Of course, in a state highway program, only a small percentage of the total program dollars is spent on new construction and major rehabilitation (about 10 percent in Maryland), and in fact only 22 percent of all roadway costs were judged size and weight related. Consequently, automobiles, pickup trucks, and vans are clearly assigned a large majority of total program costs.

Table 3 also presents a comparison of the two sets of responsibilities with the percentage of the current total Maryland user-tax payments. Thus, in Maryland, the allocations determined by the application of each method result in distinctly different policy implications. When the SIM results are used, automobiles pay slightly less than their fair share, whereas the RUM results indicate that automobiles pay much more than their fair share. For heavy combination trucks, the RUM results indicate that a doubling of the annual user taxes is appropriate in terms of equity.

CONCLUSIONS

It is not the purpose of this paper to argue which cost-allocation methodology is best; rather it is to discuss the basis of a new method, RUM, and present a comparison of the assigned cost responsibilities. Both methods have strong proponents among engineers and economists, and until a consensus determines which method is best, this subject will remain controversial.

Both of these methods, however, in their most basic framework use a cost-occasioning theory. That is, each vehicle group is assigned a share of the total roadway cost based on the costs caused or occasioned by the group. Neither method attempts to address the efficiency issue. It is clear that efficient pricing of the roadway system would rely on an application of some type of marginal cost pricing. However, until an implementable (politically and technically) marginal cost-pricing plan is developed, states will no doubt rely on a cost-occasioning methodology.

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Use of Multiple-Time-Series Framework to Identify and Estimate Quarterly Model of Gasoline Demand

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A portion of the work performed in developing a revenue-forecasting model used by the Wisconsin Department of Transportation is reported. A single-equation econometric model of gasoline demand is developed and tested by nesting the model within a more general multiple-time-series framework. Use of an appropriate disturbance structure for the model has significant effects on the model's fit and estimated elasticities. The results also indicate that direct and indirect models of gasoline demand are both consistent with the data. The forecasting performance of alternative specifications of the gasoline demand model is evaluated, and it is shown that the multiple-time-series specifications are clearly superior. These results support the use of a multiple-time-series framework and detailed diagnostic checks when time-series data are used to estimate models of gasoline demand and other economic processes.

Forecasting the demand for gasoline is of obvious importance to sound transportation planning at the state level. Over the last 10 years, considerable attention has been directed to this issue. The bulk of the research has concentrated on the identification and estimation of econometric models of demand. Typically, these models have been estimated by using either time-series or cross-sectional time-series data. Early models were often based on annual observation periods, but models based on quarterly or monthly observations are becoming increasingly common. Recent surveys of the literature on gasoline demand modeling are contained in papers by Beaton and others (1) and by Hartman, Hopkins, and Cato (2).

For the most part, the gasoline demand models in existence today have been developed by using a traditional econometric modeling approach. There has been no systematic attempt to integrate econometric and time-series-analysis techniques. In recent years, a number of authors [Zellner and Palm (3), Wallis (4), and Howrey (5)] have shown that structural econometric models are special cases of more general multiple-time-series processes. Howrey (5, p. 278) indicates the importance of this result by stating that "if the assumptions of a structural econometric model place restrictions on a more general time series model, the time series model will provide a vehicle to test the validity of those restrictions, and hence the adequacy of the econometric model." By testing restrictions in this way, it is possible to develop models that use more of the information contained in the sample data. This approach should lead to models with improved specifications and forecasting properties.

At the Wisconsin Department of Transportation (WisDOT), a multiple-time-series framework has been adapted for use in modeling and forecasting quarterly gasoline demand (highway). The results of the modeling effort highlight the advantages that a multiple-time-series framework has in terms of model identification and forecasting. The purpose of this paper is to briefly discuss the approach used and the results obtained in developing this model. The approach is easily implemented (6) and should be of value to any researcher using time-series data to model and forecast economic processes. In Wisconsin, a multiple-time-series framework has also been used to develop quarterly models for automobile and truck sales, demand for special fuel (highway), and highway construction cost inflation. A detailed study of monthly gasoline demand has been made by Wolfgram (7).

