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Data and Methodological Problems in Establishing State Gasoline Conservation Targets

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The Emergency Energy Conservation Act of 1979 gives the President the authority to set gasoline conservation targets for states in the event of a supply shortage. Data and methodological issues associated with setting state gasoline conservation targets are examined. The target-setting method currently used is considered and found to have some flaws. Ways of correcting these deficiencies through the use of Box-Jenkins time-series analysis are investigated. A successful estimation of Box-Jenkins models for all states included the estimation of the magnitude of the supply shortages of 1979 in each state and a preliminary estimation of state short-run price elasticities, which were found to vary about a median value of -0.16. The time-series models identified were very simple in structure and lent support to the simple consumption growth model assumed by the current target method. It is concluded that the flaws in the current method can be remedied either by replacing the current procedures with time-series models or by using the models in conjunction with minor modifications of the current method.

The Emergency Energy Conservation Act of 1979 (EECA) provides the executive branch of the federal government with two mechanisms for managing the impacts of a petroleum supply emergency. Title I of the Act provides authority for rationing gasoline but can be invoked only when a severe interruption of at least 20 percent exists or is judged likely to exist in the supply of gasoline, diesel fuel, and no. 2 heating oil for 30 days. For less extreme emergencies (the shortages of 1979 and 1973-1974 would not have satisfied this criterion), Title II of the Act gives the President the authority to establish gasoline conservation targets for states. As the country's only plan for coping with supply interruptions short of disastrous proportions, the target-setting provisions of EECA assume considerable importance.

Since the passage of the act late in 1979, target-setting procedures have been developed for motor-vehicle gasoline only. This paper reviews the data requirements of the motor-vehicle gasoline target system and describes the method now established for setting targets, analyzes flaws and uncertainties in the existing method, and describes an investigation of the use of autoregressive, integrated moving average (ARIMA) time-series statistical models as a substitute method for forecasting state base-period consumption. Finally, conclusion are presented.

CURRENT METHOD AND ITS DATA REQUIREMENTS

Title II of the EECA grants the President authority to set state and national conservation goals for motor fuels when he deems them necessary because of an energy supply shortfall. The EECA House-Senate Conference Report (1, p. 11) states, "The state conservation target for any energy source shall be equal to the state base period consumption reduced by a uniform national percentage." This state base-period consumption is defined by the report as the product of consumption "during the corresponding month in the 12-month period prior to the first month for which the target is established" and a growth adjustment factor "determined on the basis of trends in the use in that state of such energy source during the 36-month period prior to the first month for which the target is established." Recognizing that inequities could arise in a strict application of this method, the act gives the President authority to adjust a state's base-period consumption estimates to compensate for (a) reductions in consumption already achieved by conservation, (b) previous energy supply shortages, and (c) variations in weather from seasonal norms. It is not stated how this is to be done.

From these provisions and the purpose of the act, it is clear that data on motor fuel consumption are required that (a) are an accurate reflection of consumption, (b) are available for all states, (c) are monthly, (d) are part of a continuous time series of at least 36 months, and (e) are continually and promptly reported. Only two public data series on motor-vehicle gasoline use were found that approached these requirements: (a) Table MF-33G motor gasoline use data compiled by the Federal Highway Administration (FHWA) from data reported by states based on state tax receipts and (b) Form EIA-25, "Prime Suppliers Monthly Report," a U.S. Department of Energy form filled out primarily by producers, importers, and interstate bulk terminal operators.

An analysis of these two data sets (2) indicated that the FHWA data were preferable for establishing gasoline conservation targets for two reasons:

1. The FHWA data reflect the quantity of motor gasoline sold for taxable (and certain nontaxable) distribution (i.e., retail sale) within the state during the month. On the other hand, the Form EIA-25 data are reported to the state by the major suppliers, who are typically one more step removed from final consumption.
2. Whereas both series are known to contain reporting inaccuracies, those of Table MF-33G were, in theory, correctable. With the Table MF-33G data it was at least feasible to reconstruct an accurate time series because, although many states allowed reporting lags or were lax in their own reporting procedures, the original tax records still contained the actual date on which tax liability was incurred. Because of this there was the possibility of going back through the tax records and sorting out the actual pattern of consumption.

During the analysis of the Table MF-33G data, graphs of state time series were prepared for visual detection of outliers. This procedure quickly revealed serious data problems in many states. In some states, one or two rather obviously incorrect data points appeared to be the only problem. In others, the entire time series appeared erratic from month to month and there was no apparent seasonal pattern. Following this analysis and discussions among the states and the U.S. Departments of Energy and Transportation, states were given the opportunity to revise their historical data from 1975 onward. In all, 35 states elected to make revisions. The comparison between original and revised data series (see Figures 1 and 2) is indicative of the improvement in plausibility that resulted from the states' efforts.

