Mathl. Comput. Modelling Vol. 17, No. 2, pp. 89–107, 1993
Printed in Great Britain.
0895-7177/93 $6.00 + 0.00

LONG-TERM TIME-SERIES FORECASTING OF SOCIAL INTERVENTIONS FOR NARCOTICS USE AND PROPERTY CRIME

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Abstract—This paper presents a policy analysis based on a multivariate long-term model of narcotics-related behaviors and social interventions. We first examine the forecasting performance of the long-term model. Next, we design a simulation study to investigate the long-term impacts of hypothetical policy changes in methadone maintenance on narcotics use and property crime.

The data used for model development were based on retrospective self-report information on various narcotics-related behaviors collected from methadone maintenance patients in Southern California. For time-series analysis, we aggregated each subject's longitudinal addiction history to provide group-level data which consisted of 99 bimonthly periods for the following five variables: abstinence from narcotics, daily narcotics use, property crime, legal supervision, and methadone maintenance.

Post-sample forecasting performance is compared between the long-term time-series model and a more common time-series model which captures only short-term relationships. Overall, the results demonstrate superior performance by the long-term model, indicating its adequacy to explain the system dynamics among the five variables. For the simulation study, four hypothetical conditions of methadone maintenance are investigated, and the resultant impacts on narcotics use and property crime for each methadone maintenance condition are predicted using the long-term time-series model. The analyses lay out quantitative pictures of the effects of hypothetical changes in methadone maintenance that are consistent with *a priori* expectations. Finally, monthly average changes in cost of methadone maintenance were estimated for each simulation setup.

INTRODUCTION

In order to maximize the effectiveness of public policy, it is necessary not only to learn from past experience through policy evaluation but also to predict the likely future effects of alternative policy plans. A careful analysis of past effects enables us to develop an intelligent estimate of how the system will operate in the future. Such forecasting is rendered more useful by examining several policy options and simulating the possible resultant outcomes for each. We refer to the combination of historical analyses, forecasting, and simulation as "policy analysis." This paper reports a policy analysis based on a multivariate time-series which differentially assessed long-term and short-term relationships between narcotics-related behavior and social interventions.

Good policy analysis should make the distinction between short-run and long-run effects. Some policy changes, such as raising the excise taxes on liquor, may cause a temporary decline in alcohol consumption followed by a return to previous levels. That would be an example of a short-run or temporary effect, even though it may occur over a relatively extended time period. Other changes (e.g., prohibiting liquor sales on Sundays) may cause a permanent shift in either the level or the trend in alcohol consumption. That would be an example of a long-run or permanent

This research was supported in part by NIDA Grants DA06250 and DA05544, and NIJ Grant 90-IJ-CX-0014. Drs. Hser and Anglin are also supported by Research Scientist Development Awards (DA00139 and DA00146, respectively) from NIDA.

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effect, even though its consequences may not be apparent immediately. In most policy scenarios, the ultimate gauge of effectiveness is the long-term or permanent impact.

While policy analyses exist in a wide range of public sectors, few empirical studies have systematically distinguished between long-term and short-term policy outcomes applying appropriate methodologies. However, recent development of a new time-series technique, co-integration and error-correction modeling [1], allows us to statistically distinguish the two types of effects for examining public policy effectiveness. In the time-series context, long-term relationships compare the stochastic trend of one time-series to a stochastic trend of another series. Short-term relationships describe how changes from one time point to the next (i.e., small fluctuations around the trend) in one variable are related to changes in other variables. Using the new technique, Powers, Hanssens, Hser, and Anglin [2] developed a multivariate time-series model that assessed the long-term and short-term effects of methadone maintenance and legal supervision on narcotics use and property crime.

This paper presents a time-series based policy analysis using the long-term model developed by Powers *et al.* [2], with special reference to narcotics use and social interventions. We first examine the forecasting performance of the long-term model in contrast to a traditional time-series model that explains only short-term dynamics among the variables. Next, we perform simulation analysis of the effects of hypothetical policy changes in methadone maintenance, simulations that can provide important bases for policy decisions. The section also includes a demonstration of cost estimation method using the simulation results.

The paper is organized as follows: Section 1 provides a brief overview of the data and the final model developed in [2] and then presents research questions relevant to policy analysis. Section 2 introduces our approach, followed by the analysis results in Section 3. The final section compares the forecast and simulation performance between the long-term and short-term models and discusses policy implications of the findings.

BACKGROUND

A Long-Term Multivariate Model of Narcotics Use

The data used for model development in [2] were collected by intensive follow-up interviews of narcotic addicts during the early 1980's in several Southern California methadone maintenance clinics. These subjects provided retrospective longitudinal self-report information on their addiction histories. The sample used for model development ($N = 627$) consisted of Anglo (74%) and Chicano (26%) chronic narcotics addicts, both men (57%) and women (43%).

Five variables were selected for developing the multivariate long-term model:

(1) abstinence or no narcotics use (NNU);
(2) addictive use or daily narcotics use (DNU) for at least 30 days;
(3) property crime involvement (PC);
(4) methadone maintenance treatment (MM); and
(5) legal supervision (LS).

Because of the long assessment period (covering 16.5 years), age was included as a control variable. The value of each of these variables (except age) represented the percentage of non-incarcerated time engaged in the activity for defined time periods, e.g., monthly, quarterly, or yearly. All these variables were prepared as group-level time-series consisting of 99 bimonthly observations, starting from the time of first narcotics use.[1]

A new time-series technique, co-integration and error-correction modeling [1], was used to assess long-term relationships among the variables and to combine them with short-term relationships. (The modeling procedure will be discussed in a later section.) The results showed that

[1]All these variables were originally measured for each subject separately. To obtain the aggregate time-series, the averages of the values for each of the variables during 99 consecutive two month (bimonthly) periods were calculated by summing over the group and then dividing by the number of subjects contributing during that period. According to Hser, Anglin and Chou [3], the test-retest reliability (with a 10-year retest interval) of abstinence, daily use, and property crime measures determined in this way (based on a different sample) is 0.71, 0.63, and 0.52, respectively. Methadone maintenance and legal status measures are based on official records.

the relationships among social interventions and narcotics-related behaviors were predominantly of a long-term nature (see parameter estimates in the Appendix). They found a positive relationship between long-run movements in daily narcotics use and property crime, and a negative long-term association between abstinence from narcotics and property crime. With respect to intervention effectiveness, methadone maintenance demonstrated a negative long-term association with property crime and a positive association with abstinence from narcotics. These results suggested that methadone maintenance is an effective approach for controlling narcotics use and property crime. On the other hand, legal supervision had positive long-term associations with daily narcotics use and property crime, implying that legal supervision in this study was primarily responding to, rather than affecting, narcotics users' antisocial behaviors.

Research Hypotheses

Based on these findings noted above and the existing literature on drug abuse,[2] we address the following policy questions:

(1) Can forecasts of the five variables be improved by considering the long-term relationships among them in addition to the short-term relationships?
(2) Given that methadone maintenance is shown to be effective in reducing narcotics use and property crime, what would be the expected long-term impact of hypothetical changes in levels of methadone maintenance participation? Would the intervention impact differ when applied to different stages of the addiction career and, if so, to what extent?
(3) Is the long-term benefit of reducing narcotics use and property crime worth the cost of the intervention?

Our analytical techniques, which are described in the next section, have several advantages over other approaches to policy analysis. First, our approach gives empirical answers to "what-if" policy scenarios, which provide more concrete outcomes than "theory-only" approaches to policy analysis. Second, because the analysis is based on a time-series model, we are able to examine possible impacts of changes in a policy control variable (e.g., methadone maintenance) onto policy target variables, such as narcotics use and property crime, for a specified period of time. The outcomes based on the time-series model are more informative than prediction based on static regression models, which provide only one time-invariant prediction value for each variable [4]. Finally, whereas traditional time-series models capture short-term relationships among the variables, a co-integration and error-correction model explains both long-term and short-term movements among the variables. Such a model is suitable for long-term predictions, which provide valuable information for enduring policy planning and evaluation.