STRUCTURE OF MULTIPLE-TIME-SERIES MODELS

A linear multiple-time-series process can be represented as follows:

$$\underline{\Phi}(B)\underline{Z}_t = \underline{\Theta}(B)\underline{a}_t \quad t = 1, 2, \ldots, N \tag{1}$$

where $\underline{Z}_t' = (Z_{1,t}, Z_{2,t}, \ldots, Z_{p,t})$ is a vector of random variables, $\underline{a}_t' = (a_{1,t}, a_{2,t}, \ldots, a_{p,t})$ is a vector of random disturbances, and $\underline{\Phi}(B)$ and $\underline{\Theta}(B)$ are p x p matrices, assumed of full rank, whose elements are finite polynomials in the lag operator B, defined as $B^n Z_t = Z_{t-n}$. It is further assumed that $\underline{a}_t$ is $NID(0, \delta_{tt'}\underline{I})$, for all t and t', where $\delta_{tt'}$ is the Kronecker delta and $\underline{I}$ is an identity matrix of order N. Correlations among the disturbances can be modeled through $\underline{\Theta}(B)$.

Equation 1 can be used to analyze an economic system by partitioning $\underline{Z}_t$ into endogenous and exogenous variables. Suppose Equation 1 is partitioned as follows:

$$\begin{bmatrix} \underline{\phi}_{11}(B)\,\underline{\phi}_{12}(B) \\ \underline{\phi}_{21}(B)\,\underline{\phi}_{22}(B) \end{bmatrix} \begin{bmatrix} \underline{Y}_t \\ \underline{X}_t \end{bmatrix} = \begin{bmatrix} \underline{\theta}_{11}(B)\,\underline{\theta}_{12}(B) \\ \underline{\theta}_{21}(B)\,\underline{\theta}_{22}(B) \end{bmatrix} \begin{bmatrix} \underline{a}_{Y,t} \\ \underline{a}_{X,t} \end{bmatrix} \tag{2}$$

where $\underline{Y}_t$ is defined as a vector of endogenous variables, $\underline{X}_t$ is defined as a vector of exogenous variables, and $\underline{a}_{Y,t}$ and $\underline{a}_{X,t}$ are assumed independent. The assumption of exogeneity implies a number of restrictions on Equation 2. In particular, it implies that $\underline{\phi}_{21}(B) = \underline{0}$, $\underline{\theta}_{12}(B) = \underline{0}$, and $\underline{\theta}_{21}(B) = \underline{0}$. Thus, Equation 2 simplifies to yield

$$\underline{\phi}_{11}(B)\underline{Y}_t + \underline{\phi}_{12}(B)\underline{X}_t = \underline{\theta}_{11}(B)\underline{a}_{Y,t} \tag{3}$$

$$\underline{\phi}_{22}(B)\underline{X}_t = \underline{\theta}_{22}(B)\underline{a}_{X,t} \tag{4}$$

In this form it is clear that the exogenous variables are not influenced by the endogenous variables, a result required by definition. Equation 3 corresponds to the structural form of a linear, dynamic simultaneous-equation econometric model. Equation 4 describes the process by which the exogenous variables are generated. If $\underline{\phi}_{22}(B)$ and $\underline{\theta}_{22}(B)$ are restricted to be diagonal matrices, Equation 4 becomes a series of univariate-time-series models of the general autoregressive integrated moving-average form, one for each exogenous variable.

Consider the general linear model shown below:

$$Y_t = \beta_1 + \beta_2 X_{2,t} + \beta_3 X_{3,t} + \ldots + \beta_M X_{M,t} + a_t \tag{5}$$

The model in Equation 5 is similar to many models used in analyzing gasoline demand and is a special case of Equation 3. Equation 5 implies the following restrictions on Equation 3:

$$\underline{\phi}_{11}(B) = 1 \tag{6}$$

$$-\underline{\phi}_{12}(B) = (\beta_1, \beta_2, \ldots, \beta_M) \tag{7}$$

$$\underline{\theta}_{11}(B) = 1 \tag{8}$$

The appropriateness of the model can be examined by relaxing these restrictions (hypotheses) in such a way that they become testable.