In some cases, typographical errors were at fault. In others, consumption-to-reporting lags resulted in persistent assignment of consumption to the incorrect month. In general, however, detailed explanations for the widespread revisions that have been made by states are not available. In order to improve the accuracy of future Table MF-33G data and reduce the lag between consumption and reporting, the U.S. Departments of Energy and Transportation have designed and implemented new reporting procedures for the tax-based data. Because the political atmosphere surrounding EECA is such that states are not quite so concerned about differences in conservation targets of 2-3 percent and less, the implementation of these new procedures is all the more

Figure 1. Gasoline consumption by month for Iowa: January 1975 to December 1979.

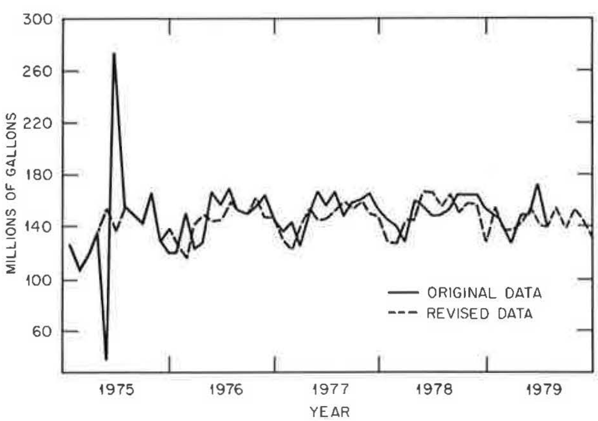
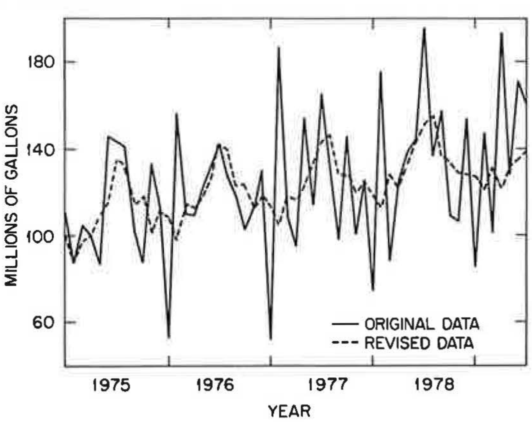


Figure 2. Gasoline consumption by month for Colorado: January 1975 to December 1979.



reason to critically review the revised state data to ensure consistency between the historical and current data.

Although the primary data requirement of EECA is monthly state gasoline consumption, it is by no means the only data need. The EECA authorizes the President to adjust estimates of base-period consumption to account for past conservation, among other things. Conservation, however, is nowhere defined. In the target-setting method described below, we use a working definition of conservation as a rate of increase of per capita gasoline use smaller than the national average. This requires 12-month (at least) total state population statistics for any arbitrary 12-month period. These data are currently interpolated from the July estimates of the U.S. Bureau of the Census (3).

CURRENT TARGET-SETTING PROCEDURE

The method of computing gasoline targets that is now in place closely follows the procedure described in the EECA House-Senate Conference Report. State consumption during the 12 months immediately preceding the target-setting period, and for which data are available for all states, is multiplied by a three-year growth rate to produce the estimate of base-period consumption. The growth rate is currently computed by using three 12-month totals rather than 36 monthly observations (note that a 12-month "year" need not correspond to a calendar year). The base-period estimate is then multiplied by three adjustment factors, or coefficients, to produce a final, adjusted estimate of base-period consumption. The three adjustment factors attempt to correct for unusual seasonal patterns, conservation (as defined above) since 1975, and recent abrupt changes in consumption such as, for example, would be caused by supply shortages or successful conservation efforts.

To more precisely describe the current method, the following notation is used:

- C = gasoline consumption,
- P = population,
- g = growth adjustment factor,
- R = growth rate of per capita gasoline use since 1975,
- r = growth rate of per capita gasoline use since previous year,
- S = historical average monthly fraction of gasoline use, and
- K = uniform national target reduction.

The subscript i will index states, t years (again not necessarily calendar years but 12-month periods), and m months. T is the most recent year (12 months) for which data are available, and a dot will indicate a national factor. The target for a month m and state i is given by

$$C_{im}^{*} = (\hat{C}_{im})(K) \quad (1)$$

where C_{im}^{*} is target and $\hat{C}_{im}$ is adjusted base-period consumption. Adjusted base-period consumption is given by

$$\hat{C}_{im} = (\sum_{m} C_{imT})(g_i)(S_{im})(R_{.}/R_i)(r_{.}/r_i) \quad (2)$$

where

$$g_i = \sum_{k=1}^{2} [(\sum_{m} C_{imT-K+1})(\sum_{m} C_{imT-K})] \Big/ \sum_{k=1}^{2} (\sum_{m} C_{imT-K})^2 \quad (3)$$

$$R_i = \sum_{k=1}^{T-1975} (\sum_m C_{imT-K+1}/P_{iT-K+1})(\sum_m C_{imT-K}/P_{iT-K}) \div \sum_{k=1}^{T-1975} (\sum_m C_{imT-K}/P_{iT-K})^2 \quad (4)$$