POLICY ANALYSIS WITH A LONG-TERM TIME-SERIES MODEL

This section discusses analytical procedures for forecasting and simulation using a long-term multivariate time-series model of the five variables. We first introduce the time-series model and then explain the analytical approach of forecasting and simulation, using the relationships among these five variables.

Long-Term Time-Series Model[3]

Powers *et al.* [2] first estimated separate 'equilibrium' regressions to represent the long-term relationships among the five variables. These equations can be combined in matrix representation as

$$\mathbf{X}_t = \mathbf{c}_0 + \boldsymbol{\beta}\, \mathbf{X}_t + \mathbf{e}_t \tag{1}$$

where $\mathbf{X}_t$ is a 5×1 random vector containing the social intervention and narcotics-related variables, all of which are non-stationary, $\mathbf{c}_0$ is a 5×1 column vector of constants, $\boldsymbol{\beta}$ is a 5×5 matrix

[2] A literature review on forecasting and policy analysis in the drug abuse field is available from the authors.
[3] This section describes the co-integration and error-correction modeling approach applied to the narcotics addiction data. For mathematical proofs and discussions, see [1].

of parameters, having 0 in diagonal entries and in some off-diagonal entries to represent parameter constraints, and $\mathbf{e}_t$ is a 5×1 column vector of error terms assumed to be i.i.d. $N(\mathbf{O}, \mathbf{\Sigma})$, with $\mathbf{\Sigma}$ being a diagonal matrix.

To explain the concept of a long-term, or equilibrium, relationship, let us focus on the relationship between an output variable, daily narcotics use (DNU), and a set of three input variables, property crime (PC), methadone maintenance (MM), and legal supervision (LS), all being non-stationary series. If we partition appropriate rows of $\mathbf{X}_t$ for the four variables and corresponding entries of the other matrices from Equation (1), the equilibrium regression for DNU can be isolated as

$$\mathrm{DNU}_t = c + \beta_1\, \mathrm{PC}_t + \beta_2\, \mathrm{MM}_t + \beta_3\, \mathrm{LS}_t + e_t. \tag{2}$$

To statistically test the existence of the equilibrium relationship between DNU and PC, MM, and LS, we obtain ordinary-least squares estimates of the parameters and check the residual series $\hat{e}_t$ from Equation (2). If $\hat{e}_t$ is a stationary series when DNU, PC, MM, and LS are non-stationary, then DNU and the remaining variables are said to be co-integrated, which implies that there is a long-term, or equilibrium, relationship between DNU and the three input variables. Stock [5] has shown that, if the variables are co-integrated, the simultaneous-equation bias in the OLS estimator vanishes in the limit. For example, if $\beta_1 > 0$, this implies that an upward drift in PC will eventually result in an increase in DNU. While a traditional time-series model (where all the variables are required to be stationary) can assess only short-term relationships, the co-integration approach allows us to examine long-term or equilibrium relationships by modeling the movements among stochastic trends of the variables.

If co-integration has been established, then as the second modeling step, the long-term relationships among the five variables are combined with their short-term relationships using an error-correction model [1]. The error-correction model for the five variables developed in [2] takes the following matrix representation:

$$(\mathbf{I} - \mathbf{L})\ \mathbf{X}_t = \mathbf{c} + \boldsymbol{\tau}\ (\mathbf{I} - \mathbf{L})\ \mathbf{X}_{t-1} + \boldsymbol{\pi}\ \hat{\mathbf{e}}_{t-1} + \mathbf{a}_t, \tag{3}$$

where $\mathbf{L}$ is a lag operator, with $\mathbf{L}^k\ \mathbf{X}_t = \mathbf{X}_{t-k}$, $\mathbf{c}$ is a 5×1 column vector of constants, $\boldsymbol{\tau}$ is a 5×5 matrix of parameters, $\boldsymbol{\pi}$ is a 5×5 diagonal matrix of parameters, and $\mathbf{a}_t$ is a 5×1 column vectors of residual series. The entries in the matrix of parameters $\boldsymbol{\pi}$ indicate how the system adjusts for the long-term mechanisms, and those of $\boldsymbol{\tau}$ represent the short-term relationships among the five variables. Note that $\hat{\mathbf{e}}_{t-1}$ is obtained from the estimated equation (1).

Short-Term (General VAR) Model

The short-term model for the present study is written as:

$$(\mathbf{I} - \mathbf{L})\ \mathbf{X}_t = \mathbf{c} + \boldsymbol{\tau}_s\ (\mathbf{I} - \mathbf{L})\ \mathbf{X}_{t-1} + \mathbf{a}_t, \tag{4}$$

where $\mathbf{c}$ is a 5×1 column vector of constants, $\boldsymbol{\tau}_s$ is a 5×5 matrix of parameters representing short-term relationships among the variables, and $\mathbf{a}_t$ is a 5×1 column vectors of residual series. Because all the variables in the model were unstationary, they were differenced (represented by $\mathbf{I} - \mathbf{L}$ in Equation (4)).

Forecasting

With the long-term multivariate model, the h-step-ahead forecasting equation using information between time interval 1 through t is

$$\mathbf{X}_{t+h} = \hat{\mathbf{c}}^* + \mathbf{X}_{t+h-1} + \hat{\boldsymbol{\tau}}\ (\mathbf{I} - \mathbf{L})\ \mathbf{X}_{t+h-1} + \hat{\boldsymbol{\pi}}\ (\mathbf{I} - \hat{\boldsymbol{\beta}})\ \mathbf{X}_{t+h-1}, \tag{5}$$

where h is called the forecast horizon, being a positive integer, and $\mathbf{c}^*$ is a 5×1 column vector of constants. Equation (5) is derived by algebraic manipulation of the equilibrium regressions (1) and the error-correction equations (3).

The concept of an equilibrium condition plays an important role in forecasting also. It has been shown that if the variables are co-integrated, the optimal forecast of these variables satisfies the equilibrium condition [6]. For example, if DNU is found to be co-integrated with PC, MM, and LS as in Equation (2), then, in theory, long-run forecasts based on the equilibrium condition follow the linear constraint

$$\mathrm{DNU}_{t+h} = c + \beta_1\,\mathrm{PC}_{t+h} + \beta_2\,\mathrm{MM}_{t+h} + \beta_3\,\mathrm{LS}_{t+h}. \tag{6}$$

This means that, under co-integration, DNU and the three input variables are tied together in long-run forecasting. On the other hand, if DNU and the three variables are not co-integrated, the forecasts of the system are not constrained by this equilibrium condition. Such forecasting will be affected only by the short-term components of the model and is therefore anticipated to be less accurate for long-term forecasting. To examine the effect of long-term components of forecasting performance, the h-step ahead forecasting equation based on Equation (4) was also prepared:

$$\mathbf{X}_{t+h} = \hat{\mathrm{c}}^{*} + \mathbf{X}_{t+h-1} + \hat{\boldsymbol{\tau}}_{s}\,(\mathbf{I} - \mathbf{L})\,\mathbf{X}_{t+h-1}. \tag{7}$$

Powers *et al.* [2] obtained parameter estimates in Equations (1) and (3) as well as Equation (4) by representing the model in vector-autoregressive (VAR) form (see the Appendix). Using these estimates, the present study performs forecasting analyses of both the error-correction-augmented VAR (or abbreviated as EQEC for 'equilibrium and error correction') and simple VAR models to compare and contrast their performance. Because the difference between the two models is the inclusion versus exclusion of long-term relationships, such a comparison should highlight the effect of the long-term component in forecasting. Engle and Yoo [6] compared the forecasting performance of an EQEC and an unrestricted VAR model with computer-generated data. They demonstrated that the forecasting accuracy with the EQEC approach was greater than that of the unrestricted VAR when the number of forecasting steps was large ($h > 6$), and the superiority of the former became progressively greater as the horizon increased. In the five-variable dynamic system under study, such superiority of the error-correction approach to the simple VAR approach is expected in multi-step forecasting. If such is the case, it would add support to our finding that the system dynamics are affected by long-term relationships.