An important, and frequently overlooked, restriction is represented by Equation 8. This restriction reflects the assumption that the disturbances of the model are uncorrelated. Pierce (8) and Granger and Newbold (9) have shown that inadequate testing of this restriction can lead to spurious regressions. It is doubtful that a priori information can be used to firmly establish this important restriction, and therefore it seems appropriate that it be tested in all applied econometric work with time-series data.

SPECIFICATION OF STRUCTURAL EQUATION

The basic specification of the structural equation for gasoline demand is similar to that for many models developed in the literature. Gasoline demand is assumed to be a function of real gasoline price, real disposable income, the fleet of gasoline-powered vehicles (automobiles and light trucks), and fleet fuel efficiency. A log-linear functional form was selected after a range of possible transformations had been considered, including the standard linear model (10, p. 87). Dummy variables were introduced to account for the effects that the 1973-1974 oil embargo and the 1979 fuel shortage had on gasoline demand (consumption). The general specification of the structural equation can be expressed as follows:

$$\begin{aligned} \ln GC_t = {} & \beta_1 + \beta_2 \ln GP_t + \beta_3 \ln DI_t + \beta_4 \ln VEH_t + \beta_5 \ln MPG_t \\ & + \beta_6 [\omega_1(B)/\delta_1(B)]\, EMB_t + \beta_7 [\omega_2(B)/\delta_2(B)]\, SHORT_t \\ & + \theta_{11}(B) a_t \end{aligned} \tag{9}$$

where

- GC_t = gasoline consumption in period t,
- GP_t = real gasoline price in period t,
- DI_t = real disposable income in period t,
- VEH_t = gasoline-powered vehicle fleet in period t,
- MPG_t = fleet fuel efficiency in period t,
- EMB_t = intervention for the 1973-1974 oil embargo (1 in 1973:3, 0 otherwise), and
- $SHORT_t$ = intervention for the 1979 fuel shortage (1 in 1979:2, 0 otherwise).

Equation 9 is obtained by placing the following restrictions on Equation 3:

$$\underline{\phi}_{11}(B) = 1$$

$$-\underline{\phi}_{12}(B) = \{\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6[\omega_1(B)/\delta_1(B)], \beta_7[\omega_2(B)/\delta_2(B)]\} \tag{10}$$

These restrictions are consistent with previous research and will be maintained throughout the analysis. The fact that all variables are expressed as natural logarithms allows the parameters of the equation to be interpreted as short-run elasticities. The operators $\omega_i(B)$ and $\delta_i(B)$, i = 1,2, are finite operators in the lag operator B and allow great flexibility in modeling the effects of the interventions (11). The specifications represented by $\omega_i(B)$, $\delta_i(B)$, and $\theta_{11}(B)$ will be determined during model identification and diagnostic checking.

The data used in this study consist of 86 quarterly observations that cover the period from 1960:1 through 1981:2. Data on real gasoline price and real disposable income were obtained from the state econometric model maintained by the Wisconsin Department of Revenue. Automobile registrations, light-truck registrations, and gasoline-consumption data were obtained from internal WisDOT sources. The gasoline-consumption series is defined in a manner similar to that for the series on the highway use of gasoline published by the Federal Highway Administration. The average fuel efficiency of the automobile fleet was used as a proxy for the fuel

Table 1. Autocorrelation functions of residual series obtained from preliminary, intermediate, and final stages in estimation of structural equation for gasoline demand.