$$r_i = [(\sum_m C_{imT})/P_{iT}]/[(\sum_m C_{imT-1})/P_{iT-1}] \quad (5)$$

S_{im}, the fraction of the annual base-period consumption to be assigned to month m, is not uniformly determined by any one formula. States were given the option to specify any set of S_{im} provided only that conditions $S_{im} > 0$ and $\sum_m S_{im} = 1.0$ were always satisfied. All but seven states, however, chose to specify S_{im} as the historical average fraction,

$$\sum_{t=1975}^{T} C_{imT} \Big/ \sum_{t=1975}^{T} \sum_m C_{imT} \quad (6)$$

The first method developed did not include the short-term conservation factor $(r_{\cdot}/r_i)$. As several states pointed out, atypically low consumption in the year immediately preceding targets lowers both the growth adjustment factor and the 12-month total by which it is multiplied. The short-term conservation factor was added to remove the disincentive for conservation in the most recent 12 months and to ensure that states that experienced shortages during that period would not be penalized.

The formulas for computing g_i and R_i are, in fact, least-squares estimators of the growth rate in the equation

$$C_t = gC_{t-1} \quad (7)$$

This is a somewhat unusual use of least squares: Only two observations are available for estimating g_i because of the use of annual totals and the legal restriction to use the most recent 36 months of data. The original motivation for using annual totals was that the original, unrevised Table MF-33G series contained gross inaccuracies in monthly figures, which tended to cancel out in annual totals. Now that these data have been thoroughly revised, the use of annual totals may no longer be justified. It is probably now possible and desirable to use statistical estimators based on monthly observations whose accuracy and goodness of fit can be measured.

Finally, the current method sets a lower bound on the product of the longand short-term conservation factors equal to two standard deviations below the mean of the product across states. This simply prevents extreme reductions from the previous year's consumption.

CRITIQUE OF THE CURRENT METHOD

The current method has the positive attributes of conforming closely to the approach specified in the EECA conference report and of being comprehensible to nonstatisticians. In addition, it is the product of extensive discussions between the U.S. Department of Energy and state representatives, discussions that led to significant reformulations of previous methods. These virtues should not be treated lightly in considering possible alternatives or modifications. Nonetheless, the method has been criticized on several grounds and can be shown to have at least one potentially serious defect.

The current method has been criticized for being overly simplistic in assuming that gasoline consumption follows the same growth function in each and every state (i.e., $C_t = gC_{t-1}$). Forecasts of base-period consumption do not allow for possible state or regional differences in consumption growth patterns. In addition, the use of a least-squares estimator for g based on only two data points understandably created some confusion. Given that the revised monthly data now appear to be reasonable, there are other more desirable statistical estimators of g that can be applied.

More important, the current method does not deal explicitly with the problems of supply shortages or extreme weather conditions. Although the historical monthly share factor s does impose a typical seasonal pattern on last year's consumption, it does not compensate states whose consumption may have been depressed by blizzards or other extreme weather phenomena. The impacts of supply shortages are only indirectly accounted for by means of the short-term "conservation" factor. Although the factor works in the right direction, it suffers from being inherently imprecise and, perhaps more significantly, creates another flaw in the method.

Simulations of the behavior of the targeting system under various hypothetical conditions revealed a potentially serious problem caused by the short-term conservation factor. Figures 3 and 4 show the two extreme effects that are possible (in both figures, targets are computed by using the U.S. Department of Energy's method to compute third- and fourth-quarter 1980 state gasoline conservation

Figure 3. Percentage cutback of target from previous year's consumption assuming each state achieves precisely its targeted level of consumption.

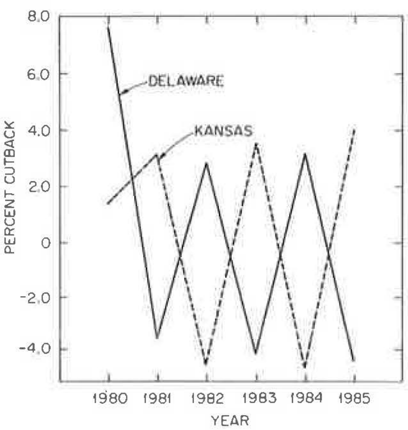
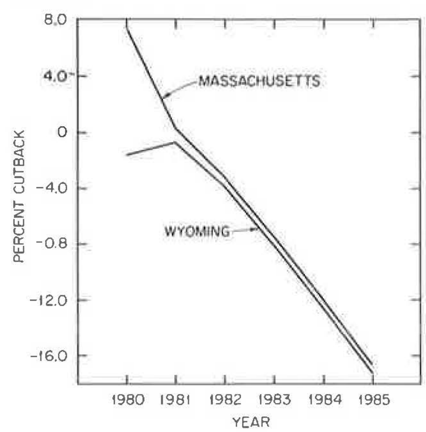


Figure 4. Percentage cutback of target from previous year's consumption assuming every state reduces its consumption by 4 percent each year, regardless of target.



targets: Population is held constant for all states after 1979, and 1975-1979 data on gasoline consumption contain all FHWA revisions prior to July 8, 1980). If targets are set for more than one period and if each state achieves its target, the targets will oscillate, without convergence, from one period to the next (Figure 3). A state that meets a low target in 1980, say, will be rewarded by the short-term conservation factor with a higher target consumption level in 1981. If this is also met, the increase in consumption will cause the state to be penalized by the short-term factor in the next period, and so on.