Simulations

By incorporating co-integration and error-correction modeling, a simulation study can lay out quantitative responses to questions such as: what would be the long-term effect of methadone maintenance on narcotics use if we increase its availability, or what are the long-term and short-term impacts on narcotics abuse and property crime if legal supervision becomes more stringent? For the present study, we manipulate methadone maintenance as the policy control variable. The analytical procedure is an extension of the forecasting described above. New data values for methadone maintenance (these values are derived from theory-based hypotheses) are fed into Equations (5) and (7), and consequential changes in policy target variables (e.g., daily narcotics use or property crime) are predicted by the EQEC and VAR models.

Some researchers have criticized the application of econometric and time-series forecasting models for policy simulation (e.g., [7,8]). Briefly, the arguments state that the application of time-series models to simulation is suspect for two reasons. First, policy analysis inherently requires causal relationships whereas the models are based on correlations. As a result, applying new values to a model estimated on historical data could cause parameter instability and result in unreliable predictions of policy target variables, such as daily narcotics use (DNU). Second, policy simulation introduces a deterministic character to the policy variables while multivariate time-series models treat them as stochastic [9]. For instance, because policy variables are not strictly exogenous in our VAR representation, a change in methadone maintenance (MM) can have an effect on future MM. However, the simulation forces the MM value to remain at some predetermined fixed value. This means that the approach does not allow any inference of the effect of, for example, DNU on MM.

The first problem, parameter instability, may be monitored by carefully combining the VAR model approach with the researcher's theory on the relationships among the variables (as was done in [2]) and by subjecting the model to a forecasting test. The second problem may be avoided by using the impulse response representation of the VAR model [9]. This approach focuses on the reaction of policy target variables at various lags to an ***unexpected shock*** in a policy control variable. The advantage of this approach is that the policy feedback effects are not forced out of the simulation analysis. However, the major drawback is that causal relationships among all the variables have to be explicitly defined *a priori*, and the difference in the defined relationships could affect response outcomes considerably, particularly when innovations of the variables are expected to be correlated. Since the main purpose of our policy simulation is to illustrate effects of the long-term components on simulation performance, we will conduct our simulation study using Equations (5) and (7).[4]

The above critiques, although important for understanding the limits of our simulation study, should be regarded as a reflection of the complex nature of policy analysis and a caution against simple-minded interpretation of the results. Although it is possible to introduce changes in the MM-DNU relationship due to a policy change, with fairly stable parameter estimates, policy simulation can lay out a good approximation of behavioral changes in NNU, DNU, and PC as responses to the policy change applied on MM (see [10] for a more comprehensive discussion on this issue).

A Method of Cost Estimation

As part of our policy analysis, the simulation outcomes are used to demonstrate how cost estimation of hypothetical situations can be carried out. For this purpose, cost assessment of MM is performed by multiplying: (a) the difference in percentage of time between the actual and simulated settings, and (b) the cost estimate for methadone maintenance per person per two-month period. The obtained estimates can be summed across the entire simulated range to derive total cost for the period of interest. Furthermore, when information on addict population size is available, multiplying the obtained individual estimate by the population size would yield the population cost estimate for the variable.

For the purpose of demonstration, we use a fixed cost estimate of $250 per month (or $500 for two-month period) for public-supported methadone maintenance [11]. The outcomes are "relative" cost estimates in the sense that the values do not reflect inflation rates and are meaningful only in a comparative sense. Although the relative cost estimates do not provide precise figures, they give a general idea of the magnitude of cost involved. Furthermore, these estimation outcomes lay out a sufficiently clear picture for comparing the cost effectiveness of various setup options of methadone maintenance in controlling narcotics use and associated crime.

RESULTS

Forecasting Performance of the Error-Correction Model

In order to examine the adequacy of the long-term multivariate EQEC model, the forecasting performance for the three target variables (i.e., abstinence from narcotics, daily narcotics use, and property crime)[5] was tested as follows:

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[4]Interested readers can obtain the simulation results based on the shock approach from Powers [10]. Briefly, the results from this approach were consistent with the present simulation results. When methadone maintenance was increased, both daily narcotics use and property crime decreased, and abstinence from narcotics increased.

[5]The age variable was not included for the forecasting analysis. During the initial model development stage using all observations, the multivariate models with and without the age variable did not differ in any significant manner, and all the remaining parameter estimates were unaffected. When the models based on 80 observations were developed, one of the error-correction terms (in DNU equation) was non-significant for the model with Age, whereas the model without Age was consistent with the pattern observed in the model developed for all 99 observations. The finding indicated an unstable nature of the relationships of the age variable with the other five variables in the present system dynamics. Because the model without Age for 80 observations was consistent with the model based on all observations and because forecasting was to be performed on the three target variables, the age variable was excluded for forecasting analysis.

(1) parameter estimation of the model based on the first 80 out of 99 observations,[6]
(2) post-sample forecasting for selected horizons (i.e., 1-step-, 4-step-, and 6-step-ahead forecasting), and
(3) comparing actual and forecast values for time intervals from 81 through 99 (1-step forecasting), 84 to 99 (4-step forecasting), or 86 to 99 (6-step forecasting) and computing the mean squared error (MSE) and the mean absolute error (MAE).

The same procedures were used to test the forecasting performance of the simple VAR model.

Table 1 presents the MSE and MAE of the three target variables for the two models, along with the MSE and MAE ratios between the two models. Overall, when compared to the actual observation values, the results of both MSE and MAE suggest superior forecasting performance by the EQEC model over the VAR model in all variables for all the steps examined. A comparison of the ratios presented in the last column of Table 1 indicates clearly that the difference in forecasting accuracy between the two models becomes greater as the number of steps increases. The results demonstrate the importance of including a long-term equilibrium factor in forecasting narcotics use and related behaviors, particularly as the forecasting horizon is expanded.

Table 1. Comparison of the forecasting performance between error correction (EQEC) and simple VAR models.

Variable = No Narcotics Use (NNU)

Measure	Number of Steps	EQEC Model	VAR Model	EQEC/VAR*100
MSE[a]	1	4.973	5.702	87
	4	4.617	11.925	38
	6	5.086	18.517	27
MAE[b]	1	1.945	2.058	94
	4	1.777	2.982	59
	6	1.869	3.583	52

Variable = Daily Narcotics Use (DNU)

Measure	Number of Steps	EQEC Model	VAR Model	EQEC/VAR*100
MSE[a]	1	7.354	7.699	95
	4	14.743	18.783	78
	6	14.159	21.874	64
MAE[b]	1	2.123	2.197	96
	4	2.765	3.221	85
	6	2.770	3.762	73

Variable = Property Crime (PC)

Measure	Number of Steps	EQEC Model	VAR Model	EQEC/VAR*100
MSE[a]	1	0.961	1.160	82
	4	2.292	2.830	81
	6	2.311	2.932	78
MAE[b]	1	0.805	0.841	95
	4	1.037	1.186	87
	6	1.222	1.397	87

[a]MSE = Mean squared error; [b]MAE = Mean absolute error.

