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Illegal drug markets and victimizing crime in New York

David F. Greenberg[1]

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It is an embarrassment to criminology that the causes of the great American crime drop are so poorly understood. The essay "More Drugs, Less Crime," by Wendel et al. (2016) adds a new idea to the body of explanations that earlier theorists have proposed—that falling prices of illegal drugs reduced property crime and violent crime. Unique to the literature on the crime drop, Wendel et al. (hereafter WDCH) draw on both ethnographic study of New York's market for illegal drugs, and an econometric analysis of quantitative time series data, in support of their thesis. Regrettably we do not have comparable ethnographic observations of victimizing crime in New York, to help specify the relationship between the sale and use of illegal drugs, and victimizing crime. The WDCH proposal is all the more intriguing because it is directly contradictory to some journalistic accounts linking recent crime spikes in St. Louis to conflicts among suppliers stemming from a drop in the price of heroin (Williams 2016).

The statistical method WDCH use to relate drug prices to crime rates is Granger causality, sometimes known as "Granger (non)-causality." When I read studies using this method, I often come away thinking that the authors want to have their econometric cake and eat it too. On the one hand, they remind us that Granger causality is not necessarily the same as ordinary causality. It tells us whether lagged values of a particular variable (call it x) contribute significantly to the explanation of a second variable, y, above and beyond what lagged values of y alone contribute. This is not sufficient to establish causality in the sense that statisticians use this term nowadays. Yet the analyses are undertaken in a context where the question of

✉ David F. Greenberg
dg4@nyu.edu

[1] New York University, New York, NY, USA

interest is a causal question, pure and simple. In the case of WDCH's essay, that question is why crime dropped in New York City between 1985 and 2007.

On the face of it, the analysis of New York data is a dubious strategy for studying the crime decline, because the decline occurred throughout the USA and in a number of other countries at around the same time. This makes it implausible that the explanation of the decline can be explained exclusively by reference to events in New York (Greenberg 2014). Yet, as WDCH observe, the New York decline was especially large, making it an especially appealing site for inquiry. Moreover, prospective criminals are presumably responsive primarily to local social and economic developments. If drug prices influence crime rates, it is presumably local prices that are most relevant. This suggests that something might be learned from studying New York.

My comments on the WDCH analysis concern the statistical methods. There are some fine points in conducting a Granger analysis that were overlooked in the WDCH analysis. Unit root tests for the variables in their analysis show that all of them are nonstationary. Under these circumstances, the estimation procedures used to conduct tests of Granger causality need to be modified. In particular, the Wald statistical test must be adjusted (Dolado and Lütkepohl 1996; Toda and Yamamoto 1995; Lütkepohl 2005: 103–104, 316–320). The routines offered by commercial statistical packages like Stata (which WDCH used) do not incorporate this modification. They can be tweaked for this purpose (Giles 2011), but WDCH did not implement the tweak.

It would be easy to redo the analysis, but I do not do so because there are several reasons why the vector autoregression model used to test for Granger causality might not tell us about true causality. One of them is that the model assumes that x influences y with a lag of one year. Yet some of the processes by which illegal drug transactions might lead to victimizing crime (such as the psychopharmacological properties of the drugs) are likely to play out on a very short timescale—a matter of hours or days, not months. If this is so, a Granger analysis could mean that the model suffers from temporal misspecification. However, my examination of bivariate cross-correlations between homicides and drug prices suggests that the influences are not primarily instantaneous.

A second concern is spuriousness. In a world where many influences are likely to influence crime rates, an analysis in which the only explanatory variables are drug prices may suffer from omitted variable bias. This problem is ubiquitous in non-experimental research, and there is no easy remedy. Still, a model of crime in which the only explanatory variable is drug prices inevitably arouses suspicions of misspecification. In addition, nonstationarity can bring about spurious regressions. This is a matter of concern in the WDCH analysis because their variables are, in fact, not stationary.

To illustrate an alternative approach, I estimate a vector error correction (VEC) model for the relationship between homicide rates in New York and drug prices for heroin, powder cocaine, and crack cocaine for the same years as WDCH—1985 through 2007. I supplement this analysis by adding an additional variable to the model—the divorce rate. VEC modeling yields information about the effects of short-run changes in explanatory variables, and also about long-term equilibrium relationships among a set of cointegrated variables with unit roots. Cointegration refers to a relationship among a set of variables in which a linear combination of the variables is stationary, even though each one individually is not. Though change scores for each variable are random noise, the variables tend to move together. When a random shock to one variable leads it to move away from the equilibrium relationship, a restoring force tends to pull it back toward equilibrium. This restoring force prevents the variables from diverging over the long run. Analyzing a set of cointegrated variables that each have a unit root process (i.e., a process by which change scores are random noise) avoids the biases associated with ordinary regression procedures on first differences (a common procedure used when variables are non-stationary but not cointegrated).