Figure 4 shows the other extreme of the possible effects of the conservation factors. It assumes that every state reduces its consumption by 4 percent each year, regardless of its target. In this case, the short-term conservation factor is equal to 1.0 after the first year (assuming the population is constant) and the long-term conservation factor has only a limited effect. Once the short-term conservation factor has been effectively nullified, state targets tend to converge toward a uniform reduction.

If targets are set for only one time period, the oscillatory behavior described above will not arise. Because this cannot be guaranteed, a way must be found to prevent the oscillation from occurring. Since the short-term conservation factor is at fault, it would seem logical to search for a more direct way to account for shortages and weather effects.

ARIMA TIME-SERIES ANALYSIS

A combination of concern about flaws in the target-setting method, the lack of explicit shortage and weather adjustments, the target oscillations in simulation runs, and the rather vaguely defined second conservation factor, together with the view expressed by some states that more sophisticated forecasting approaches be explored, all motivated the statistical analysis described below.

A few states advocated an econometric approach in which consumption forecasts could be made sensitive to trends in income, population growth, and other factors. Because it did not seem likely that consensus estimates of future state conditions could be readily obtained, we avoided the econometric modeling approach in favor of building statistical time-series models. The advantage of these is that they require little, if any, exogenous data and at the same time are flexible and state specific.

The class of ARIMA models developed by Box and Jenkins (4) provides a highly flexible set of possible models for the gasoline consumption time series. What is more, the Box-Jenkins model-building procedure allows individual state models to be inferred from the state data structure rather than assumed a priori. In this way, ARIMA models address state concerns about individualistic growth patterns.

ARIMA models express the current value of a time series in terms of past values and past "shocks" to the system. The general multiplicative seasonal model (5) can be written

$$(1-\Gamma_1 B^s-\ldots-\Gamma_P B^{sP})(1-\phi_1 B-\ldots-\phi_P B^P)(1-B^s)^D(1-B)^d c_t = (1-\Delta_1 B^s-\ldots-\Delta_Q B^{sQ})(1-\theta_1 B-\ldots-\theta_q B^q)u_t+\delta \quad (8)$$

where

B = backward operator,
s = seasonal lag,
P and p = orders of seasonal and nonseasonal autoregressive factors,
D and d = orders of seasonal and nonseasonal differencing,
Q and q = orders of seasonal and nonseasonal moving average factors,
c_t = monthly gasoline consumption,
u_t = random shock,
Γ's, ϕ's, Δ's, and θ's = parameters to be estimated, and
δ = term included to allow for the possibility that the differenced time series, $(1-B^s)^D (1-B)^d c_t$, may have a nonzero mean (δ).

The model allows considerable complexity or great simplicity. The "philosophy" of Box-Jenkins modeling is to choose the simplest model that adequately captures the systematic components of the time series.

Extensions of the general ARIMA model permit quantitative estimation of the impacts of both discrete events (e.g., shortages or weather) or other variables (e.g., gasoline price) on the behavior of the time series. Intervention analysis is a technique that allows the estimation of the effects of discrete events (e.g., supply shortages) on the time series. Through intervention analysis a forecasting model can be estimated that is in effect "corrected" for the occurrence of such events. The transfer-function ARIMA model allows the model to incorporate the effect of another time series (e.g., gasoline price) on the series to be forecasted. When autocorrelation and moving-average terms drop out of the transfer function and intervention models, a relatively simple model results:

$$c_t = \omega_0 B^b x_t + \mu y_t + [(1-\theta_1 B-\ldots-\theta_q B^q)/(1-\phi_1 B-\ldots-\phi_p B^p)]u_t+\delta \quad (9)$$

where

ω_0 and μ = coefficients,
b = transfer-function lag parameter, and
x_t and y_t = transfer-function input and intervention variables, respectively (6).

In fact, the simple model did turn out to be satisfactory for every state. In this model, if y_t represents a month in which a supply shortage is believed to have occurred, then μ estimates the size of that shortage. The seasonal version of Equation 9 was developed for every state, the District of Columbia, and Puerto Rico.

