

MEASURING THE LONG-TERM EFFECTS OF PUBLIC POLICY: THE CASE OF NARCOTICS USE AND PROPERTY CRIME*

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The effects of treatment and legal supervision on narcotics use and criminal activities were assessed by applying newly developed time-series methods that disentangle the long-term (permanent) and the short-term (temporary) effects of intervention. A multivariate systems approach was used to characterize the dynamic interplay of several related behaviors at a group level over a long period of time. Five variables—abstinence from narcotics use, daily narcotics use (or addiction), property crime, methadone maintenance treatment, and legal supervision—were derived by aggregating information from over 600 narcotic addiction histories averaging 12 years in length. Because of the long assessment period, age was also included as a control variable.

Overall, the system dynamics among the variables were characterized by long-term rather than short-term relationships. Neither methadone maintenance nor legal supervision had short-term effects on narcotics use or property crime. Methadone maintenance treatment demonstrated long-term benefits by reducing narcotics use and criminal activities. Legal supervision, on the other hand, did not reduce either narcotics use or property crime in the long run. Instead, there was a positive long-term relationship in which a higher level of legal supervision was related to higher levels of narcotics use and criminal activity. This latter finding is consistent with the observation that either narcotics use or criminal activity is likely to bring addicts to the attention of the legal system. However, these addicts, as a group, did not directly respond to legal supervision by changing their narcotics use or crime involvement except perhaps through coerced treatment. The paper explores the policy implications of these findings.

(PUBLIC POLICY EFFECTIVENESS; NARCOTICS USE; TIME SERIES ANALYSIS; PERMANENT AND TEMPORARY EFFECTS; UNIT ROOTS)

Introduction

A critical issue in the evaluation of public policy effectiveness is the distinction between short-term and long-term effects. In the former case, an action (e.g., the provision of a health care service) has a temporary or transitory effect on some desired outcome (e.g., the reduction in the incidence of a communicable disease), and, in the latter case, it has a permanent or trend-setting effect. The difference is of fundamental importance in deciding whether or not the benefits of public policy programs outweigh their costs.

Three recent major advances in multivariate time-series analysis have made it possible to empirically differentiate long-term and short-term effects when equal-interval time-series data are available. First, new techniques are available that measure the presence of permanent versus transitory movements in individual time-series data. These methods are known as tests for unit roots in time series (e.g., Dickey, Bell and Miller 1986). Second, if long-term movements in individual time series are discovered, then the existence of long-term relationships among variables can be investigated using a method known as cointegration (Engle and Granger 1987). Finally, the long-run and short-run

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relationships among a set of variables may be combined in one model, known as an error-correction model (Engle and Granger 1987).

In spite of their compelling theoretical appeal, these new methods have not been used in a comprehensive evaluation of policy effects at the aggregate level. The only published applications of cointegration and error-correction modeling have involved testing a few macro-economic time series to verify whether or not they are related to each other in the long run (e.g., Hendry 1986). No attempts have been made to apply the statistical methodology to the analysis of the effectiveness of public policy programs.

The present study uses long-term multivariate time-series modeling to understand one of modern society's most urgent problems: narcotics abuse and the associated property crime and how these behaviors can be influenced by social intervention. Our intended contribution is twofold. First, from a methodological perspective, we demonstrate how these new methods may be used with data collected at the individual level and then aggregated in order to be relevant for policy evaluation. Second, from the viewpoint of the substantive issue, our study is a first attempt to differentiate the long-term versus the short-term effects of public policy in a systematic fashion. In examining possible strategies to curb the current narcotics abuse problem, we are interested in the permanent as well as the temporary effect of social interventions. Understanding the difference between the two effects can contribute to the improvement of the intervention effectiveness.

Our paper is organized as follows. First, we provide a brief overview of the current social interventions designed to control narcotics abuse and property crime. This review leads to the formulation of some key research hypotheses about long-term and short-term policy effectiveness and to a discussion of the data by which they are tested. Next, we focus on the methodological issues involved in unit-root testing, cointegration, and error-correction modeling, and we describe a multi-step approach for measuring long-term and short-term relationships in the data. The paper concludes with an analysis of the empirical results and a discussion of their policy implications.

Background

The two main programs that society currently uses to respond to individuals with problems of illegal drug use are health system interventions and legal system controls. The health system deals with physical, mental, and some behavioral aspects of drug use but does not necessarily address crime and violence. The legal system, which views drug use from the perspective of criminal justice, focuses on the criminality of drug users and imposes penalties for illegal activities. Both the medical and the criminal aspects of drug use, however, are intricately related. The strong linkage between narcotics addiction and crime has been well documented (see a recent review by Speckart and Anglin 1986), and a similar linkage is reported for cocaine dependence (Johnson et al. 1985).¹ Virtually all studies in this area have shown that people who become narcotic addicts either resort to criminal activity or increase their involvement in it. Furthermore, the higher the level of narcotics use, the higher is the degree of concomitant criminal activity (McGlothlin, Anglin and Wilson 1978). From these findings, many researchers have become convinced that narcotics use is the principal cause of high crime rates among addicts, even after controlling for other contributing factors (Ball et al. 1981). The social policy implication of this research is that one strategy for reducing the crime committed by narcotics addicts is to control addiction. Furthermore, several researchers argue that the most effective control involves a combination of intensive legal supervision and community-based drug treatment (Anglin, McGlothlin and Speckart 1981).

¹ A detailed literature review is available in Powers (1990).

Studies evaluating the effectiveness of treatment, especially methadone maintenance, consistently show that treatment reduces narcotics use and related crime among chronic narcotic addicts (Anglin and Hser 1990). Evidence for the direct effects of legal supervision, while promising, is more equivocal (Simpson and Friend 1988). Even fewer studies have investigated the joint effectiveness of criminal justice system interventions and community drug treatment on drug use and crime, especially over a long period of time (Collins and Allison 1983). As a result, the relative contributions of methadone maintenance and legal supervision to combatting drug use and crime remain unclear. Nor is it known how these two types of intervention should be combined for maximum efficacy. Furthermore, before policy decisions can be made, it is necessary to determine whether such interventions continue to have beneficial effects over the long run for a sufficiently large number of drug-dependent persons to be cost effective.

In order to explore these questions, the present study will develop a multivariate time-series model using cointegration and error-correction modeling to understand the long-term and the short-term relationships among the intervention and behavioral variables (Engle and Granger 1987). Long-term, or "permanent," relationships refer to how a stochastic trend in a given variable is related to the stochastic trends of other variables. Short-term relationships measure how temporary fluctuations from the means, or trends, of the measured variables are related to each other.