[6]In deciding on the number of observations for model development, two criteria were considered, and their needs were balanced out. It was necessary to retain a sufficient number of observations for model development but, at the same time, the number of forecasting points needed to be sufficiently large to derive reliable mean error measures.

Simulations with the Error-Correction Model

Table 2 summarizes four hypothetical situations that tested effects of policy changes in methadone maintenance on narcotics use and property crime.[7] In Simulations 1 and 2, MM values were changed to a fixed number (i.e., 16 or 64) during periods 81 to 99. In Simulations 3 and 4, the original MM values were multiplied by a constant (i.e., 0.5 or 1.5) for the entire time period. In all cases, the values of LS were retained at their original levels so that the effects of MM changes on the narcotics and crime variables could be observed separately from effects of LS.

Table 2. Simulation design for methadone maintenance.

	Four Simulation Settings			
	1	2	3	4
Periods Used for Model Estimation	1–80	1–80	1–99	1–99
MM Values Changed to	16[a]	64[a]	50% actual	150% actual
Periods of MM Value Changes	81–99	81–99	1–99	1–99

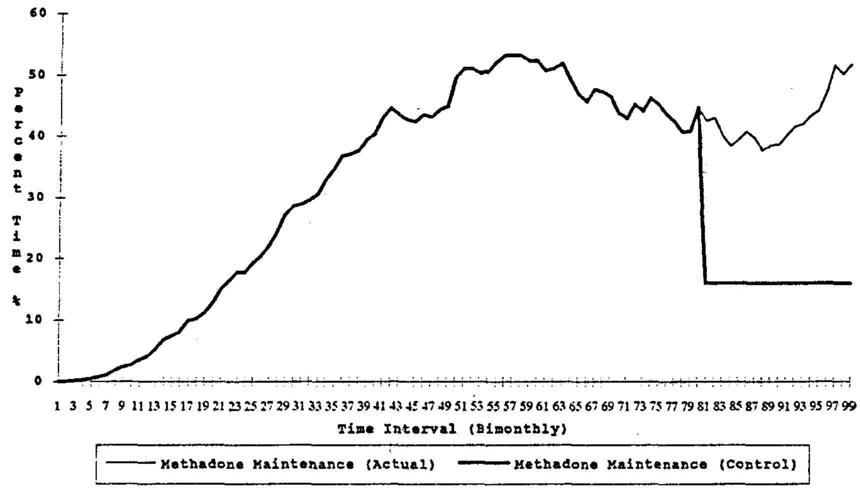
[a]These values are 50% or 200% of the historical mean of 32 for MM, respectively.

In Simulations 1 and 2, the outcomes are less vulnerable to the problem of parameter instability described in the analysis procedure section. Since the period of MM change is relatively short, the assumption of parameter stability is less likely to be violated. The disadvantage of these setups is the fact that the policy change was introduced late in the addiction career (between years 32.7 and 35.7 of the average addict's age). This choice of time period may make the outcomes less interesting from a substantive point of view. One may be more interested in, for example, the impact of MM change toward the beginning of an addiction career. In Simulations 3 and 4, the outcomes are more interesting in the long-term context of the narcotics abuse problem. The hypothetical situation affects the entire addiction career from the date of first narcotics use at average age 19.2 years to the end point at average age 35.7 years. However, these settings have the higher risk of parameter instability because the MM value change is introduced over the entire period.

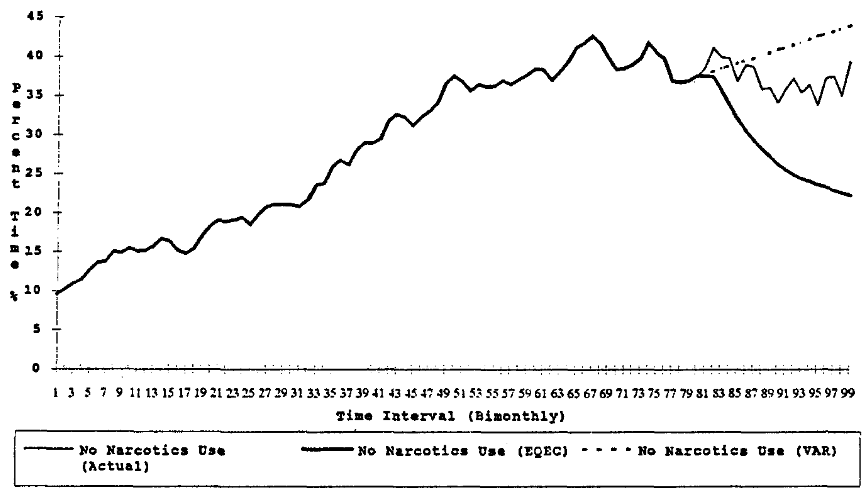
Figures 1 through 4 depict the changes in MM as well as the consequential responses of the narcotics-behavioral variables predicted by the EQEC and VAR models. The results of the EQEC model display a pattern consistent with our expectation for both Simulations 1 and 2 (Figures 1 and 2). When the value of MM is increased, the level of NNU increases, and DNU and PC decrease. On the other hand, when the level of MM is lowered, the opposite pattern emerges: a decrease in NNU and increases in DNU and PC. The predicted values for all the policy target variables by the EQEC model display a consistent and steady divergence from the actual data values as the number of intervals increases from the forecast origin. As for the results of the VAR model, the predicted responses result in values that are closer to the actual data values. Furthermore, many of these response patterns are inconsistent from theory-based predictions: an increase in NNU and decreases in DNU and PC for decreased MM (Simulation 1) and an increase in DNU for increased MM (Simulation 2). Only the response patterns of NNU and PC in Simulation 2 are consistent with outcomes based on the EQEC model.

The results of the full-range MM multiplication setups with the EQEC model (Simulations 3 and 4) are basically similar to the response patterns reported above (see Figures 3 and 4). Under the halved MM condition (Figure 3), the EQEC model predicts a decrease in NNU and increases in DNU and PC, and vice versa for the MM increase (Figure 4) condition. NNU for the lowered MM and all the three policy target variables for the increased MM show either expansion or

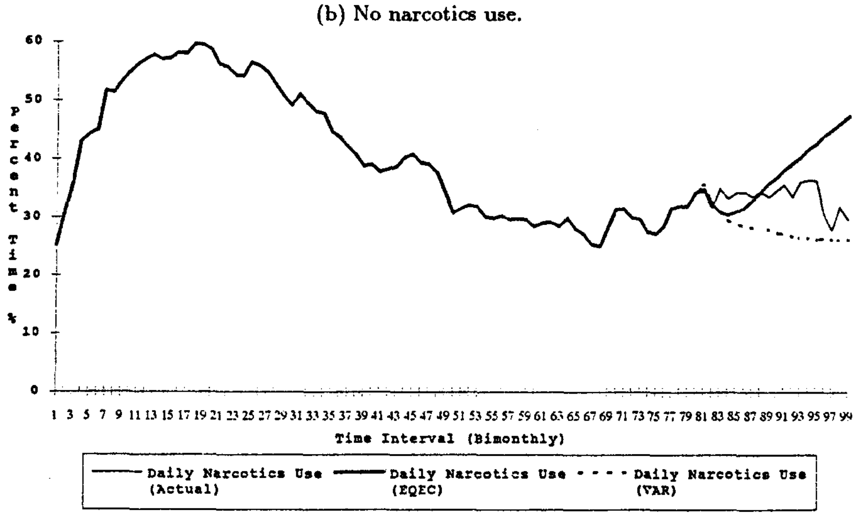
[7]Because only MM (but not LS) in the present model was demonstrating effects for controlling narcotics use behaviors and property crime, we manipulated the values for MM only (i.e., treating MM as a policy control variable) and examined the impact of the policy choice on NNU, DNU, and PC. We analyzed various simulation setups of methadone maintenance and selected the four setups in Table 2 as a representative sample of policy alternatives. The other simulations displayed consistent patterns as the results presented in this paper.