DATA

Monthly gasoline consumption data were taken from the revised MF-33G data base for the period from January 1975 to December 1979. National-level price data were taken from Platt's Oil Price Handbook (7). National-level data on personal disposable income (8) and the consumer price index (9), used to convert to constant dollars, were taken from the relevant issues of the Survey of Current Business. National price and income data were used because of the lack of consistent state or regional data series. State prices should be highly correlated with national prices because of the exogenous nature of gasoline price determination and because the national Entitlements Program tends to equalize gasoline prices throughout the country regardless of the source of petroleum. However, the transfer-function model identification procedure was severely handicapped because only seasonally adjusted data series were available for income.

Finally, (0,1) intervention variables were introduced to represent the months of April, May, June, and July of 1979--the months in which the petroleum supply shortage of 1979 is believed to have affected retail supplies of gasoline.

RESULTS

The models were identified, estimated, and checked by using a computer program written by Pack (10). All models were estimated by using both the original data and a simple logarithmic transformation. Both produced satisfactory results. Since state model structures were virtually identical, only the linear model results are presented in detail.

Given the potential complexity of ARIMA model structures, the final state models were remarkably simple (see Table 1). For 25 states, it was found that the simplest possible model (which we will call the naive model) was appropriate. This model ignores intervention and input variables and simply states that this month's consumption is equal to consumption 12 months ago plus a trend constant (or times a growth factor in the case of the log transform). For 24 more states, the appropriate model added only moving-average factors to the simple model. In forecasting, moving-average terms disappear at lead times greater than the lag of the factor. Thus, if a model contains a second-order moving-average term only, forecasts three or more periods ahead ignore that term and are produced by the naive model. Only three states--Kansas, Idaho, and New Mexico--required models that involve autoregressive factors and thus implied a different growth pattern.

This finding is remarkable. After accounting for price and shortage effects, only three states required something more complex than the simplest possible forecasting model. The implications of this for the method of forecasting base-period consumption suggested by Congress are quite favorable. Consider the log transform model. When transfer-function inputs, intervention effects, and moving-average terms are ignored, 49 states showed the following model for consumption:

$$\log(c_t) - \log(c_{t-12}) = \theta_0' + u_t \tag{10}$$

Exponentiating both sides gives

$$c_t/c_{t-12} = (e^{\theta_0})(e^{u_t}) \tag{11}$$

Letting $e^{\theta'_0} = \theta_0^*$ and $e^{u_t} = u_t^*$, we have

$$c_t = (\theta^* c_{t-12})(u_t^*) \tag{12}$$

In essence, this is the model proposed by Congress. Thus, although the model proposed by Congress is simple, it is essentially correct. Price shocks and shortages aside, gasoline consumption growth, in the short run at least, appears to be a rather simple and stable phenomenon.

Table 2 gives the pattern of the significance of coefficients across states. Almost all states had price and trend parameters significant at the 0.05 level. Certainly these results are encouraging. On the other hand, surprisingly few shortage intervention variables turned out to be significant. The results support inferences based on casual observation that the 1979 shortage was not equally distributed nationwide but instead affected some states more than others. This conclusion must be tempered with the caution that variances in model error differed considerably across states. In states that have a large "noise" component, it would, of course, be more difficult to detect a shortage of a given size than in states with more accurate data.

In the log transform model, the estimated coefficient of price constitutes an estimate of price

Table 1. Summary of state models.

Model	States
$C_t = \theta_0 + \omega_0 P_{t-b} + \sum_{i=1}^{4} \psi_i x_{it} + [a_t/(1 - B^{12})]$	Alabama, Alaska, California, Connecticut, Delaware, Florida, Georgia, Illinois, Indiana, Iowa, Kentucky, Maryland, Mississippi, Missouri, Montana, Nebraska, North Dakota, Ohio[a], Oregon, Texas, Vermont, Virginia, West Virginia, Wisconsin, Wyoming
$C_t = \theta_0 + \omega_0 P_{t-b} + \sum_{i=1}^{4} \psi_i x_{it} + [(1 - \theta_1 B^1)a_t/(1 - B^{12})]$	Arizona[a], Arkansas, Minnesota[a], New York, Oklahoma, Pennsylvania[a], Utah[a]
$C_t = \theta_0 + \omega_0 P_{t-b} + \sum_{i=1}^{4} \psi_i x_{it} + [(1 - \theta_2 B^2)a_t/(1 - B^{12})]$	Nevada[a]
$C_t = \theta_0 + \omega_0 P_{t-b} + \sum_{i=1}^{4} \psi_i x_{it} + [(1 - \theta_3 B^3)a_t/(1 - B^{12})]$	Colorado, Maine, New Hampshire[a], Washington
$C_t = \theta_0 + \omega_0 P_{t-b} + \sum_{i=1}^{4} \psi_i x_{it} + [(1 - \theta_4 B^4)a_t/(1 - B^{12})]$	North Carolina, South Dakota
$C_t = \theta_0 + \omega_0 P_{t-b} + \sum_{i=1}^{4} \psi_i x_{it} + [(1 - \theta_{12} B^{12})a_t/(1 - B^{12})]$	Massachusetts, Michigan, New Jersey, Rhode Island, South Carolina
$C_t = \theta_0 + \omega_0 P_{t-b} + \sum_{i=1}^{4} \psi_i x_{it} + [(1 - \theta_1 B^1)(1 - \theta_{12} B^{12})a_t/(1 - B^{12})]$	District of Columbia, Hawaii, Louisiana
$C_t = \theta_0 + \omega_0 P_{t-b} + \sum_{i=1}^{4} \psi_i x_{it} + [(1 - \theta_2 B^2)(1 - \theta_{12} B^{12})a_t/(1 - B^{12})]$	Tennessee
$C_t = \theta_0 + \omega_0 P_{t-b} + \sum_{i=1}^{4} \psi_i x_{it} + [(1 - \theta_1 B^1)a_t/(1 - B^1)]$	Puerto Rico
$C_t = \theta_0 + \omega_0 P_{t-b} + \sum_{i=1}^{4} \psi_i x_{it} + [a_t/(1 - \phi_{12} B^{12})(1 - B^{12})]$	Kansas
$C_t = \theta_0 + \omega_0 P_{t-b} + \sum_{i=1}^{4} \psi_i x_{it} + [(1 - \theta_{12} B^{12})a_t/(1 - \phi_1 B^2)(1 - B^{12})a_t]$	Idaho, Mexico