	Residual from		
Lag	Equation 11	Equation 12	Equation 17
1	0.20	0.30[a]	−0.04
2	0.26[a]	0.15	0.07
3	−0.04	0.01	0.14
4	0.47[a]	−0.24[a]	−0.02
5	−0.12	0.04	0.09
6	0.02	0.01	−0.01
7	−0.20	0.06	0.11
8	0.30[a]	−0.01	0.02
9	−0.17	0.08	0.06
10	0.05	0.08	−0.01
11	−0.16	0.07	0.01
12	0.23	0.11	0.09
13	−0.28	−0.16	−0.06
14	−0.08	−0.14	−0.07
15	−0.29	−0.13	0.00
16	0.12	−0.18	−0.14

[a]Statistically significant at $\alpha = 0.05$.

efficiency of the gasoline-powered vehicle fleet. Data on fuel efficiency for the light-truck fleet were not available consistently. The fuel-efficiency series was adjusted to account for quarterly temperature variations in Wisconsin.

ESTIMATION OF STRUCTURAL EQUATION

The estimation of the structural equation for gasoline demand takes place in stages. In stage 1, Equation 9 is estimated with the restriction that $\theta_{11}(B) = 1$; i.e., the disturbances are assumed to be normally and independently distributed. The second stage involves an analysis of the autocorrelation function of the residuals and, if necessary, the identification of a model for the disturbances. In the third stage, the equation is reestimated by using the modifications identified in stage 2. As a check, the autocorrelation function is again examined. The model is accepted when further modifications are unnecessary.

As noted above, the first step in the analysis is to estimate Equation 9 with the restriction that $\theta_{11}(B) = 1$. The intervention terms are also ignored initially, so as to allow gasoline price per mile to explain as much of the variation in gasoline demand as possible. The results of the initial estimation phase are as follows (standard errors are given in parentheses):

$$\begin{aligned}\ln GC_t = &-5.60 - \underset{(0.05)}{0.72}\ln GP_t + \underset{(0.20)}{0.33}\ln DI_t + \underset{(0.21)}{0.97}\ln VEH_t\\ &+ \underset{(0.08)}{1.31}\ln MPG_t + e_t\end{aligned} \tag{11}$$

where

sum of squared errors (SSE) = 0.2030,
degrees of freedom (df) = 81, and
mean-squared error (MSE) = 0.0025.

Equation 11 explains 96.0 percent of the total sum of squares (total sum of squares about the mean = 5.065). The estimated coefficients are generally many times greater than their respective standard errors, which gives an impression of high statistical significance. However, an examination of the autocorrelation function of the residuals (Table 1) suggests that the residuals are seasonally nonstationary and autocorrelated, which makes the results of t-tests on the coefficients invalid. Seasonal nonstationarity is indicated by the fact that the residual autocorrelations fail to die out at integer multiples of the seasonal period (12, Chap. 9).

Seasonal nonstationarity can be addressed by taking a fourth-order difference of the data and reestimating the model. The results after reestimation are as follows:

$$\begin{aligned}(1 - B^4)\ln GC_t = &-\underset{(0.04)}{0.22}(1 - B^4)\ln GP_t + \underset{(0.13)}{0.44}(1 - B^4)\ln DI_t\\ &+ \underset{(0.15)}{0.44}(1 - B^4)\ln VEH_t - \underset{(0.22)}{0.60}(1 - B^4)\ln MPG_t + e_t\end{aligned} \tag{12}$$

where

SSE = 0.0608,
df = 78, and
MSE = 0.0008.

Use of a fourth-order difference reduced the SSE by 70 percent. Note that the values of the estimated coefficients have changed dramatically from those in Equation 11. These results confirm the importance of using both levels and differences of the data when modeling economic time series (9). However, a check of the autocorrelation function of the residuals from Equation 12 (see Table 1) indicates that the specification is still deficient. The residuals display significant autocorrelation at lags 1 and 4.