(a) Methadone maintenance.



(b) No narcotics use.

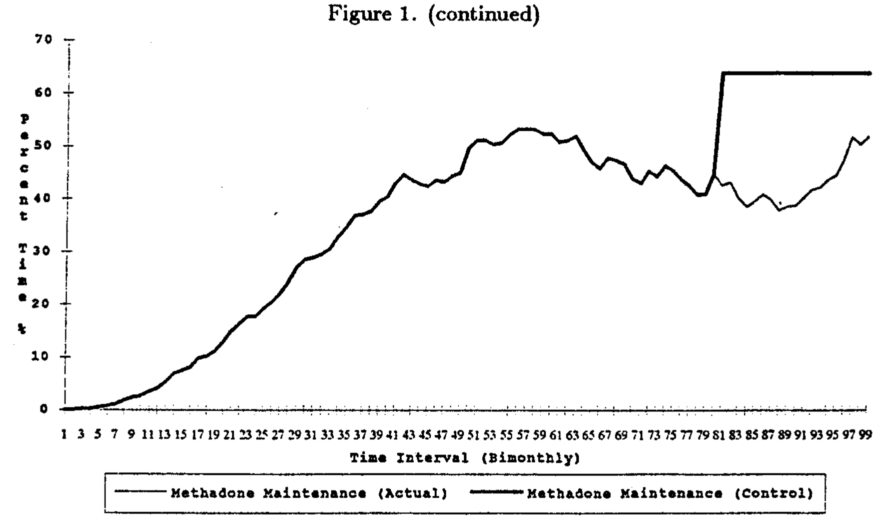


(c) Daily narcotics use.

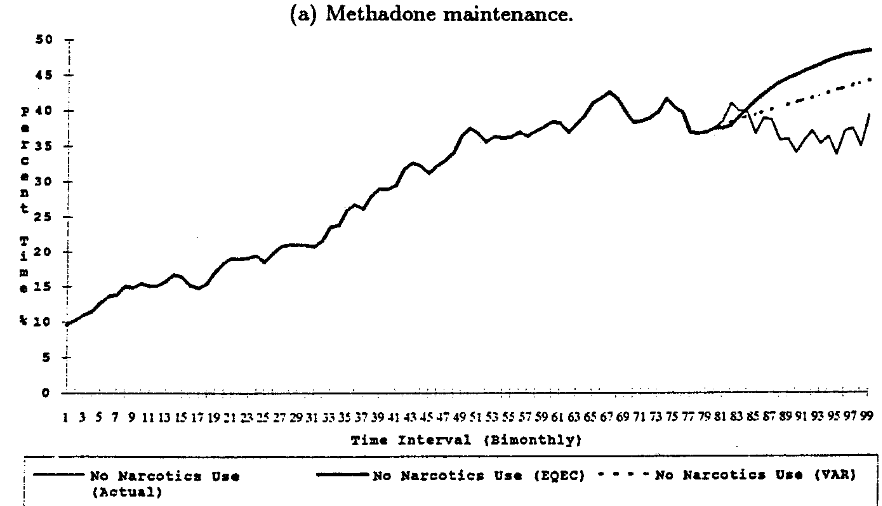
Figure 1. Simulation 1.

(d) Property crime.

Figure 1. (continued)

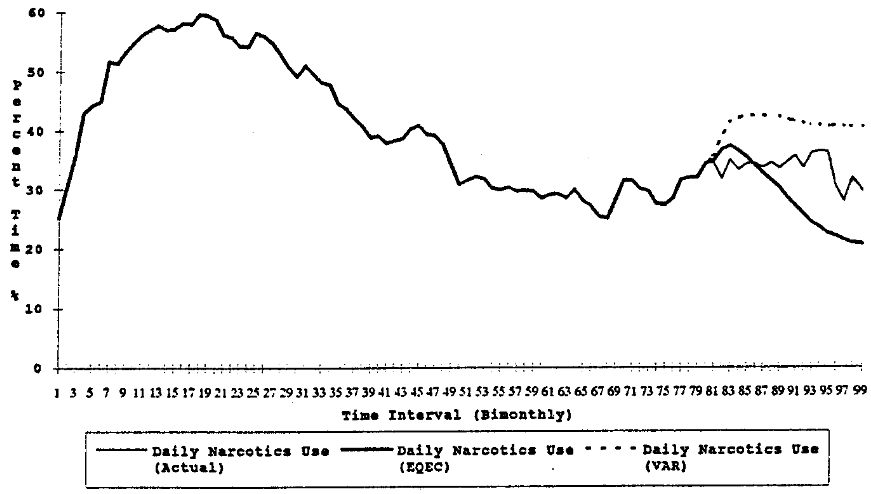


(a) Methadone maintenance.

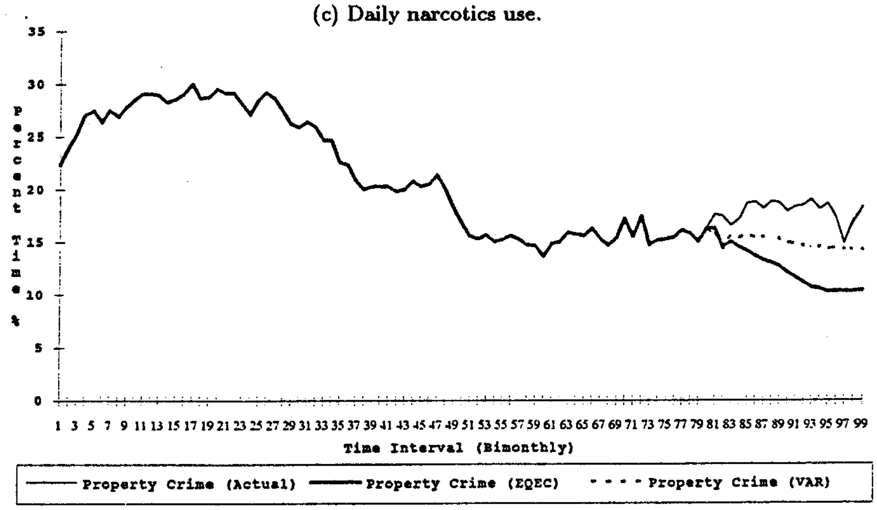


(b) No narcotics use.

Figure 2. Simulation 2.

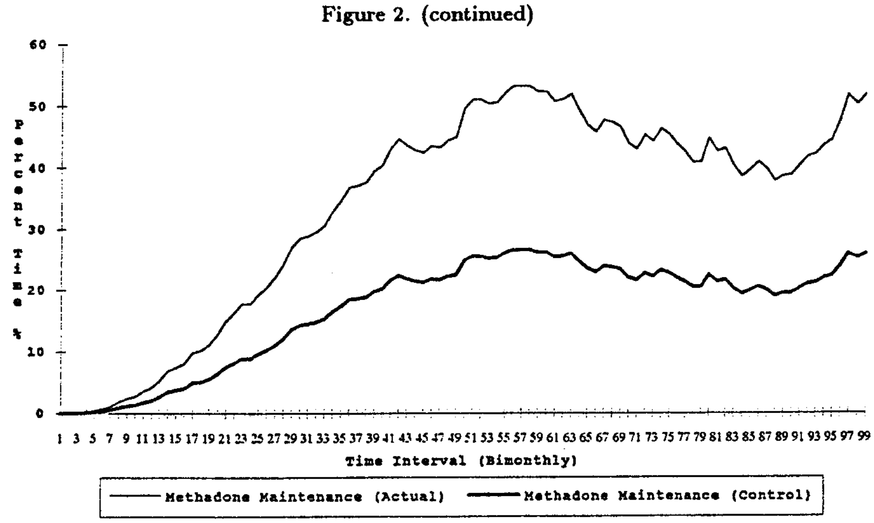


(c) Daily narcotics use.