[a]b = 0 for all states except those footnoted.

Table 2. Coefficients of parameters determined to be significantly different from zero at 0.05 level.

State	Trend	Price	April	May	June	July
Alabama	X	X			X	
Alaska						
Arizona	X	X				X
Arkansas	X	X				
California	X	X		X	X	
Colorado	X	X				X
Connecticut	X	X			X	
Delaware						
District of Columbia	X	X				
Florida	X	X				
Georgia	X	X				
Hawaii	X	X				
Idaho	X	X			X[a]	
Illinois	X	X				
Indiana	X	X				
Iowa	X	X			X	
Kansas	X	X	X	X	X	X
Kentucky	X	X				
Louisiana	X	X				
Maine	X	X			X	X
Maryland	X	X			X	X
Massachusetts	X	X				
Michigan	X	X				
Minnesota	X	X				
Mississippi	X	X				
Missouri	X	X			X	
Montana	X	X			X	X
Nebraska	X	X				
Nevada	X	X				
New Hampshire	X	X			X	X
New Jersey	X	X			X	
New Mexico	X	X				
New York		X				
North Carolina	X	X		X		
North Dakota		X				
Ohio	X	X		X	X	
Oklahoma	X	X	X	X[a]	X	
Oregon	X	X			X	X
Pennsylvania	X					
Puerto Rico	X					
Rhode Island		X				
South Carolina	X	X			X	
South Dakota		X				
Tennessee	X	X				
Texas	X	X		X		
Utah	X	X		X	X	
Vermont	X	X			X	X
Virginia	X	X			X	
Washington	X	X			X	
West Virginia	X	X		X		
Wisconsin	X	X			X	
Wyoming	X	X				

[a]Positive.

elasticity (assumed constant over all consumption levels). Because a consistent set of state price-elasticity estimates is a rarity, these estimates are given in Table 3. For the model that contains price only, all estimated elasticities are negative and all but three are significant at the 0.05 level. The range of estimates (not counting Puerto Rico) is from -0.164 (Pennsylvania) to -0.445 (New Hampshire). At first, these results seem remarkably good, although the elasticities are a bit high in comparison with previous estimates (11). However, the simple model ignores the fact that in the second quarter of 1979, at the same time that prices rose rapidly, the economy went into a recession. Because the simple model includes a time trend and price only, in effect it assumes that consumption would have continued growing at its pre-1979 rate, save only that prices increased, reducing demand. Because the price increase and cessation of economic growth were contemporaneous, the price variable may be capturing both effects.

A second model estimation, which eliminated the trend parameter and included national personal disposable income, appears to confirm that conjecture. As Table 3 indicates, the absolute values of price elasticities drop considerably. Some confusion in the estimates is to be expected, since we used national income as a substitute for state income. Nonetheless, the conjecture that our original price elasticities were overestimated is supported by these results. Without income in the model, the median price elasticity estimate was -0.333; when income is included, this falls to -0.165.

In the time between the beginning of the ARIMA analysis and the writing of this paper, 10 additional months of data became available. These data were used to investigate the forecasting accuracy of the ARIMA models versus the current method of determining base-period consumption. By using the data through December 1979 as a base, forecasts for the first 6 months of 1980 were made by using both methods. The linear ARIMA models were used. Gasoline price was held constant at its December 1979 level. In using the current target method, the long-term conservation factor was dropped, but monthly shares and the short-term conservation factor were included. The long-term conservation factor was omitted on the grounds that it was intended as an adjustment to the forecast to reward states for conservation. The short-term factor was included since it was seen as an attempt to correct the forecast for such events as supply shortages and weather. Its omission would have resulted in far poorer forecasts.