The identification of the precise form of a VEC model is a complicated process that is characterized by uncertainty stemming from the existence of multiple criteria for model selection that may not all agree. In addition, the inferential statistics used for this assessment are valid only asymptotically (Lütkepohl 2005), and our time series is short. To illustrate the procedure while at the same time avoiding the complexities that would accompany a model involving a crime rate and all three drug prices (heron, powder cocaine and crack cocaine), I will focus on the model relating homicide rates to the price of heroin. Then I will say something about what happens to our results when an additional explanatory variable is added to the model.

In choosing an optimal model for the relationship between homicide rates and the price of heroin in New York, likelihood ratio tests led us to estimate models with no constant term or trends in the short-term or cointegrating equation. However, to improve the appearance of Fig. 2, I estimated and report estimates for a model that incorporates a constant term in the cointegrating equation.[1] Residuals for this model are consistent with a normal distribution, with no serial correlation of errors. The estimates are stable. The estimates are displayed in Table 1.

The estimates for the short-term equation show a restorative coefficient of −.1978. When the homicide rate exceeds its equilibrium level, this effect pulls it back toward the equilibrium rate. It is moderate in magnitude, indicating that it would take several years for an increase to be pulled back. As can be seen in Fig. 1, the model captures the ups and downs of the yearly fluctuations in homicide rates quite well. The correlation between the observed and predicted differences in homicide rates is .69.

The cointegrating equation shows a positive and highly significant relationship between the price of heroin and the homicide rate. The range of heroin prices over the time span covered goes from \$301.51 to \$1138.32. Thus this is a large effect. The cointegrating equation represents the equilibrium relationship between homicides and drug prices, and is not expected to match the observed homicide trends perfectly. We see some discrepancy in levels, diminishing in magnitude over time. The model seems to capture the downward trend in homicides, including the turning point around 1990, quite well.

[1] The estimates for the constant term are not statistically significant. The inclusion of this term in our model does not affect our substantive conclusions.

Table 1 Homicide rates and heroin prices in New York

Predictor	Coefficient	Standard error	*z*	Prob
Panel A: Short-term influences				
_ce (lag1)	−.1978	.0488	−4.06	.000
Homicide (LD)	.2065	.1519	1.36	.174
Heroin price (LD)	−.0067	.0025	−2.63	.0091
R-square = .5666				
Panel B: Cointegrating equation				
Homicide rate	1			
Heroin price	−.0361	.0008	−5.29	.0000
Constant	6.3926	4.4163	1.45	.148
Chi-square 1051.2437, $df = 1$, Prob. = 0.0000				

_ce is the cointegrating equation. LD is the lagged difference score

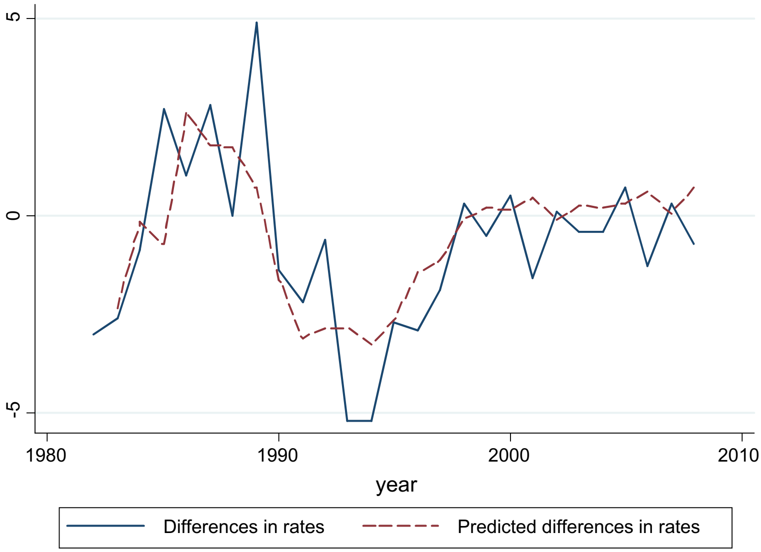

Fig. 1 Observed and predicted short-term changes in New York homicide rates

If interpreted naively and prematurely, these results are inconsistent with claims that innovative policing tactics adopted by the New York Police Department were the main reason crime dropped in New York. Yet this inference would be improper, as NYPD tactics may have been important in reshaping New York drug markets. However, a further reservation is in order as can be seen in Fig. 2.