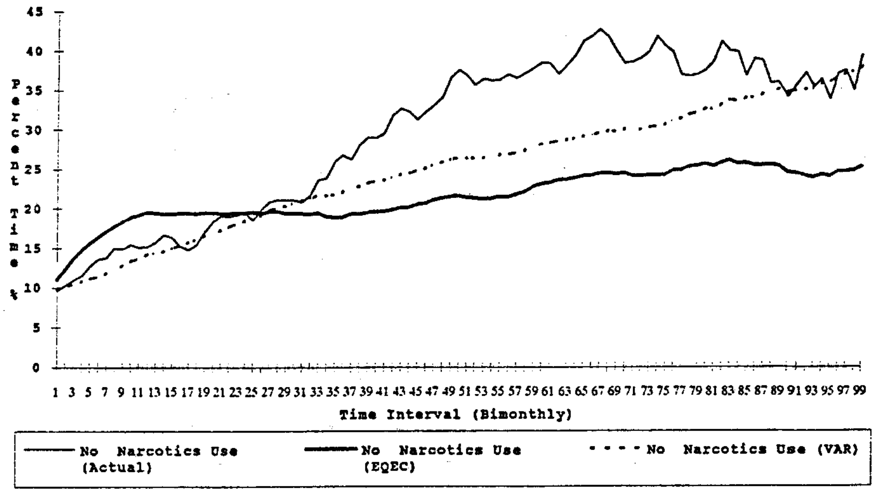
(d) Property crime.

Figure 2. (continued)

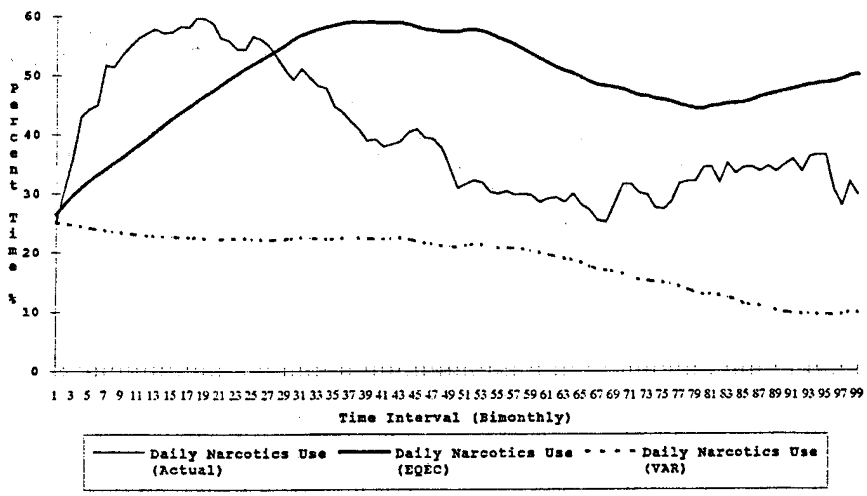


(a) Methadone maintenance.

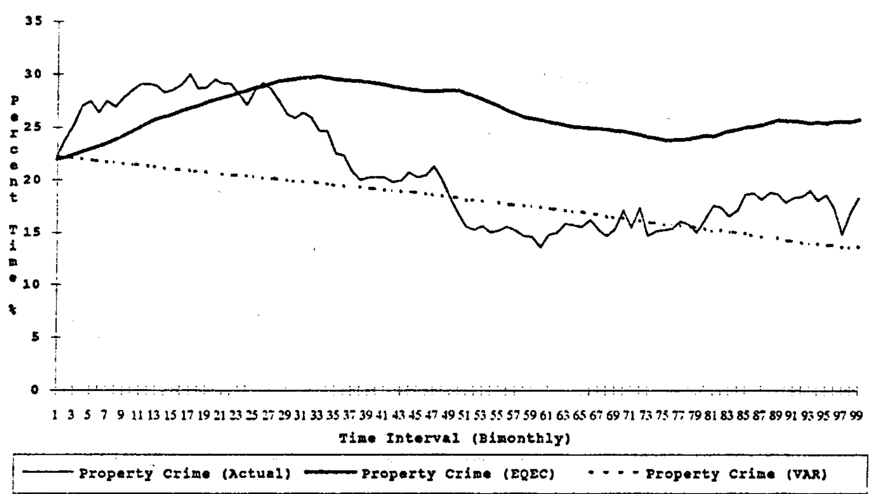
Figure 3. Simulation 3.



(b) No narcotics use.

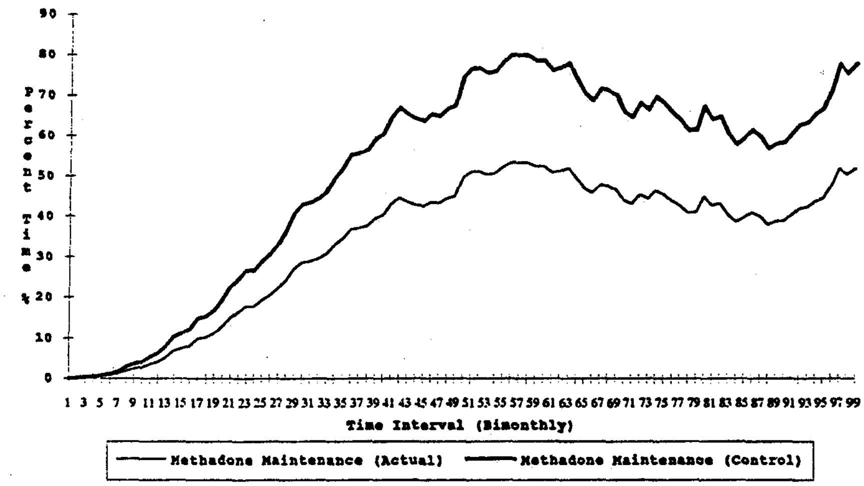


(c) Daily narcotics use.

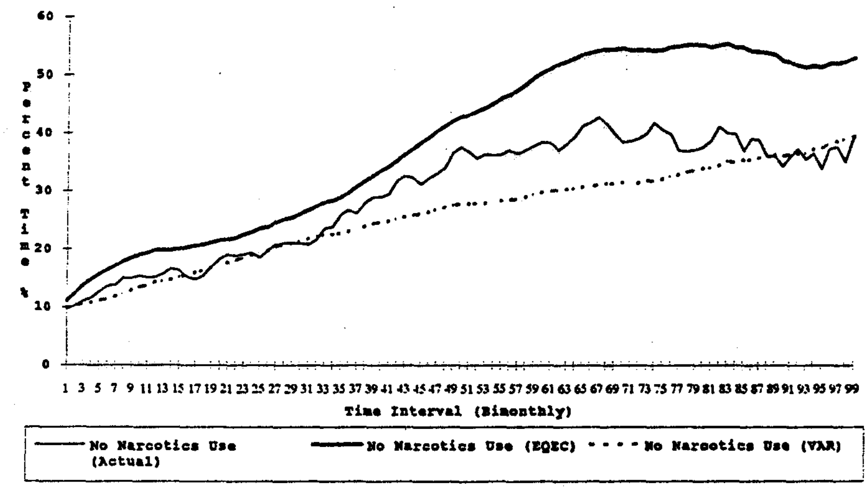


(d) Property crime.