The forecasting accuracies are compared in Table 4. The values presented are the percentage forecast error determined by the following formula: (actual reported consumption - forecast consumption)/actual reported consumption.

The ranges of forecast errors do not suggest that either method produced clearly better forecasts. The medians of the absolute value of forecast errors for months suggest that the target method did better for January and February whereas the ARIMA models were superior in March, April, May, and June. This is reflected in the quarterly statistics. For the 6-month total, the ARIMA models forecast consumption for 50 percent of the states within 2.5 percent of the actual use whereas the median error for the target method was 5.0 percent. Although the ARIMA models appear to have performed slightly better, the evidence is certainly not overwhelming.

CONCLUSIONS

This investigation has demonstrated that it is feasible to use ARIMA models for forecasting state base-period consumption. These models have the advantage over the current method of being capable of explicitly and quantitatively estimating the impacts of supply shortages, weather (and other discrete events), and price changes on gasoline use. In our opinion, this eliminates the need for a short-term conservation factor and would thereby eliminate the problem of oscillating targets.

The simple structure of the ARIMA models, however, has in a sense validated the simple exponential growth process assumed by the current target method. Prices and intervention effects aside, the ARIMA consumption growth model is essentially the same as the assumed exponential growth model. As a result, we see two reasonable strategies for correcting the flaws in the current method described above. The first is to replace the current method with the ARIMA forecasting models except that the long-term conservation factor would be applied to the ARIMA forecasts to produce the adjusted base-period consumption estimate. This has the advantage of correcting all the deficiencies that we have

Table 3. Estimated state price elasticities for models that include or exclude income.

State	Model 1[a]	Model 2[b]	State	Model 1[a]	Model 2[b]
Alabama	-0.333	-0.149 13	Montana	-0.397	-0.211 62
Alaska	-0.326[c]	-0.303 44[c]	Nebraska	-0.312	-0.180 37[d]
Arizona	-0.225	+0.089 347[c]	Nevada	-0.441	-0.113 49[c]
Arkansas	-0.343	-0.162 49[c]	New Hampshire	-0.445	-0.269 85
California	-0.377	-0.147 43	New Jersey	-0.327	-0.201 76
Colorado	-0.373	-0.111 49[d]	New Mexico	-0.310	-0.048 60[c]
Connecticut	-0.316	-0.236 06	New York	-0.277	-0.254 26
Delaware	-0.229	-0.209 92[d]	North Carolina	-0.379	-0.194 03
District of Columbia	-0.250	-0.451 45	North Dakota	-0.357	-0.240 97[d]
Florida	-0.221	-0.007 852 7[c]	Ohio	-0.309	-0.178 31
Georgia	-0.290	-0.114 11	Oklahoma	-0.205	-0.089 25[c]
Hawaii	-0.257	-0.037 587[c]	Oregon	-0.388	-0.148 47
Idaho	-0.341	-0.096 587[c]	Pennsylvania	-0.164[d]	-0.024 141[c]
Illinois	-0.396	-0.302 94	Puerto Rico	-0.116[d]	+0.164 89[c]
Indiana	-0.335	-0.197 47[c]	Rhode Island	-0.270	-0.191 77[c]
Iowa	-0.255	-0.112 52[c]	South Carolina	-0.358	-0.157 09
Kansas	-0.172	-0.110 86[d]	South Dakota	-0.393	-0.430 08
Kentucky	-0.362	-0.198 41	Tennessee	-0.436	-0.267 85
Louisiana	-0.232	+0.046 62[c]	Texas	-0.167	+0.084 178[c]
Maine	-0.439	-0.325 12	Utah	-0.438	-0.183 52
Massachusetts	-0.288	-0.182 25	Vermont	-0.249	-0.080 253[c]
Maryland	-0.368	-0.246 10	Virginia	-0.360	-0.169 90
Michigan	-0.438	-0.324 79	Washington	-0.365	-0.128 64
Minnesota	-0.313	-0.175 69[c]	West Virginia	-0.333	-0.140 22[c]
Mississippi	-0.438	-0.241 73[d]	Wisconsin	-0.338	-0.167 14
Missouri	-0.351	-0.217 41	Wyoming	-0.443	-0.104 40[c]

[a]Constant elasticity form, income not included in model.
[b]Constant elasticity form, income included in model with lag 0.
[c]Not significant.
[d]Statistically significant at the 0.10 level.

Table 4. Percentage forecasting errors of ARIMA and target-method forecasts: January to June 1980.

	Range of Percentage Errors				Median of Absolute Values	
	ARIMA		Target Method			
Category	Min	Max	Min	Max	ARIMA	Target Method
Monthly						
January	-16	33	-15	19	7.2	3.1
February	-20	22	-25	19	8.3	4.1
March	-14	15	-20	16	3.7	6.2
April	-19	19	-21	14	4.6	5.5
May	-35	38	-30	33	5.2	7.3
June	-140	9	-129	18	9.3	12.1
Quarterly						
First quarter	-7	17	-9	17	4.7	2.3
Second quarter	-15	10	-16	8	4.4	8.0
Total	-10	12	-12	12	2.5	5.0

described in the current method. It has the disadvantage of far greater complexity, and it may or may not be judged consistent with the intent of the EECA conference report.