The following model was initially proposed for the disturbances:

$$e_t = \{(1 - \theta_4 B^4)/[(1 - \phi_1 B)(1 - B^4)]\}\, a_t \tag{13}$$

Equation 9 was reestimated with this disturbance structure, which produced the following result:

$$\begin{aligned}\ln GC_t = &-\underset{(0.06)}{0.24}\ln GP_t + \underset{(0.15)}{0.42}\ln DI_t + \underset{(0.17)}{0.59}\ln VEH_t - \underset{(0.26)}{0.69}\ln MPG_t\\ &+ \{(1 - \underset{(0.10)}{0.52}B^4)/[(1 - \underset{(0.11)}{0.44}B)(1 - B^4)]\}\, a_t\end{aligned} \tag{14}$$

where

SSE = 0.0452,
df = 75, and
MSE = 0.0006.

The autocorrelation function of the residuals from Equation 14 indicates that the model is adequate. Other disturbance structures were considered, but Equation 13 was shown to be most consistent with the data. The need for a seasonal difference was tested by replacing $(1 - B^4)$ with $(1 - \phi_4 B^4)$. The estimated value of ϕ_4 approached 1, which supported the use of a seasonal difference. A test of the restriction that $\theta_{11}(B) = 1$ was performed by using a likelihood-ratio procedure, and the restriction was rejected with $\alpha = 0.05$.

The residuals from Equation 14 were examined in an effort to determine plausible intervention structures. Initially, the following functional forms were proposed for the interventions:

$$\omega_1(B)/\delta_1(B) = \omega_1/(1 - \delta_1 B) \tag{15}$$

$$\omega_2(B)/\delta_2(B) = \omega_2 \tag{16}$$

The intervention structure given by Equation 15 allows an initial intervention effect (ω_1) to decay over time. If $\delta_1 = 0$, the effect disappears immediately, and if $\delta_1 = 1$, the effect is permanent. Further analysis indicated that Equations 15 and 16 were adequate representations of the effects caused by the interventions. By using these intervention structures, the final structural equation for gasoline demand becomes the following:

$$\begin{aligned}\ln GC_t = &-0.22\ln GP_t + 0.43\ln DI_t + 0.59\ln VEH_t - 0.92\ln MPG_t\\ &\quad(0.06)\qquad(0.14)\qquad(0.15)\qquad(0.26)\\ &-[0.07/(1-0.70B)]\,EMB_t - 0.02\,SHORT_t\\ &\quad(0.02)\quad(0.18)\qquad(0.02)\\ &+\{(1-0.47B^4)/[(1-0.32B)(1-B^4)]\}\,a_t\\ &\quad(0.10)\qquad(0.12)\end{aligned} \tag{17}$$

where

SSE = 0.0376,
df = 72, and
MSE = 0.0005.

Equation 17 explains 99.3 percent of the total sum of squares. The residuals (see Table 1) are uncorrelated and have a mean insignificantly different from zero. Skewness and kurtosis statistics indicate that the distribution of the residuals is consistent with an assumption of normality. Cross-correlations between the residuals and the stationary forms of the input series did not suggest the need for additional dynamic elements. Lagged values of ℓnGP and ℓnDI were introduced but yielded insignificant coefficients. The possibility that automobile and light-truck registrations should enter the equation separately was tested but yielded inconclusive results. There is no apparent need for further modification of Equation 17.

To this point, a direct-demand model has been used to specify the demand for gasoline. Indirect-demand models are also frequently used in analyzing gasoline demand, and closer examination of Equation 17 suggests that it may be consistent with an indirect modeling framework. This possibility can be tested by embedding an indirect model within Equation 9. An indirect model would take the following form:

$$\begin{aligned}\ln[(GC_t{*}MPG_t)/VEH_t] = &\beta_1 + \beta_2\ln(GP_t/MPG_t) + \beta_3\ln DI_t\\ &+[\omega_1(B)/\delta_1(B)]\,EMB_t\\ &+[\omega_2(B)/\delta_2(B)]\,SHORT_t + \theta_{11}(B)a_t\end{aligned} \tag{18}$$