A multivariate time-series approach has several advantages over other statistical techniques for understanding long-term and short-term relationships. First, when lengthy chronological data are available, such as the present data, the entire time span of the narcotics addiction history can be incorporated in the analysis. Since it is not necessary to choose only certain time points (e.g., treatment admission or discharge) to assess the relationships between the variables of interest over time, the amount of information for data analysis can be maximized, and the dynamic nature of the relationships can be fully examined. Second, the analysis is carried out at the group rather than the individual level. Such an approach allows us to derive policy implications in terms of overall costs/benefits. Third, the developed time-series model can be used to forecast future behavior. Such predictive power is appealing from both the theoretical and the practical points of view (e.g., for policy planning). Finally, while short-term effects can be adequately measured by other methods, cointegration and error-correction modeling allow the investigation of both long-term and short-term relationships among the variables. The assessment and understanding of long-term effects of social interventions on drug-related behavior can contribute to improving the effectiveness of drug intervention strategies. In addition, the multivariate systems approach enables us to investigate the relationship between narcotics use and property crime within the larger context.

Research Hypotheses

From the literature, it is clear that methadone maintenance and legal supervision do not typically operate in isolation from each other, and both are often imposed, either alone or in combination, in response to illicit drug use or criminal involvement. Therefore, their effects should be evaluated within a system framework. Such a system approach allows the appropriate characterization of each relevant variable as either an input that affects the system or an output affected by the system, or both. In the present case, this system approach allows us to assess the dynamic interplay between narcotics use and property crime and to examine how this relationship influences and is influenced by methadone maintenance and legal supervision. Because we examine the interrelationships within the system over a long period of time, we will also consider the possible interaction of maturation, or aging, with the relevant variables. Therefore, the aggregate group age is incorporated, but only as an exogenous variable, that is, one which may influence, but is not influenced by, other variables within the system.

The specific hypotheses to be tested in the analyses are:

Narcotics Use and Property Crime: The two behaviors are expected to influence each other in the long run. Narcotics use should be the short-term driving force for property crime, but the converse is not true.

Methadone Maintenance: Treatment is expected to reduce narcotics use and property crime in contemporaneous, short-term, and long-term time scales. High levels of narcotics use and/or high levels of legal supervision should increase the likelihood of methadone treatment.

Legal Supervision: Supervision is expected to reduce narcotics use and property crime, contemporaneously or in the immediate short-term. Persistent narcotics use and property crime should each increase the likelihood of prolonged or recurrent legal supervision.

Age: Aging (as a proxy for maturation or burn-out) should contribute to decreased narcotics use and property crime in the long run.

Data

Sample

The data for the present analysis were taken from extensive retrospective longitudinal interviews with 720 heroin addicts who entered methadone maintenance programs in Southern California in the years 1971-1978. Detailed descriptions of sample selection and sample characteristics are available elsewhere (Anglin and McGlothlin 1984; Hser, Anglin and Chou 1988).

The original sample consisted of 251 Anglo men, 283 Anglo women, 141 Chicanos, and 45 Chicanas.² The average period from initial treatment entry to the time of interview ranged from four to six years. The length of the narcotics use career, from first narcotics use to the time of interview, averaged about 12 years, with a range between 3 years and 45 years. Because the length of the observation period had to be sufficiently long for the results of time-series analysis to be reliable and because we needed to retain a sufficient number of subjects for the results to be generalizable, subjects who did not have at least 80 months of observation were eliminated, providing 627 subjects (87% of the original sample) for the time-series analysis. To ensure that the reduced sample was representative of the original group, background characteristics of both samples were compared and are presented in Table 1. No apparent differences were observed between the two samples.

The selected sample consisted of Anglo (74%) and Chicano (26%) chronic narcotic addicts, both men (57%) and women (43%). Most were from middle- or working-class families and had semiskilled or unskilled occupations. The mean ages at which initial addiction, treatment, and legal system contact occurred indicate that, as a group, first arrest preceded first narcotics use; first use was followed by continued daily narcotics use, first legal supervision, and then methadone maintenance treatment. All the following analyses are based on the selected sample.

Interview Procedure

The interview schedule was adapted in part from one developed by Nurco and colleagues (Nurco, Bonito, Lerner and Balter 1975) and has been described in detail in an earlier paper (McGlothlin, Anglin and Wilson 1977). Briefly, a schematic time chart is prepared before the interview showing all official records of arrests, intervals of incarceration, legal

² Since there were less than 5% black patients and since blacks constitute a small percentage of California methadone maintenance patients, they were excluded from the present study to avoid the possible misinterpretation that the data could be representative of blacks. The terms "Chicano" and "Chicana" are used for a person who identified him- or herself as a member of the Mexican-American community, but not as a Hispanic or a Spanish-speaking person.

TABLE 1
Background Characteristics

	Original Sample (N = 720)		Selected Sample (N = 627)	
	N	%	N	%
Ethnicity				
Chicano	186	25.8	163	26.0
Anglo	534	74.2	464	74.0
Gender				
Men	392	54.4	357	56.9
Women	328	45.6	270	43.1
Socioeconomic status of family (%)				
Poor		7.1		7.1
Working class		33.4		33.4
Middle		45.5		44.9
Upper-middle		13.9		14.6
Problems in family ^a		2.8		2.8
Gang membership (%)		17.7		18.7
Problems in school (%)		72.0		72.0
Mean highest grade completed		10.9		10.9
Main occupation (%)				
Skilled		19.6		19.9
Semiskilled		56.3		57.6
Unskilled		19.0		17.5
Never worked		5.1		4.9
Mean age at ^b				
First arrest		17.4 (671)		17.3 (587)
Time left home		17.7 (706)		17.4 (616)
First narcotic use (FNU)		19.5		19.2
First daily use (FDU)		20.8		20.6
First legal supervision		22.4 (549)		22.3 (484)
First MM entry		26.6		26.9
Interview		31.9		32.5
Incarcerated >30 days prior to FNU (%)		25.1		25.6
No. of mos. incarcerated prior to FNU (%)				
None		75.0		74.5
1-12		17.4		18.0
13-24		5.2		5.4
25 or more		2.4		2.1
No. of incarcerations prior to FNU (%) ^c				
None		66.7		65.6
1-5		28.3		29.5
6 or more		5.0		4.9

^a Measured by self-reported problematic relationships with parents; a higher value indicates more serious problems (range 1-6).