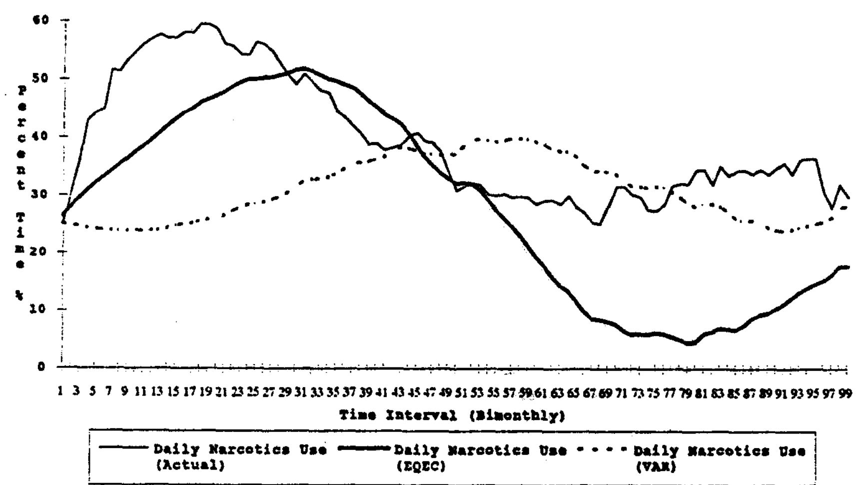
Figure 3. (continued)



(a) Methadone maintenance.

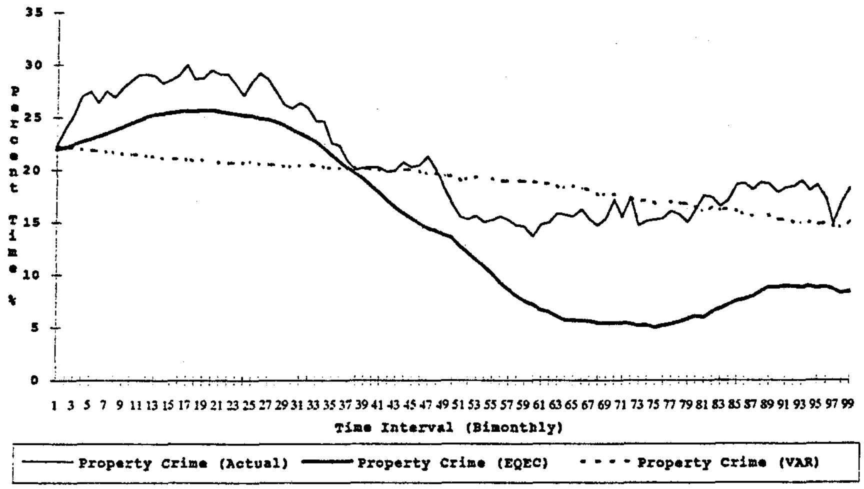


(b) No narcotics use.



(c) Daily narcotics use.

Figure 4. Simulation 4.



(d) Property crime.

Figure 4. (continued)

contraction of the original time plots but with the same shape retained. The predicted values of DNU and PC by the EQEC model for the lowered MM condition (Figure 3) display time delay in their peaks compared to the corresponding actual plots and are lower than the actual data values during intervals 1 and 30. The response patterns predicted by the VAR model are consistently less pronounced than those by the EQEC model, with many of them displaying a very flat line. Furthermore, the estimated values by the VAR model tend to be closer to the actual data values compared to the EQEC outcomes. Overall, outcomes by the EQEC model are more consistent with hypothesized expectation than those by the VAR model, particularly for longer-term predictions. These differences in the response patterns clearly illustrate effects of long-term components in the model on policy simulation.

Estimation of Methadone Maintenance Cost

In order to discuss intervention effectiveness of MM, we computed monthly averages (across the simulated period) of differences between the actual and simulated values of MM and the three policy target variables (i.e., NNU, DNU, and PC). We also estimated monthly average cost differences of MM using a monthly cost estimate of $250 per person by Bjorklund [11]. These computed values are summarized in Table 3.

Table 3. Simulation results of methadone maintenance effectiveness by the EQEC Model.

	Four Simulation Settings			
	1	2	3	4
Periods of MM Value Changes	81–99	81–99	1–99	1–99
MM Average Monthly Changes	−54% ($68)[a]	+42% ($53)	−50% ($42)	+50% ($42)
	Monthly Average Responses			
No Narcotics Use (NNU)	−25%	+19%	−28%	+31%
Daily Narcotics Use (DNU)	+12%	−14%	+24%	−29%
Property Crime (PC)	+30%	−31%	+26%	−29%

[a]A monthly estimate of MM cost change per person.

The EQEC model predicted the following proportional changes in the policy target variables. For Simulation 1, decreasing MM by 54% (or $68) every month per addict resulted in 25%

decrease in NNU, and 12% and 30% increase in DNU and PC, respectively. For Simulation 2, increasing MM by 42% ($53) per addict resulted in 19% more NNU, and 14% and 31% less DNU and PC. Simulations 3 and 4 also demonstrated a consistent pattern of the effects of methadone maintenance in controlling narcotics use and associated crime. In Simulation 3, decreasing MM by 50% ($42) per month showed 28% decrease in NNU, 24% increase in DNU, and 26% increase in PC. Although the change in MM values was the same between the two simulations (i.e., the difference in percentage between the actual and simulated settings), the policy target variables showed a greater magnitude in the monthly changes for Simulation 4 than Simulation 3; 50% ($42) monthly increase for MM resulted in 31% more NNU, 29% less DNU, and 29% less PC.[8]

Finally, a comparison between Simulations 2 and 4 allows us to examine the long-run effects of an increased level of participation to methadone maintenance during the early addiction career on the later involvement in narcotics use and property crime. During intervals 81 to 99, the average monthly increase of MM per addict is comparable at 42% ($53) between the two simulations. Therefore, we can interpret differences in NNU, DNU, and PC predicted by the EQEC models (between Simulations 2 and 4 and during intervals 81 to 99) as long-term impacts of more participation in methadone maintenance at earlier time. The long-term models predicted that when MM participation is 50% more between intervals 1 and 80 (Simulation 4), NNU increased by 43%, DNU decreased by 67%, and PC decreased by 55% during intervals 81 and 99. These values are substantially greater than those of Simulation 2 (see Table 3), indicating more improved status for all the three policy target variables in Simulation 4.

DISCUSSION

Long-Term versus Short-Term Model for Policy Analysis

Using a multivariate long-term time-series model, the present study demonstrated how long-term components in the model improve and affect forecasting performance and effects of hypothetical policy changes. Our forecasting results are consistent with those of Engle and Yoo [6] for long-term forecasting. Using computer-generated data, they found that the long-term model outperformed the VAR model for horizons greater than six. With the present study, the EQEC model had more accurate predictions when the horizon was as low as four. By using actual rather than computer-simulated data, the present study augments the evidence of the superior long-term post-sample forecasting performance of the EQEC model. The finding supports the idea that the long-term model is a better representation of the narcotics data than a traditional VAR model focusing only on short-term relationships. The superior long-term forecasting by the EQEC model is of particular benefit to policy-makers.

The importance of the long-term component was further demonstrated by the policy simulations. Unlike the short-term VAR model, the response patterns of the policy target variables predicted by the EQEC model were consistent among the four simulation setups. When MM was decreased, NNU decreased, and DNU and PC increased. On the other hand, when MM was increased, the opposite patterns emerged. One exception to this pattern is the observed decreases in DNU and PC between intervals 1 and 30 in Simulation 3. This response pattern illustrates that policy simulation results can be sensitive to the choice of a time point to introduce policy changes. However, under the influence of the error-correction mechanism, the longer-term responses of DNU and PC to a decrease in MM gradually shift into the expected direction. Overall, the results supported the idea that methadone maintenance is a valuable social policy strategy to control these narcotics-related behaviors.