Equation 18 implies the following restrictions on Equation 9:

$$\beta_4 = 1 \quad \beta_5 = -(\beta_2 + 1) \tag{19}$$

This relationship was estimated and yielded the following result:

$$\begin{aligned}\ln[(GC_t{*}MPG_t)/VEH_t] = &-0.29\ln(GP_t/MPG_t) + 0.10\ln DI_t\\ &\quad(0.04)\qquad\qquad(0.05)\\ &-[0.07/(1-0.74B)]\,EMB_t - 0.02\,SHORT_t\\ &\quad(0.02)\quad(0.15)\qquad(0.02)\\ &+\{(1-0.55B^4)/[(1-0.37B)(1-B^4)]\}\,a_t\\ &\quad(0.10)\qquad(0.11)\end{aligned} \tag{20}$$

where

SSE = 0.0400,
df = 74, and
MSE = 0.0005.

The intervention and disturbance structures are identical to those of Equation 17. A likelihood-ratio test of the restrictions given by Equation 19 indicates that the restrictions cannot be rejected at $\alpha = 0.5$. Equations 17 and 20 are therefore both consistent with the data. To a degree, preference for one representation over the other depends on one's point of view. A preference for Equation 20 can be based on the fact that it involves fewer parameters. Equation 17 is, however, less restrictive. At WisDOT, Equation 20 was selected based on the principle of parsimony (13, pp. 5-6).

EVALUATION OF STRUCTURAL EQUATION AND MODELING APPROACH

The results of this analysis indicate that gasoline demand is sensitive to changes in the size and fuel efficiency of the gasoline-powered vehicle fleet and is relatively insensitive to changes in real gasoline price and real disposable income. These results are in general agreement with other studies and indicate that increased fuel efficiency is perhaps the most effective means of reducing gasoline consumption.

The short-run elasticities estimated in this analysis are very sensitive to the specification of the model's disturbance structure. The elasticities obtained at different stages in the analysis are shown in Table 2. The most significant changes take place in the elasticities for fuel efficiency and real gasoline price. If the specification of Equation 11 had been accepted, the fuel-efficiency elasticity would have been estimated at 1.31 instead of -0.92 (or -0.71 if Equation 20 were used), and the real-gasoline-price elasticity would have been estimated at -0.72 instead of -0.22 (or -0.29). These results highlight the importance of diagnostic checking in the model-building process and demonstrate the effects that autocorrelated disturbances can have on estimated economic parameters. There is clearly a need to go beyond the standard first-order autoregressive model when alternative disturbance structures for econometric relationships are considered.

The similarities in the elasticities for Equations 12 and 17 (see Table 2) suggest that seasonal nonstationarity was a major contribution to the differences in elasticities noted above. Many studies of gasoline demand, or economic processes in general, deal with seasonality through the use of either dummy variables or sine/cosine functions. These approaches have important limitations. The use of seasonal dummy variables treats seasonality as a deterministic phenomenon, and this assumption is not likely to apply to economic processes. While sine/cosine functions can adapt to changing seasonal patterns, there is no assurance that they can represent seasonality in an economical manner. In contrast, Equations 17 and 20 contain a parsimonious specification of seasonality that adapts to changes in seasonal behavior [for further discussion of this topic, see paper by Cleveland and Tiao (14)]. This is an important property of disturbance structures from the autoregressive integrated moving-average class and can be particularly significant when a model is used for forecasting.

ANALYSIS OF FORECASTING PERFORMANCE

Forecast evaluation is an important part of any model-building exercise. In this section, Equations 11, 17, and 20 will be evaluated based on their root-mean-squared (RMS) forecast errors and their performance in terms of one-step-ahead forecasts. The forecasts analyzed here are conditional on the actual values of the exogenous variables during the period from 1981:3 through 1982:2. Box and Jenkins (12, Chap. 11) discuss the procedures used in producing forecasts by using economic models with generalized disturbance structures. The intervention effects estimated in Equation 17 have been added to Equation 11 so that the disturbance structures and accompanying economic parameter estimates are the only differences between these equations.

The gasoline-consumption forecasts produced by the alternative forms of the structural equation for

Table 2. Short-run elasticities obtained from preliminary, intermediate, and final stages in estimation of structural equation for gasoline demand.