^b The values in parentheses are the number of cases for mean computation after exclusion of missing cases. When not specified, the entire sample was used.

^c Includes incarcerations <30 days.

status, and treatment. The interviewer establishes the date of first narcotics use on the time chart and then augments the time chart with the respondent's reports of other important life events suitable to assist in recall. Starting from the time of first narcotics use, the interviewer records all time points when narcotics use changed from less than daily use to daily use (or vice versa), or when the respondent's legal supervision or treatment status changed. These time points are used to divide the respondent's addiction history into several intervals, which are uniform in terms of narcotics use, legal status,

and drug treatment enrollment. Self-reported data are collected for each of these intervals on narcotics, alcohol, and other drug use, on employment, on drug dealing and criminal behavior, and on certain other variables. In this way, the entire addiction history is recorded, from a year before the first narcotics use to the time of interview.

Variables

Five outcome variables were selected for the present analysis: (1) abstinence or no narcotics use (NNU), (2) addictive use or daily narcotics use (DNU) for at least 30 days,³ (3) property crime (C), (4) methadone maintenance treatment (MM), and (5) legal supervision (LS). The value of each of these variables was the percentage of time engaged in the activity (or the percentage of time in the status) during 99 successive two-month periods starting at first narcotics use.⁴ Periods of incarceration were excluded from the calculation. Variables were measured in terms of the percentage of time to quantify the amount of each behavior or time-in-status rather than simply noting whether or not it occurred. In addition, the mean age of the group at each two-month period was included as a control variable.

These five outcome variables were measured individually for each subject. As described in the earlier section on the sample, only those subjects with an addiction career spanning at least 80 months (40 two-month periods) were included in the analysis, and the maximum number of observations for the group was set at 99. For these subjects ($N = 627$), the averages of the values for each of the variables during 99 consecutive periods were calculated by summing over the group and then dividing by the number of subjects contributing during that period. These aggregated values were then used for the time-series analysis. The time-series plots of the five outcome variables are given in Figure 1.

Methodology

Our research objectives called for a multivariate time-series, or "systems," analysis of the dynamic relationships among narcotics use, criminal behavior, and intervention programs, while controlling for age. Using aggregate data allows us to distinguish between program or policy response effects (such as the impact of methadone treatment on narcotics use) and policy feedback effects (such as the presence of narcotics use leading to methadone treatment or legal supervision). In particular, we are interested in the existence, of lack thereof, of long-term and short-term policy response and policy feedback effects within this system. Recent developments in time-series analysis have made it possible to make an empirical distinction between the long-term and short-term effects. The following is a step-by-step description of our analytic procedure, which is graphically depicted in Figure 2.⁵

³ Drug use patterns can generally be characterized by three levels of use: abstinence, frequent use, and addictive use. The individuals included in this study have been addicted, by definition, but their drug-use pattern may vary during different observation periods. Because abstinence is a traditional goal for social intervention and because addictive use is highly associated with property crime, these two conditions were chosen as major indicators of level of drug use. It has been suggested that both legal supervision and methadone maintenance achieve their favorable effects on criminality through moderating rather than preventing narcotics use (McGlothlin, Anglin and Wilson 1978).

⁴ All subjects retained for analysis had at least 80 months (40 two-month periods) of observation. However, the number of subjects contributing to the aggregate data decreased as the number of periods increased.

⁵ This description uses recent contributions in unit-root analysis and cointegration, with special emphasis on their implications for model building and public policy assessment. The interested reader may refer to the quoted references for mathematical and statistical proofs.

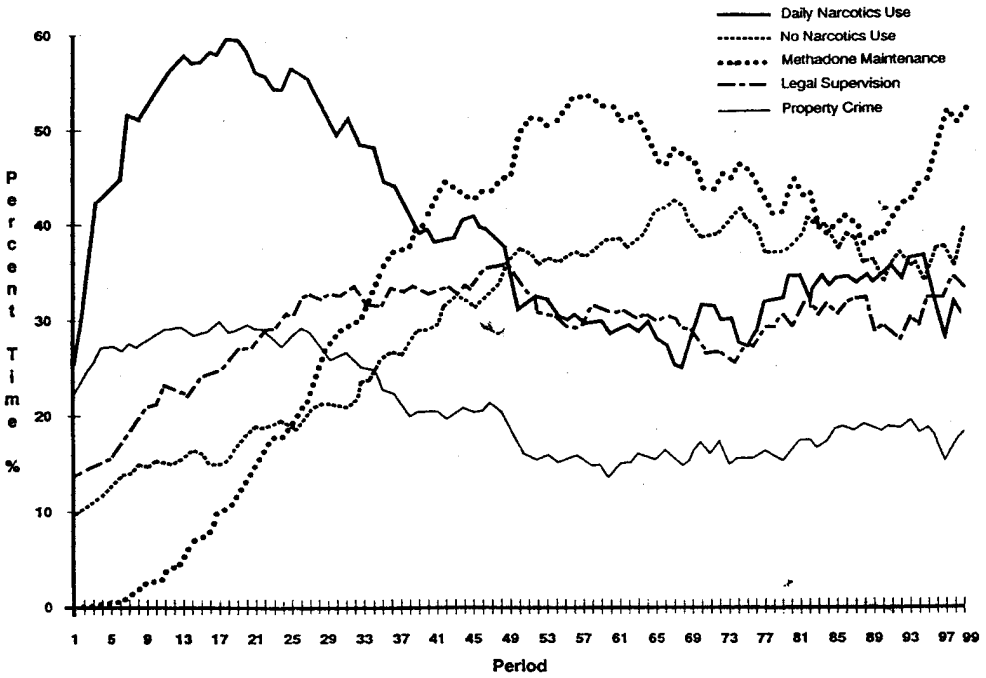


FIGURE 1. Sample Data.