One interesting finding is that the simulated responses of the policy target variables to hypothetical changes in MM indicate an asymmetric nature between MM increase and decrease. For example, the results for Simulations 3 and 4 show that although the amount of MM cost involved is the same between the two setups, the changes in the target variables are not; the impact of MM

[8]Population cost estimates of MM for different simulations enable us to assess the impacts of MM changes on the policy target variables at a more global level. For example, using 200,000 as the narcotics addict population estimate for the State of California, we can derive a monthly average decrease or increase of $8,400,000 (the estimate does not consider inflation) for change in methadone maintenance cost in Simulations 3 and 4.

change is greater for the increased MM scenario than for the reduced (e.g., 29% versus 24% for DNU, respectively). These findings imply that if the social cost of the narcotics-related activity of addicts is found to be greater than the methadone maintenance cost, then resulting social cost/benefits can be predicted from increasing the number of addicts in methadone maintenance treatment.

The long-term impact of changes in participation to methadone maintenance was demonstrated by the cross-simulation comparison between Simulations 2 and 4. The substantial improvement in narcotics use and property crime involvement in Simulation 4 compared to Simulation 2 during time periods 81 to 99 suggests that if methadone maintenance treatment is increased at the early stage of addiction careers, the expected benefit is twofold. Not only does it reduce narcotics and property crime during the earlier time period, but also more improvement in their narcotics-related behaviors can be expected in their later life with the same level of methadone maintenance participation.

Policy Implications

Public concerns about drug abuse and dependence and efforts to understand and ameliorate its consequences are evidence that the associated social costs are substantial and rising. Fundamental to creating a national policy to improve and expand any intervention is the question of efficacy and cost effectiveness. Among the alternative social strategies designed to intervene with drug use, treatment—as opposed to incarceration—has been consistently demonstrated as being more effective [12] and it is also more cost-effective [13]. However, there is no single type of treatment that is effective for all types of drug addicts. Recommendations on how to improve treatment services to meet disparate individual needs may have to rely on clinical and other research. Public policy that focuses on achieving an overall maximal return of investment to society must also ensure that the beneficial effects accrued from the intervention will last long enough and are cost effective for sufficiently large numbers of drug-dependent individuals. The present study explored these policy considerations using the long-term multivariate time-series model.

Our assessment of methadone maintenance effectiveness, especially as indicated by cost estimation in Table 3, demonstrates the levels of expected reductions in adverse behaviors according to variations in per-person treatment costs. Some may argue that the calculated return of investment presented here is not drastic. It should be reminded that the cost estimates are presented as a demonstration of the method, and comprehensive cost/benefit analysis is beyond the scope of the present paper. Such a comprehensive cost/benefit analysis would involve an approximation of the social costs for operating treatment and drug-related legal interventions on the one hand, and a cost assessment of the social loss due to such drug-related factors as property crime or unemployment on the other [13].

According to related literature, treatment-generated benefits in terms of reductions in both crime and drug use far exceed the costs of that treatment. At a national level, a recent report estimated that the annual cost of illicit drugs to American society has risen to far more than $60 billion in 1985 [14]. A majority of these costs are due to criminal justice processing, lost productivity, and health care. Others have estimated that treatment expenditures are a very small percentage of the total cost of drug abuse to society—on the order of 3 percent [15].

In conclusion, the present paper has demonstrated how a long-term time-series model can be used as a policy analysis tool. Future research should apply such techniques to explore alternative policy options. For example, before the AIDS epidemic, most states required a two-year documented addiction history and two other treatment admissions (and failures) before admission to a methadone maintenance program. Under such regulations, many drug-dependent users are not eligible for methadone maintenance until farther into their addiction careers. Because of the high risk for AIDS among intravenous drug users (IVDUs), such restrictions have been relaxed (one-year documented history and no prior treatment) to allow more IVDUs to access MM. The results from our cross-simulation comparison predict that methadone maintenance introduced earlier in the career produces more benefits than when introduced later. The methods illustrated here can be applied to further explore these alternative policy decisions.

As future research possibilities, several additional forecasting scenarios may be of interest from the policy perspective. For example, the present analysis was applied up to the last observation in the time-series, which corresponds to the average group age of about 36, and did not go beyond the last observation point. Because some addicts' addiction careers can last well into middle age, additional forecasting analysis covering the period beyond age 36 (or the 100th and subsequent observation points) can provide information concerning the later stages of the addiction career. It would be interesting to compare and contrast how the EQEC and VAR models predict behavior in this period. Finally, as mentioned above, cost/benefit analyses in more precise terms enable both actual and simulated policy alternatives to be more meaningfully evaluated by policy-makers.

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APPENDIX

Table A. Long-Term (EQEC) Model.

(1) Long-Term Relationships.

	NNU	DNU	PC	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]
PC	−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 co-integration on the residuals with critical values obtained from Engle and Yoo [6].

(2) Short-Term Relationships (based on differenced variables).

Parameter estimates of the lagged structure					
	NNU	DNU	PC	MM	LS
Lag 1					
NNU	0.112(0.095)*	—**	—	—	—
DNU	—	0.438(0.104)[a]	0.200(0.052)[a]	−0.124(0.085)	0.096(0.071)
PC	0.243(0.138)[c]	−0.372(0.246)	−0.151(0.119)	−0.075(0.187)	−0.161(0.146)
MM	−0.050(0.093)	0.144(0.146)	0.019(0.069)	0.226(0.111)[b]	0.134(0.087)
LS	0.129(0.109)	−0.018(0.172)	0.001(0.076)	0.079(0.128)	−0.008(0.101)
AGE	0.208(1.932)	2.630(3.048)	−0.033(1.341)	2.635(2.224)	1.545(1.783)
EQ Error	−0.178(0.053)[a]	−0.143(0.058)[b]	−0.347(0.110)[a]	−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****					
	NNU	DNU	PC	MM	LS
NNU	1				
DNU	−0.594	1			
PC	−0.372	0.519	1		
MM	0.376	−0.471	−0.206	1	
LS	−0.134	0.087	0.198	−0.109	1

[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 transfer functions.

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

Table B. Short-Term (VAR) Model (based on differenced variables).

Parameter estimates of the lagged structure					
	NNU	DNU	PC	MM	LS
Lag 1					
NNU	0.037(0.096)*	—**	—	—	—
DNU	—	0.449(0.105)[a]	0.236(0.056)[a]	−0.132(0.084)	0.137(0.075)[c]
PC	0.220(0.145)	−0.285(0.243)	−0.317(0.116)[a]	−0.190(0.179)	−0.038(0.152)
MM	−0.023(0.095)	0.197(0.147)	0.050(0.069)	0.139(0.107)	0.214(0.090)[b]
LS	0.166(0.115)	−0.031(0.174)	0.020(0.081)	0.158(0.125)	−0.107(0.104)
AGE	0.471(2.038)	2.083(3.082)	−0.151(1.429)	2.291(2.229)	2.266(1.811)
R^2***	0.061	0.092	0.164	0.119	0.105
$F_{(5,91)}$	1.175	1.847	3.564[a]	2.460[b]	2.126[c]
Residual Correlations****					
	NNU	DNU	PC	MM	LS
NNU	1				
DNU	−0.578	1			
PC	−0.329	0.506	1		
MM	0.402	−0.434	−0.181	1	
LS	−0.106	0.045	0.156	−0.146	1

[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 transfer functions.

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