With many other social changes taking place in the years being studied, the findings reported here can only be regarded as suggestive. To assess how robust our findings for heroin prices might be when these other changes were taking place, I estimated another set of models that incorporated the divorce rate as an additional

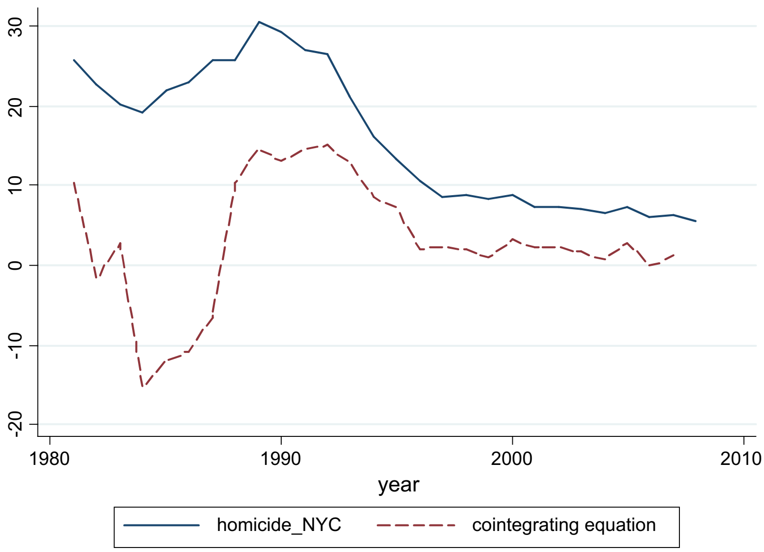

Fig. 2 Observed New York homicide rates and predicted cointegrating equation for homicide rates

Table 2 Homicide rates, heroin prices and divorce in New York

Predictor	Coefficient	Standard error	z	Prob
Panel A: Short-term influences				
_ce (lag1)	−.122	.029	−4.15	.000
Homicide (LD)	.124	.162	.77	.442
Heroin price (LD)	−.004	.002	−1.83	.067
Divorce rate (LD)	12.597	4.628	2.72	.006
Constant	.744	.482	1.54	.123
R-square = .6105				
Panel B: Cointegrating equation				
Homicide rate	1			
Heroin price	−.011	.020	−0.55	.582
Divorce rate	130.288	35.969	3.62	59.790
Trend	8.966	2.514	3.57	.000
Constant	−691.3939			
Chi-square = 15.8848, df = 2, Prob. = .0004				

_ce is the cointegrating equation. LD is the lagged difference score

explanatory variable.[2] I use this variable because earlier research found a strong positive relationship between the divorce rate and rates of violent crime such as homicide and robbery (Greenberg 2001). In this analysis the divorce rate is taken to

[2] Because published divorce rates for New York City do not exist, I substituted the rates for the United States. This is a potential source of measurement error.

be an imperfect measure of stress on an important social institution. That stress, I conjecture, also has consequences for the level of crime.

In a model that allows constant terms in both the short-term equation and the equilibrium relationship, and a linear trend in the latter, we see a significant positive effect of divorce in the short-term equation. The price of heroin is now no longer significant. The *R*-square value for the short-run equation is .61. In the cointegrating equation, the price of heroin is not significant, but the divorce rate has a significant positive effect on homicides. In addition, there is a positive linear trend in the cointegrating equation (See Table 2).

Our bivariate results are consistent with WDHC's suggestion that changes in New York's drug markets have been important determinants of changes in its crime rates. However, our additional analyses provide us with a cautionary message that bivariate relationships can be misleading. The kinds of analyses presented here need to be replicated for other offenses, other cities, and other variables. It would also be desirable to extend the analysis backward in time so as to assess the ability of the WDCH proposal to explain earlier trends in crime rates. However, data on drug prices for earlier years are not available, seriously limiting our ability to assess the "more drugs, less crime thesis" to explain historical trends in victimizing crime.

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