Overview of Analytic Procedure

To explain the difference between long-term and short-term effects, let us focus on the hypothesized relationship between methadone maintenance treatment (MM) and narcotics abuse or, in this case, daily use of narcotics (DNU). From a time-series perspective, the first question to be answered is whether the observed levels of DNU and MM are stationary or nonstationary. The distinction between the two terms can be explained as follows:

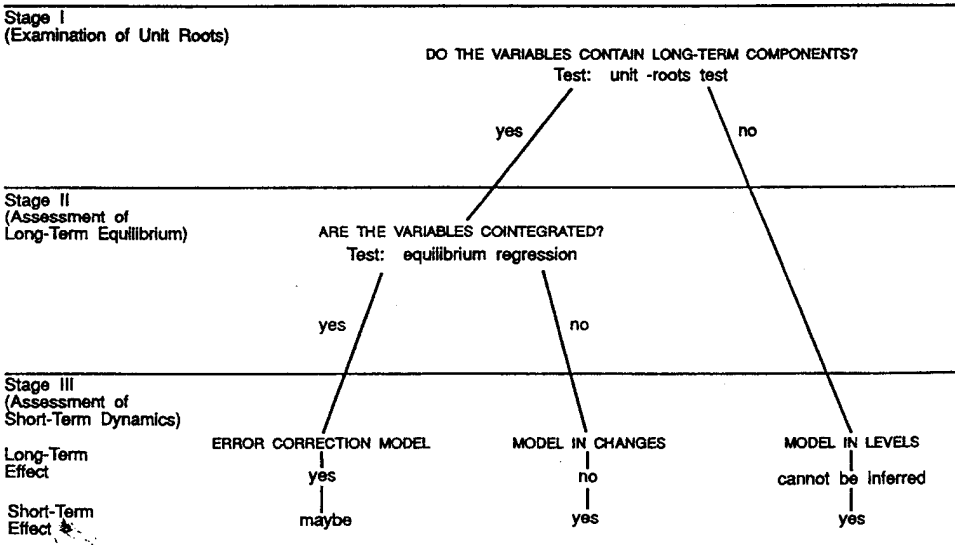


FIGURE 2. Analytical Procedures.

Assume that the over-time behavior of a series $\{Z_t\}$ representing a variable such as MM or DNU can be modeled as a simple stochastic time series process

$$(1 - \phi L)Z_t = c + a_t \quad \text{where} \quad (1)$$

ϕ is the parameter relating the present to the past of Z ,

L is the lag operator such that $L^k Z_t = Z_{t-k}$ with k being a positive integer,

Z_t is a random variable measured at time t with $t = 1, 2, \dots, T$,

c is a constant, and

a_t is a white noise random shock at time t , which is assumed to have a normal distribution with mean 0 and constant variance σ_a^2 .

When $|\phi| < 1$ holds for this model, the series $\{Z_t\}$ is said to be stationary, having finite mean $E(Z_t) = c/(1 - \phi)$, and variance $\text{Var}(Z_t) = \sigma_a^2/(1 - \phi^2)$. In this case, all observed fluctuations in $\{Z_t\}$ are temporary in the sense that the series does not systematically depart from its mean value, but rather reverts to it. On the other hand, if $|\phi| = 1$, the series is said to be a nonstationary, or evolutionary, series (a random walk, in this case) whose mean and variance are functions of time t . For this condition, the observed fluctuations are permanent in the sense that the series wanders freely without any mean reversion. If $|\phi| > 1$, the series explodes toward $+\infty$ or $-\infty$, which is also nonstationary. For the above model, determining whether the series is stationary or not is equivalent to testing whether the root of the characteristic equation, $1 - \phi L = 0$, is greater than one. When $|L| \leq 1$, we conclude that the series is nonstationary.

If MM and DNU are stationary, this implies that no long-term change in these variables is observed over the observation period. Thus, if MM has an effect at all on DNU, then the effect must be transitory, or short-term, since the level of DNU will eventually return to its mean. Under these conditions, we would argue that methadone treatment has only temporary effects on narcotics use. On the other hand, if MM and DNU are nonstationary, then we may investigate whether the observed random walk, or stochastic trend, in DNU can be explained by the stochastic trend in MM. For example, can a gradual decrease in DNU be explained by a gradual increase in MM? A positive answer would imply that there is a long-term, or equilibrium, relationship between the two. A negative answer still does not rule out the effectiveness of methadone maintenance, but it would imply that the treatment produces only temporary deviations in the level of narcotics use. Finally, it is possible that a mixed scenario occurs, such as the presence of a stochastic trend in narcotics abuse, but not in methadone treatment. If the change in narcotics use could be related to the level of methadone treatment, that would imply an even stronger long-term effectiveness of treatment. For example, a gradual decrease in narcotics abuse could be related to the steady maintenance of treatment at a certain level. This same type of development applies to legal supervision when we evaluate its effect on the dependent variables.

Testing the Existence of Unit Roots (Stage I)

In order to disentangle the various scenarios mentioned above, we start by performing a univariate analysis of the data, i.e., we examine the pattern over time of each of the five variables separately. We investigate whether a variable such as narcotics use behaves as a stationary (i.e., mean-reverting process) or as a nonstationary (e.g., random-walk) process. We identify the variable's behavior by applying the well-known Box-Jenkins method for univariate ARIMA modeling to each series, with particular attention to the existence of unit roots, or nonstationary components, in the data (e.g., Dickey and Fuller 1979). The general integrated autoregressive moving average, or ARIMA (p, d, q), model is defined as

$$\Phi(L)\Delta^d Z_t = c + \Theta(L)a_t \quad \text{where} \quad (2)$$

$$\Phi(L) = 1 - \phi_1 L - \dots - \phi_p L^p, \quad (3)$$

$$\Theta(L) = 1 - \theta_1 L - \dots - \theta_q L^q, \quad (4)$$

are polynomials in the lag operator L for autoregressive parameters and moving average parameters, respectively, and $\Delta^d = (1 - L)^d$ is the difference operator.

The difference operator performs a transformation that often induces stationarity to a nonstationary time series. For example, first-order differencing $\Delta Z_t = (1 - L)Z_t = Z_t - Z_{t-1}$ eliminates a linear trend in the series. Higher-order differences, such as second-order or third-order differencing (Δ^2 and Δ^3 , respectively), are used to remove a nonlinear trend from the series. Note that if we specify $p = 1$ and $d = q = 0$ for equation (2), the resulting ARIMA (1, 0, 0) model is equivalent to equation (1).

If the data are generated by an ARIMA model with $d = 0$, they are stationary; then all movements in the data should be interpreted as temporary deviations from a fixed mean, which would limit our ability to derive long-term inferences from the results.⁶ In this case, only short-term relationships can be assessed. If, on the other hand, one or more unit roots are found (i.e., $d \geq 1$), then we may investigate whether these nonstationary components, or stochastic trends, are related to each other.