	Elasticity from			
Variable	Equation 11	Equation 12	Equation 17	Equation 20
GP	-0.72	-0.22	-0.22	-0.29[a]
DI	0.33	0.44	0.43	0.10
VEH	0.97	0.44	0.59	1.00[b]
MPG	1.31	-0.60	-0.92	-0.71[b]

[a]Variable defined as real gasoline price per mile.
[b]Elasticities obtained by expanding all terms in model.

Table 3. Gasoline-consumption forecasts and RMS forecast errors for alternative forms of structural equation for gasoline demand.

Period	Actual Gasoline Consumption (gal 000 000s)	Forecast Gasoline Consumption[a] (gal 000 000s)		
		Equation 11[b,c]	Equation 17[d]	Equation 20[e]
1981:3	541.4	637.3	544.8	550.9
1981:4	495.3	549.1	512.0	521.8
1982:1	416.0	528.7	452.6	459.2
1982:2	490.7	632.4	530.6	540.5
Total	1943.4	2347.5	2040.0	2072.4

[a]Forecast origin, 1981:2.
[b]Intervention effects from Equation 17 are added to Equation 11 in order to allow a fair comparison.
[c]RMS forecast error = 0.1994; actual and forecast consumption expressed as natural logs so that RMS forecast errors can be interpreted as approximate percentage errors.
[d]RMS forecast error = 0.0599.
[e]RMS forecast error = 0.0744.

Table 4. Gasoline-consumption forecasts for 1982:2 by using sequential forecast origins and alternative forms of structural equation for gasoline demand.

Forecast Origin	Forecast Gasoline Consumption for 1982:2[a] (gal 000 000s)		
	Equation 11[b]	Equation 17	Equation 20
1981:2	632.4	530.6	540.5
1981:3	632.4	530.5	540.0
1981:4	632.4	528.8	536.7
1982:1	632.4	516.5	521.3

[a]Actual gasoline consumption = 490.7.
[b]Intervention effects from Equation 17 are added to Equation 11 in order to provide a fair comparison.

gasoline demand are shown in Table 3. These forecasts indicate that Equations 17 and 20 are definitely superior to Equation 11. The RMS forecast error for Equation 11 is more than three times as large as that for Equation 17. This result demonstrates that the disturbances of a standard econometric model can contain significant amounts of information (in the form of autocorrelation) that can be used to develop models with improved forecasting performance. The forecasting results for Equations 17 and 20 indicate that Equation 17 outperforms its more restrictive competitor over the evaluation period used here. However, more experience is necessary before a decision can be made on which specificatión is superior. Examination of the squared forecast errors suggests that the performance of Equation 20 improved significantly in the first two quarters of 1982. In the end, it may not be possible to use forecast performance to discriminate between the equations. At this point, WisDOT is continuing to produce its forecasts by using Equation 20.

Table 4 demonstrates that updated forecasts of increasing quality can be obtained from the multiple-time-series specifications of gasoline demand. For 1982:2, the errors associated with forecasts produced by Equations 17 and 20 drop continuously as the forecast origin is moved forward. Updated forecasts for the other quarters (not shown) improved as well. Equation 11 cannot provide updated forecasts (without new forecasts of the exogenous variables) since it does not contain terms relating to the past history of gasoline consumption and previous forecasting errors.

WISDOT FORECASTING PROCESS

At WisDOT, the gasoline-demand model presented above (Equation 20) is one of a series of multiple-time-series models used in forecasting. Other models relate to automobile sales, truck sales, and the demand for special fuel. Automobile and truck sales forecasts are updated each quarter and are then used to produce revised forecasts of vehicle registrations and vehicle registration revenue. Gasoline and special fuel forecasts are updated and provide revised forecasts of motor fuel tax revenue. Forecasts for the exogenous variables driving these models are obtained from the state econometric model and from Data Resources, Inc.

The process of producing revised forecasts has received a positive response from WisDOT management. Previously, revised forecasts would be developed in a largely subjective manner. Some subjective elements still remain (and well they should), but tendencies to be either overly optimistic or pessimistic after a particularly good or bad quarter have been tempered by the rigor imposed by the models.

