to 161 per month in 1989, a 6 percent increase in 9 years. We estimate that murders will increase another 6.8 percent to 172 per month, between 1989 and 1991, with the rate of increase slowing substantially between 1990 and 1991. The magnitude of the increase in murders is thus far from the "tidal wave" effect depicted in the media. Further, if our population estimates underrepresent the true New York City counts, then we have overstated the rise in murder rates. Moreover, it is the steep drop in murders from 1981 to 1985 that has made the subsequent rise so alarming. One would have had little reason to suspect an intervention in 1985 without the decline after 1981. Perhaps the introduction of crack caused an upturn in murders that otherwise would have continued on its downward path. If the decline in 1981 is part of the inherent variability in murders, however, then crack is a convenient confounder of more fundamental causes.

FIGURE 7.13. ACTUAL AND FORECASTED MURDERS
JANUARY 1980–DECEMBER 1991

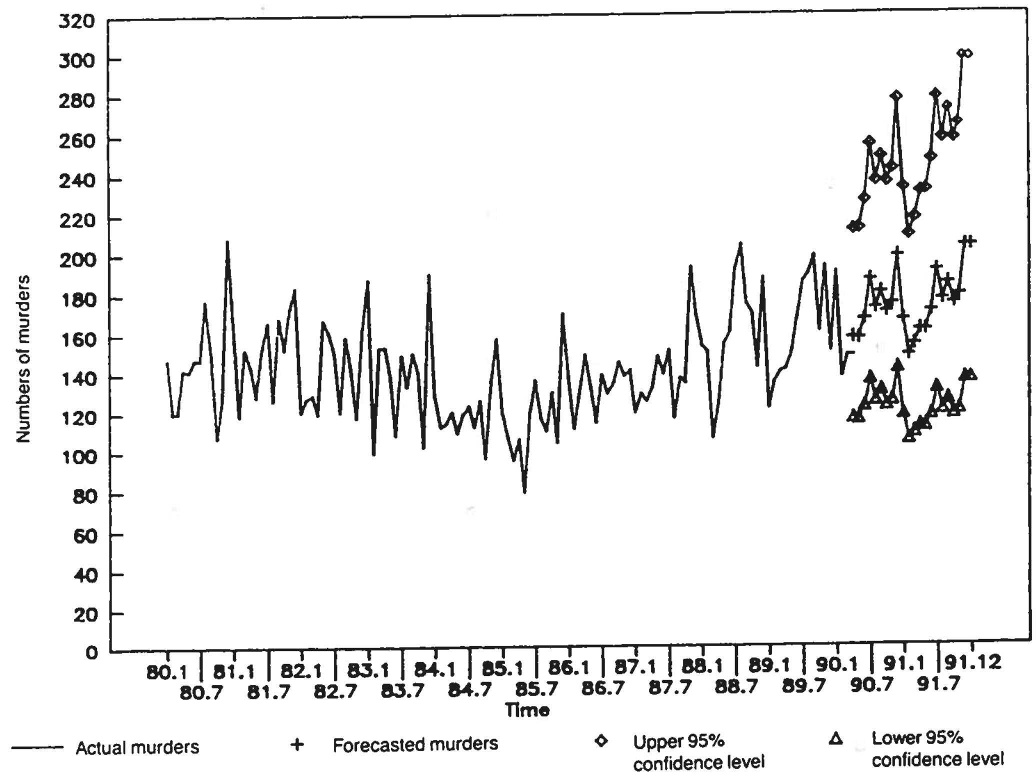
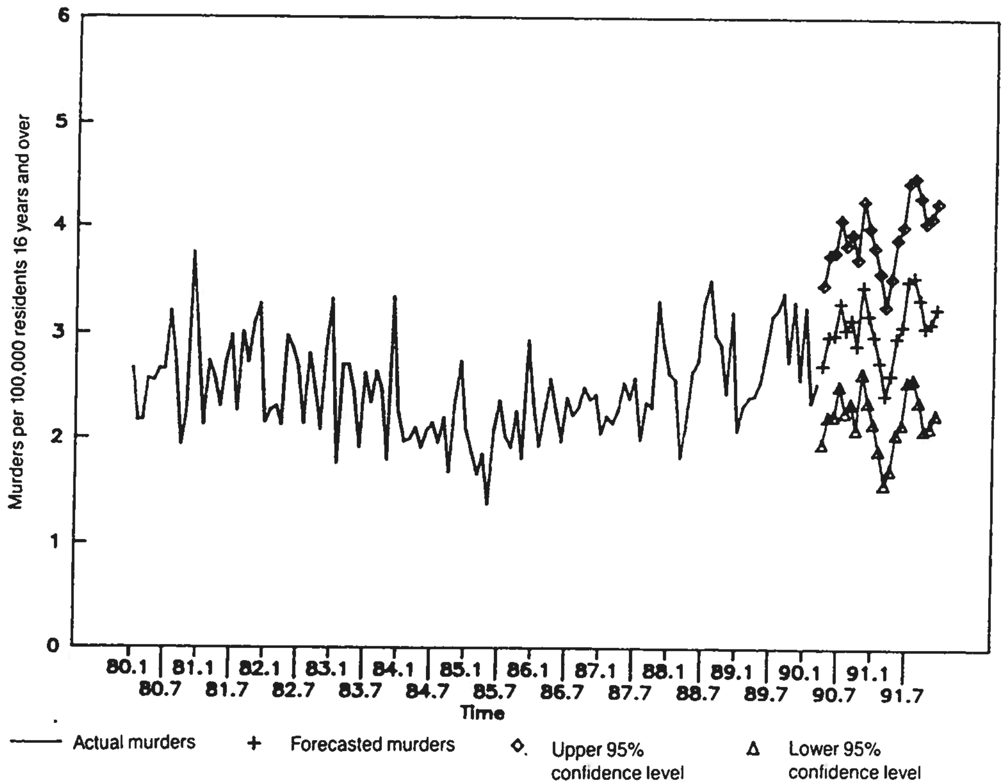