Assessment of Long-Term Equilibrium (Stage II)

The analysis of nonstationary components is accomplished by specifying the "equilibrium regression" proposed by Engle and Granger (1987). An equilibrium regression, for example between methadone treatment and narcotics use, would establish that the two time series representing these variables are related to each other in the long run.

In theory, if the equilibrium relationship holds between MM and DNU, then they relate to each other under the linear constraint

$$\text{DNU}_t - \beta \text{MM}_t = c \quad (5)$$

where β is a constant. Suppose $\beta < 0$; then, if the level of MM increases, DNU must eventually decrease in order to maintain the equilibrium. On the other hand, with $\beta > 0$, if DNU is on the rise, the amount of treatment will eventually increase. In reality, the linear constraint (5) may not exactly hold in each time period. The difference between the observed level of, say, DNU_t and its equilibrium level given the observed level of MM_t is called the equilibrium error. It may be estimated by calculating the residuals from an equilibrium regression, for example,

$$\text{DNU}_t = c + \beta \text{MM}_t + e_t \quad (6)$$

where β is called the cointegrating constant. The existence of a long-term relationship implies that the equilibrium errors e_t do not have permanent components in them, i.e., e_t is a stationary time series even though DNU_t and MM_t are not. Indeed, if e_t were nonstationary, then there would be no mechanism for tying DNU and MM together in the long run.

The statistical test determining an equilibrium relationship amounts to estimating the hypothesized equilibrium regressions by ordinary least squares (Stock 1987)⁷ and verifying that the residuals of these regressions have only transitory components, i.e., unit roots are not present in the residual series. This regression interpretation is unusual and innovative in the sense that we are not testing for the usual condition of uncorrelated residuals over time. Instead, we verify that the nonstationary movement in one variable

⁶ If comparable data from various regions or nations were available, a cross-sectional regression design could be used to make long-run inferences. However, establishing the direction of causality would be difficult.

⁷ A key contribution by Stock is the proof that the simultaneous-equation bias in the OLS estimator vanishes in the limit if the variables are cointegrated.

removes the nonstationary fluctuations in another variable, such that only transitory (though possibly autocorrelated) components are left in the residuals. Such a condition is called "cointegration."

Assessment of Short-Term Dynamics (Stage III)

Next, we proceed to modeling the short-term dynamic relationships in the system while controlling for long-term effects where applicable. Depending on the outcomes from Stage I (the presence/absence of unit roots in each univariate time series) and from Stage II (the existence/nonexistence of cointegration among the variables), the analytical procedure for assessing short-term dynamics will take one of the following three approaches:

- (1) an error-correction model for cointegrated variables,
- (2) a model in changes for nonstationary but non-cointegrated variables,
- (3) a model in levels for stationary variables.

Each of the three approaches is described below.

For the purpose of illustration, we will concentrate on the relationship between MM and DNU and assume that MM and DNU are an input and an output series, respectively.

(1) *Nonstationary System with Cointegration.* If cointegration has been established between MM and DNU, then the long-term relationship between the variables must be incorporated in their short-term behavior. Engle and Granger (1987) have shown that the existence of an equilibrium relationship implies that the data are generated according to a special partial adjustment, or error-correction mechanism. For example, observed changes in narcotics-use levels could be explained not only by lagged changes in narcotics use and by changes in methadone treatment, but also be the "equilibrium error" in the previous period. The equilibrium error is the amount of excessive, or insufficient, narcotics use given the observed level of methadone treatment. A fraction of this error is corrected in the subsequent period so that the system partially adjusts toward equilibrium.

The error-correction model for MM and DNU is expressed as

$$\Delta DNU_t = c_0 + \gamma \hat{e}_{t-1} + \omega(L)\Delta MM_t + \delta(L)\Delta DNU_{t-1} + u_t \tag{7}$$

where \hat{e}_{t-1} is the estimate of the equilibrium error correction term obtained from equation (6), and $\omega(L)$ and $\delta(L)$ are parameter polynomials in L :

$$\omega(L) = \omega_0 + \omega_1 L + \dots + \omega_r L^r, \tag{8}$$

$$\delta(L) = 1 - \delta_1 L - \dots - \delta_s L^s. \tag{9}$$

The contemporaneous and lagged effects of MM are measured by the terms of $\omega(L)$. Any additional autocorrelation in DNU is captured by the terms of $\delta(L)$ so that the error term u_t is a white noise series. The error-correction model posits that, in each period, the dependent variable will adjust itself partially (by a factor γ) toward the equilibrium level.

(2) *Nonstationary System without Cointegration.* If the data are nonstationary but not cointegrated, we first perform a simple transformation to stationarity (differencing) and then develop a model on these differences. For example, we may empirically investigate the effect of a change in methadone treatment level on a change in narcotics use using the model,

$$\Delta DNU_t = c_0 + \omega(L)\Delta MM_t + \delta(L)\Delta DNU_{t-1} + u_t. \tag{10}$$

The results would reveal the short-term dynamics of the system, but they would not explain the long-term behavior of the variables. Notice that equation (10) is a restricted form of equation (7), where the error correction term is absent.

(3) *Stationary System*. Finally, if the data are stationary, we develop a model on the levels of narcotics use and methadone treatment,

$$\text{DNU}_t = c_0 + \omega(L)\text{MM}_t + \delta(L)\text{DNU}_{t-1} + u_t \quad (11)$$

and the results are, again, interpreted as short-term dynamics.

Parameter Estimation Methods for Short-Term Dynamics

Parameter estimation for short-term relationships can be carried out either by using separate distributed-lag models or by developing a system of equations in vector-autoregressive (VAR) form. In the first case, we make an a priori distinction between input (exogenous) and output (endogenous) variables; in the second case, this distinction is not necessary. Equations (7), (10), and (11) are examples of distributed-lag models, and we focused on these models to illustrate the underlying concepts of cointegration and error-correction mechanisms. For the present analysis, however, we will not attempt to develop a set of distributed-lag structural models of narcotics use, crime, and intervention variables, because such a system would likely be underidentified due to a lack of specified exogenous variables. Indeed, our database contains five possibly jointly endogenous variables (no narcotics use, daily narcotics use, property crime, methadone maintenance treatment, and legal supervision) and only one strictly exogenous variable (age). Instead, we adopt the vector-autoregressive (VAR) approach advocated by Sims (1980). For k time series $\{Z_{1t}, \dots, Z_{kt}\}$, the VAR(J) model is defined as

$$\tilde{Z}_t = \tilde{c} + \sum_{i=1}^J \tilde{\Phi}_i \tilde{Z}_{t-i} + \tilde{a}_t \quad \text{where} \quad (12)$$

$\tilde{Z}_t = a(k \times 1)$ random vector observed at time t for $t = 1, 2, \dots, T$,

$\tilde{c} = a(k \times 1)$ vector of constants,

$\tilde{\Phi}_i = a(k \times k)$ parameter matrix, and

$\tilde{a}_t = a(k \times 1)$ white-noise vector assumed to be i.i.d. $N(\tilde{O}, \tilde{\Sigma})$.