SUMMARY AND CONCLUSIONS

This paper has shown how a standard single-equation econometric model of gasoline demand can be embedded within a multiple-time-series framework. Use of this framework allowed the restrictions placed on the model to be tested for consistency with the data. The disturbances of the model were found to be seasonally nonstationary and autocorrelated at a number of lags. The values of the estimated short-run elasticities changed significantly when the disturbance component of the model was appropriately specified and estimated. The forecasts produced by the more general model were shown to be superior to those produced by the model that ignored the information contained in the disturbances.

The findings of this study underscore the need to test restrictions placed on econometric models. These tests are facilitated by the concept of nesting proposed models within a more general model structure and are discussed in detail by Harvey (13). In this study, specification tests that use nested models have lead to simplification of the original economic model and an adequate specification of its disturbance structure. The result is a parsimonious model, efficient parameter estimates, valid tests of those parameters, and improved forecasts.

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New Funding Sources for Public Transit: Who Pays?

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As financial crises have increasingly plagued transit systems, new and/or additional sources of funding have been sought. One issue that has not been well documented in this area is the question of who pays for each source. A number of potential household-based funding sources and their general impact on families at different income levels can be analyzed by using data published by the U.S. Bureau of Labor Statistics. Sixteen options including fares were examined and compared as to their relative regressivity (burdens). This was accomplished through a three-step process. First, relevant consumer expenditures by income levels were noted. Next, expenditures as a percentage of income were calculated. Finally, percentage expenditures by each income level relative to those of the highest income level were determined. The results can be used to compare the impact of one source versus another or to choose a source to minimize negative distributional impacts. Subject to certain qualifications, it was found that most household-based sources were regressive. The most regressive were household (head) tax, cigarette tax, and transit fares. Progressive alternatives include parking, income, and stock-transfer taxes. It is suggested that decreased federal funding will lead to the tapping of more regressive sources as well as to increasing reliance on business-based taxes, service cutbacks, and fare increases.

The financial problems of mass transit have become increasingly severe in recent years and are likely to get worse. Proposed budget cuts for the Urban Mass Transportation Administration (UMTA) could have significant consequences for transit systems. In particular, elimination of federal transit operating-assistance programs (Sections 5 and 18 of UMTA Act of 1964, as amended) has been anticipated. A recent survey by the American Public Transit Association (APTA) suggests that a majority of transit systems face reduced service, increased fares, and the need for new tax revenues and/or state and local assistance as a result (1).

Over the last dozen years, the financial condition of public transit has deteriorated markedly. In 1980, operating revenues of transit systems amounted to \$2.6 billion versus operating expenses of \$6.0-6.5 billion, a deficit of almost \$4 billion. This compares with an operating deficit of less than \$300 million in 1970 (operating revenue of \$1.7 billion, operating expenses of only \$2.0 billion) (2). In the past, this deficit has been largely closed by subsidies; the largest growth of these came from the federal government. With proposed reductions from this source, increased subsidies from other levels of government (state, regional, local), higher operating revenues (fares), or reduced operating costs (improved efficiency, reduced service) will be necessary.

There are a number of important issues that can be addressed in this area. For example, does transit offer benefit to nonusers to justify subsidies? Are the cities and suburbs being treated equally as far as transit benefits and costs are concerned? Are road versus transit funding being treated equitably? Should social considerations (e.g., taxes on cigarettes or alcohol) be involved? What funding sources are politically acceptable and substantial enough to offer short-term or long-term assistance? Should subsidies come from nontransportation users? Notably absent from most discussions of transit finance is the issue of how different income groups would be affected by the employment of different funding sources. While this may be due in part to the lower priority given this question, it may also be due to the lack of information available. It is the purpose of this paper to consider the general differences in who pays from various financing alternatives and to hold the profile of who benefits constant for simplicity.

In economic terms, the differential tax incidence of one source will be compared with that of another