FIGURE 7.14. ACTUAL AND FORECASTED MURDER RATES
JANUARY 1980–DECEMBER 1991



Notes

1. For example, see Anglin and Speckart (1988), in the Bibliography.

2. See notes to Tables 7.2 and 7.3 for a description of the (nonintervention) ARIMA model.

3. More technically, we used a first-order transfer function for the intervention component. The notes to Tables 7.2 and 7.3 give the detailed specification.

4. See McCleary and Hay (1980), in the Bibliography.

5. In results not shown we tested other intervention dates around January 1985 for murders and July 1984 for murder rates. The results were also inconclusive.

6. Note the estimated model that generated the forecasts used the entire series on murders and murder rates.

7. Note the averages for 1990 include the three actual figures for January, February, and March.

Bibliography

Anglin, M. Douglas, and Speckart, George. "Narcotics Use and Crime: A Multisample, Multimethod Analysis," *Criminology* 26, no. 2 (1988), pp. 197–233.

Bachman, James E., and Witte, Ann D. "The Effectiveness of Legal Sanctions on Individuals Addicted to Alcohol or Drugs," in Leveson, Irving, ed., *Quantitative Explorations in Drug Abuse Policy* (New York: Spectrum Publications, 1980), pp. 111–27.

Becker, Gary S. "Crime and Punishment: An Economic Approach," *Journal of Political Economy*, 76 (1968), pp. 169–217.

Becker, Gary S., and Murphy, Kevin M. "A Theory of Rational Addiction," *Journal of Political Economy* 96, no. 4 (August 1988), pp. 675–80.

Goldstein, Paul J. "Drugs/Violence Nexus: A Tripartite Conceptual Framework," *Journal of Drug Issues* 15, pp. 493–506.

Johnson, Bruce D., et al. "Drug Abuse in the Inner City: Impact on Hard-Drug Users and the Community," in Tonry, Michael, and Wilson, James Q., eds. *Drugs and Crime*, Vol. 13 (Chicago: University of Chicago Press, 1990), pp. 9–67.

McClearr, R., and Hay, R. A. *Applied Time Series Analysis for the Social Sciences* (Beverly Hills: Sage, 1980).