The dynamics of the VAR(J) model are specified as follows: the j th sample partial autoregression matrix $\hat{P}(j)$ can be obtained from

$$\hat{P}(j) = \hat{\tilde{\Phi}}_j \quad \text{with} \quad j = 1, 2, \dots, J,$$

when a VAR(J) is fitted by generalized least squares. If a VAR(p) model holds for \tilde{Z}_t , then for $j > p$, $\hat{P}(j) = 0 \cdot \tilde{I}$, and therefore the corresponding matrix of estimates $\hat{P}(j)$ is expected to have all elements near zero. The well-known Akaike Information Criterion is used to establish the maximum needed value of j (e.g., Priestley 1981, p. 372).

The VAR approach focuses on the lagged structures in the data, both within and across time series, leaving any contemporaneous effects directionally unspecified. However, the covariance matrix of the residuals of a VAR model contains information that may be interpreted as contemporaneous effects among the variables.

In summary, our data analytic plan is as follows: First, we develop univariate ARIMA models for each of the five variables in the system. If unit roots are not found, then a simple VAR model on the levels in the data would conclude the analysis. If unit roots are found, we perform an equilibrium regression test to establish the presence of long-term relationships in the system. If the data pass the test, the model combining long-term and short-term effects would be a VAR system on the differences, augmented by the equilibrium error term. If the data do not pass, then a simple VAR model on the differences in the data will be used to estimate short-term dynamics.⁸

⁸ When unit roots are found in some of the variables but not in the others, an appropriate modeling approach would be to first perform differencing on the nonstationary series and then develop a model among the differenced series and the stationary series. For example, if a unit root is present in narcotics use but not in methadone maintenance, we would develop a model relating the change in narcotics use and the level of methadone maintenance. This procedure could be used for both distributed-lag models and VAR models.

Results⁹

Univariate ARIMA Models

The Box-Jenkins modeling approach was applied to each of the five outcome variables. Diagnostic checking of each model was performed by means of the Box-Pierce Q statistic and visual inspection of the residual autocorrelation function (ACF) and partial autocorrelation function (PACF).¹⁰ Furthermore, Dickey-Fuller unit roots tests were carried out to statistically examine the existence of unit roots in each of the five variables. The five univariate ARIMA models are presented below, with parameter standard errors in parentheses:

(1) No Narcotics Use: ARIMA (4, 1, 0)

$$(1 + 0.319L^4)(1 - L)NNU_t = 0.368 + a_t$$

(0.111)

(2) Daily Narcotics Use: ARIMA (1, 1, 0)

$$(1 - 0.258L)(1 - L)DNU_t = -0.026 + a_t$$

(0.095)

(3) Property Crime: ARIMA (0, 1, 0)

$$(1 - L)C_t = -0.041 + a_t$$

(4) Methadone Maintenance: ARIMA (5, 1, 0)

$$(1 - 0.201L - 0.380L^5)(1 - L)MM_t = 0.264 + a_t$$

(0.095) (0.101)

(5) Legal Supervision: ARIMA (1, 1, 2)

$$(1 + 0.204L)(1 - L)LS_t = 0.230 + (1 + 0.274L^2)a_t$$

(0.102) (0.104)

The above models indicate that a unit root is present in all the variables, and the outcomes of the Dickey-Fuller tests were consistent with these results. Because a unit root was present in each of the five outcome variables, as well as in the control variable age, we can proceed to test the long-term relationships among the variables using equilibrium regressions.

Equilibrium Regressions

Table 2 summarizes the results of equilibrium regressions for the five outcome variables. The unit root tests performed on the error terms of these five equilibrium regressions confirmed that all residuals were stationary, indicating the presence of long-term associations among the dependent variables.¹¹ The R^2 for each of the five regressions show

⁹ The computer programs SCA for time series (Liu and Hudak 1986) and SAS implemented on an IBM 3090 were used to carry out the identification and estimation of the models.

¹⁰ For a detailed description of the identification and estimation procedure for these models, see Powers (1990).

¹¹ According to Engle and Yoo's (1987) critical value table for the Dickey-Fuller (DF) test, the equilibrium regressions for DNU, C, MM, and LS all indicate cointegrated relationships among the variables. On the other hand, the DF test for NNU did not quite reject the null hypothesis of no cointegration. However, the residuals from the equilibrium regression follow an AR(1) the first-order autocorrelation of 0.783. Engle and Granger (1987) reported a problem of low-power associated with Dickey-Fuller tests. Furthermore, since it was observed that the autocorrelations for the residuals die out very rapidly, we concluded that the residuals are integrated at order zero.

TABLE 2
Equilibrium Regressions

	NNU	DNU	C	MM	LS
Const.	14.874 (4.404)*	-20.127 (5.965)	14.930 (1.196)	36.258 (5.560)	-14.383 (3.600)
DNU	—**	—	0.213 (0.023) ^a	0.062 (0.109)	0.120 (0.062) ^c
C	-0.656 (0.178) ^a	2.236 (0.242) ^a	—	-2.412 (0.252) ^a	0.925 (0.183) ^a
MM	0.196 (0.072) ^a	0.055 (0.097)	-0.204 (0.021) ^a	—	0.509 (0.029) ^a
LS	0.057 (0.121)	0.317 (0.164) ^c	0.232 (0.046) ^a	1.509 (0.085) ^a	—
AGE	0.746 (0.091) ^a	0.075 (0.123)	-0.085 (0.037) ^b	0.066 (0.131)	0.074 (0.076)
R^2 ***	0.958	0.927	0.972	0.969	0.880
$F_{(4,94)}$	506.455 ^a	298.034 ^a	810.362 ^a	738.956 ^a	171.750 ^a
t ****	-3.763	-4.649	-5.245	-5.560	-5.069
Unit Root?	No	No	No	No	No

^a Significant at $p < 0.01$.