The second option is to retain the current method but discard the short-term conservation factor. In lieu of it, one could adjust historical state data by using the ARIMA model estimates of state shortages, weather effects, and so on. This would have virtually all of the simplicity of the current approach but at some cost in statistical rigor and, apparently, in a small amount of forecast accuracy. We see either of these two options as being reasonable and valid. If the second option is chosen, however, it would be desirable to investigate the use of statistical procedures of estimating the growth rate and long-term correction factor.

With respect to data, it is clear that the revisions states have made to their original MF-33G data on motor-vehicle gasoline consumption have radically improved their plausibility. This is evidenced not only by a graphical inspection of the data but also by the fact that acceptable ARIMA models could be constructed from it. Large variances still remain in the data of several states, however, as shown by ARIMA monthly forecasts for nine states that have 95 percent confidence intervals of greater than ±20 percent. Because of this and because no checks were made on state revisions to the historical data, the data series is in need of validation. There should also be an investigation of the consistency between the revised historical data and the new reporting system, which has since been implemented by the U.S. Department of Energy in cooperation with the U.S. Department of Transportation.

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Impact of Travel Survey Sampling Error on Travel Demand Forecasting

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Alternative models of urban travel demand and the data used to estimate them are reviewed. The study focuses on the sampling error in origin-destination trip data and the impact that sampling error has on the estimation of a direct-demand travel model. High sampling errors in origin-destination trip data are found to significantly inhibit the performance of the direct-demand travel model.

The home-interview origin-destination (O-D) travel survey has been developed for most major metropolitan areas as a major data resource for the urban transportation planning process (UTPP). The Bureau of Public Roads, and later the U.S. Department of Transportation, provided funding for the UTPP and the home-interview O-D surveys that the UTPP required. The sample rates used in the home-interview surveys were typically less than 10 percent. The sample rate recommended for each urban area was based on total urban-area population, as given below (1):

Population	Sample of Households (%)
<50 000	20.0
50 000 to 150 000	12.5
150 000 to 300 000	10.0
300 000 to 500 000	6.7
500 000 to 1 000 000	5.0
>1 000 000	4.0

Larger cities (>500 000 population) were generally sampled at 4 or 5 percent.

A substantial amount of research was performed to guarantee that the chosen sampling strategy would be adequate for the UTPP models that the O-D data would be used to estimate. A major study by Sosslau and Brokke (2) showed that the chosen sampling strategy produced travel estimates that corresponded to screenline crossing data applicable to the corridor level. This level of aggregation corresponded to the UTPP model system typically used by local institutions that administered the UTPP [metropolitan planning organizations (MPOs)]. This model system consists of a series of sequential modeling steps: (a) trip generation, (b) trip distribution, (c) modal split, and (d) traffic assignment. Each of these models uses the available travel data in different ways. The trip-generation model uses data on the number of trip ends produced or attracted to an areal zone or district. The trip-distribution model is calibrated by using data aggregated to the corridor level (3). In modal split, the ratio of trips by highway or transit is the estimated variable. At no point in the conventional UTPP modeling process is the accuracy of the zone-to-zone or district-to-district O-D trip matrix ever a factor in model calibration or application. Consequently, the sampling error of the O-D trip matrix has never been examined.

The sequential modeling system used in the UTPP has a serious flaw. The trip-generation model has not typically responded to variables that characterize the transportation system (3). Since the endogenous variable of the trip-generation model is the number of trips produced by or attracted to a particular zone or district, changes in the transportation system have to be characterized in terms of how they affect the accessibility of the zone or district to all other zones or districts. Unfortunately, these accessibility measures have not been statistically significant variables in trip-generation models. When trip generation is insensitive to changes in transportation supply, the entire UTPP model process assumes that total travel demand is perfectly inelastic with respect to the quantity, quality, or cost of transportation services. This is not a novel observation but one that has been made before, as illustrated by the following quote from Wohl and Martin (4):

> [In] virtually every study this (calculation of trip ends by zone or district) has been accomplished independently from the travel conditions or the price of travel and with empirical observation of existing trip generation rates being used. Implicitly it has been assumed either that the price of travel will not change in the future compared with the present or that the demand for travel is entirely insensitive to the price of travel, i.e., that demand is perfectly inelastic.

In direct response to this deficiency in UTPP models, the direct-demand model was developed to make travel characteristics between zones or districts an important exogenous variable in determining not only the ratio of travel demand by automobile and transit but also the total number of trips. Direct-demand travel models accomplish this by integrating the three submodels (trip generation, trip distribution, and modal split) into a one-step model. This model has as its endogenous variable the demand for travel by a particular mode between origin district (or zone) i and destination district