^b Significant at $p < 0.05$.

^c Significant at $p < 0.10$.

* The standard error of the estimate is included in parentheses.

** The sign '—' indicates that the row variable is assumed to have no effect on the dependent variable in the corresponding column.

*** Results are based on the individual regressions.

**** Dickey-Fuller unit-root test for cointegration on the residuals with critical values obtained from Engle and Yoo (1987).

that significant amounts of variance, ranging from 88% to 97%, are explained by the models.

Examining the coefficients of the equilibrium regressions provides the following results. Long-term movements of narcotics use and property crime go hand in hand. As the crime level rises, abstinence from narcotics use eventually decreases and daily use increases. Furthermore, increased crime is associated with lower methadone maintenance involvement and higher legal supervision. Reciprocally, narcotics use has a positive long-term association with crime involvement. In terms of social intervention effects, methadone maintenance has a significant long-term association with no narcotics use and property crime, indicating its desirable effects. Addict involvement in either methadone maintenance or legal supervision increases the likelihood of involvement in the other. Finally, contrary to our expectation, legal supervision shows a positive long-term association with narcotics abuse and crime involvement; that is, as legal status persists, so do narcotics use and property crime. Some possible justification and explanation for this last finding will be presented in the discussion section.

Overall, the five outcome variables form a cointegrated system. *While each variable individually may move up or down over time without mean reversion, there exists a dynamic equilibrium state toward which all other variables will adjust.* Therefore, an error-correction model can be used to examine the short-term relationships within the system in conjunction with partial adjustment for the long-term behavior of the variables.

Combining Short-Term and Long-Term Dynamics

The procedure advanced by Tiao and Box (1981) was used to estimate a VAR model augmented with equilibrium error-correction terms. In order to determine how many lags were needed for developing a model, the pattern of the partial autoregression matrices was examined. Based on the Akaike Information Criterion, specifying one lag was found to be sufficient to represent short-term dynamics in the system.

The error-correction equations for the five outcome variables were estimated simultaneously. The generalized least-squares parameter estimates and the residual correlation

matrix are given in Table 3. The error-correction terms in the five equations were all significant at $p < 0.05$ or better. On the other hand, only a few parameter estimates for the short-term effects were significant (4 out of 25 estimates, one of which was only marginally significant). These significant estimates reflect the persistence of narcotics abuse over time and the contribution of narcotics-use behavior to subsequent crime involvement. However, it should be emphasized that the observed changes in the five outcome variables were explained mainly by the error-correction terms, i.e., partial adjustments toward equilibrium.

The importance of the long-term components in the model can be clearly demonstrated by comparing the error-correction model to a simple VAR model. The latter is a VAR model without the equilibrium error-correction terms and therefore captures only short-term dynamic behavior in the system. When the two models are compared, the superiority of the error-correction model over the simple VAR model is evident. First, the system-weighted R^2 for the error-correction model is 0.213, as compared with 0.132 for the VAR model. Furthermore, the R^2 values for each of the five separate error-correction equations (ranging from 0.126 to 0.272) are substantially higher than those of each simple VAR equation (ranging from 0.061 to 0.164). Also, only two overall F values for the VAR equations are significant, against five significant F values for the error-correction equations. These results demonstrate the improvement in goodness of fit of the model by incorporating partial adjustments toward equilibrium into the system.

Finally, the residual correlation matrix of Table 3, describes the contemporaneous

TABLE 3
Error Correction Models on First Differences

	Parameter Estimates of the Lagged Structure				
	Δ NUU	Δ DNU	Δ C	Δ MM	Δ LS
<i>Lag 1</i>					
Δ NUU	0.112 (0.095)*	—**	—	—	—
Δ DNU	—	0.438 (0.104)*	0.200 (0.052)*	-0.124 (0.085)	0.096 (0.071)
Δ C	0.243 (0.138) ^c	-0.372 (0.246)	-0.151 (0.119)	-0.075 (0.187)	-0.161 (0.146)
Δ MM	-0.050 (0.093)	0.144 (0.146)	0.019 (0.069)	0.226 (0.111) ^b	0.134 (0.087)
Δ LS	0.129 (0.109)	-0.018 (0.172)	0.001 (0.076)	0.079 (0.128)	-0.008 (0.101)
Δ AGE	0.208 (1.932)	2.630 (3.048)	-0.033 (1.341)	2.635 (2.224)	1.545 (1.783)
Δ EQ Error	-0.178 (0.053) ^a	-0.143 (0.058) ^b	-0.347 (0.110)*	-0.126 (0.049) ^b	-0.273 (0.072) ^a
R^2 ***	0.167	0.126	0.272	0.136	0.212
$F_{(6,90)}$	2.995 ^a	2.163 ^c	5.606 ^a	2.367 ^b	4.046 ^a
Residual Correlations****					
	Δ NUU	Δ DNU	Δ C	Δ MM	Δ LS
Δ NUU	1				
Δ DNU	-0.594	1			
Δ C	-0.372	0.519	1		
Δ MM	0.376	-0.471	-0.206	1	
Δ LS	-0.134	0.087	0.198	-0.109	1

* Significant at $p < 0.01$.

^b Significant at $p < 0.05$.

^c Significant at $p < 0.10$.

* The standard error of the estimate is included in parenthesis.

** The sign '—' indicates the row variable is assumed to have no effect on the dependent variable in the corresponding column.

*** Results are based on the individual transfer functions.

**** The approximate standard error for the estimated correlations is 0.10.

relationships among the variables. The results are mostly consistent with prior expectations, e.g., negative correlations between NNU and DNU, NNU and C, and DNU and MM, and positive correlations between C and DNU, and MM, and NNU. However, the contemporaneous correlations of LS with the other variables, except Crime, are not significant.

Discussion

A conceptual framework using the systems approach and the analytical techniques applied here have successfully characterized the dynamic interplay among narcotics-using behaviors, criminal involvement, and social interventions over time. The techniques have allowed the disentanglement of long-term, short-term, and contemporaneous effects of these variables on each other. In the following discussion, we compare the results found in the present study, which are pertinent to Southern California heroin addicts, with our understanding of how current interventions operate in reality. We also discuss social policy implications based on the results from this and other studies.

Narcotics Use and Property Crime: Reciprocal Dynamics

Despite consistent demonstration of high correlations between measures of narcotics use and crime in the literature, findings from research that has attempted to determine the causal relationship between the two have not been accepted by all as conclusive (Speckart and Anglin 1986). Countervailing positions argue that (1) the heterogeneity of addicts' characteristics and life style prevent such a simplistic causal connection and (2) the complexity of the real-life crime situation involving crime activity probably deserves a more diverse delineation than that of a simple cause-and-effect relationship involving only two variables.

In the present study, a major focus was the assessment of the dynamic equilibrium relationship between narcotics use and property crime within the larger social context. The results demonstrate that, at least at the group aggregate level, *there is an interlocked reciprocal response between the two behaviors that persists over time*. Criminal activity contributes to long-term narcotics use, while, at the same time, narcotics use increases long-term property crime. This implies that addicts develop a special lifestyle commitment from their long-term involvement in both narcotics use and criminal activities. When the long-term component is partialled out, current changes in the crime level are driven by the changes in narcotics use in the immediately previous period, *but not vice versa*. The contemporaneous relationship (where causal direction cannot be statistically specified) is strong, as has been shown in most of the previous research.

It should be emphasized that, although previous studies have speculated on this reciprocity, the present study has provided quantitative evidence of the long-term reciprocal interaction between narcotics use and property crime. The findings here establish that increases in current crime are driven by current and previous narcotics use and suggest that controlling narcotics use reduces crime.

Methadone Maintenance Treatment: Its Impact and Its Role as an Outcome Measure

Addicts qualify themselves for admission to methadone maintenance treatment because of problems associated with narcotics dependence. Admission may also be coerced by referral from the legal system. The present study confirms previous evaluation studies showing that methadone maintenance has significant long-term effects in reducing narcotics use and related crime. However, no short-term effectiveness of methadone maintenance was observed.

In addition to individual needs motivating treatment entry, treatment retention at a group level may depend on program policy and legal pressure. Because treatment results

in positive effects, retaining clients over suitable periods has been one of the goals of treatment or has been considered itself as an outcome measure. Because of the high risk of AIDS infection among intravenous drug abusers from sharing contaminated needles, methadone maintenance has been suggested as a means to reduce narcotics abuse and thus the practice of needle sharing. While restrictions on methadone maintenance admission have recently been eased for this reason, previous and current funding limitations have severely curtailed treatment availability. (In Figure 2, participation in methadone maintenance peaked about interval 60, or month 120, and decreased steadily thereafter for 30 intervals, a period approximately from 1976 to 1978. The period of declining participation corresponds to the declining governmental funding for drug treatment in general and methadone maintenance in particular.)

The social benefits demonstrated by methadone maintenance cannot be maximally obtained without further commitment of resources to increasing treatment availability. Our study also suggests that legal supervision may increase long-term methadone maintenance involvement, both in motivating entry and in prolonging retention. However, the negative long-term association between property crime and methadone maintenance indicates that narcotics abusers who are heavily involved in criminal activity tend to resist methadone maintenance treatment. Therefore, more coercive intervention efforts may be necessary to first bring them into treatment and then to retain them for a sufficiently long period in order to maximize social benefits.

Legal Supervision: Maximizing Effectiveness

In contrast to methadone maintenance, legal supervision operates solely in a mandatory, or imposed, manner. The period of legal sanction is determined by the detected levels of deviant behaviors such as drug use or crime. Continued offenses or violations of probation or parole may result in prolonged or recurrent sentences. The positive relationship observed in the equilibrium regressions between narcotics-related behaviors and legal supervision reflects the response of the legal system to continued antisocial acts.

As for the impact of legal supervision on narcotics use and property crime, no direct effect was demonstrated in the five-variable system. Only indirect effects, mostly through methadone maintenance treatment, were observed. Additional analyses indicated that legal supervision by itself does not remove the unit roots in daily narcotics use and property crime, even though the observed effect is negative and statistically significant (at $p < 0.05$), as expected in the equilibrium regressions ($R^2 = 0.05$, $F(1, 97) = 4.68$ and $R^2 = 0.16$, $F(1, 97) = 19.00$, respectively). When methadone maintenance is considered in addition to legal supervision, the R^2 's of the equilibrium regressions rise to 0.86 and 0.94, respectively, while the coefficients for legal supervision become positive in both cases. The high correlation between methadone maintenance and legal supervision apparently contributes to this phenomenon. Overall, the above results imply that effective legal supervision can occur only in conjunction with methadone maintenance treatment.

Age Effects on the System Dynamics

Previous studies (e.g., Winick 1962) on "maturing out" of addiction have shown that, over time, some addicts cease their addiction and associated antisocial behaviors. Because of the time-trend nature of the present study, the group's mean age was included in the analyses as a control variable to avoid the possibility of spurious correlations in the five-variable dynamic system. The results indicated that while age contributes to the long-term increase in narcotics abstinence and decrease in property crime, it does not affect daily narcotics use, methadone maintenance, or legal supervision. Furthermore, results of additional analyses not reported in the results section showed that excluding age from the model does not alter the relationships among the other variables. Thus, including age as a variable does not affect the dynamic system to any insignificant degree.

Whether or not age can be quantitatively controlled in the manner used here is questionable. It is possible that age is a proxy for qualitative changes, such as lifestyle or maturation, that come with age and that are not easy to quantify. Therefore, it is important to replicate the present study with other samples.

Conclusions

The present study has demonstrated that the newly developed techniques of unit-root testing, cointegration, and error-correction modeling can be applied for evaluating social interventions. The results provide strong evidence of the effectiveness of methadone maintenance treatment, particularly in the long term. The findings on the effectiveness of methadone maintenance combined with the importance of legal coercion in forcing individuals into treatment suggest that compulsory treatment should be considered for chronic narcotic addicts convicted of crimes.

The results of this study raise several questions that merit further research. One is the existence versus nonexistence of group differences in intervention effectiveness. It seems reasonable to expect that some types of intervention will work more effectively with some groups of narcotics users than with others. For example, differences in intervention effectiveness due to gender and ethnicity are worth investigating. Furthermore, previous research has shown that a high level of pre-treatment criminality is associated with poor treatment outcome. Therefore, in a future study, subjects could be grouped in terms of differences in pre-treatment crime to investigate if their crime levels in fact influence intervention effectiveness. Finally, in order to better understand the long-term effectiveness of intervention, future research will focus on simulation, or "what-if," studies in which various hypothetical intervention policies are empirically examined using the long-term time series model developed in the present study.¹²

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