Temporal Effects of Incidents on Transit Ridership in Orange County, California

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Aggregate level transit ridership forecasting models often are based on time series data, with potential serial autocorrelation properties that can bias parameter estimates upward and error estimates downward, and skew forecasting confidence intervals and their resulting interpretation significantly. A combined time series and cross-sectional regression model of transit ridership is developed that incorporates temporal variations as well as supply, demand, and pricing characteristics of the market for transit services in Orange County, California, between 1973 and 1989. It was found that Orange County transit ridership exhibits significant serial and seasonal fluctuations, which were captured in the model. The temporary and lingering effects of incidents were also tested. The 1979 oil shortage was shown to have a large positive impact on transit ridership, which dwindled quite rapidly once the oil shortage ended. A work stoppage of 6 weeks' duration in 1981 had a large negative impact on transit ridership, which dwindled only slowly. A shorter work stoppage in 1986, during which limited service was provided by transit agency administrative personnel, had a much smaller negative impact than the 1981 work stoppage, which dwindled much more rapidly. Transit fare and gasoline pricing variables were found to have no significant effect on transit ridership in the preferred temporally based model. Transit fares did not increase much in real terms over the period covered, and did not reflect variations in transit service provided, being predicated on a simple county-wide flat fare basis. Over 70 percent of all Orange County transit riders were captive riders in 1987, having no car available to them for commuting or other travel purposes, making the price of gasoline basically irrelevant to the majority of such transit riders in the shorter term.

Many problems in urban and regional transportation analysis have important temporal dimensions. Forecasting changes in employment, population, or travel behavior are just a few examples of areas where temporal processes and interactions may be important in identifying existing conditions, explaining past trends, or forecasting future outcomes of urban and regional policies and planning. Time series analysis is one method of explicitly incorporating temporal phenomena in regression analysis for forecasting purposes. Time series analysis often is used as a projection method, based exclusively on the past performance of specific exogenous output variables. Policy input variables, such as spatial or socioeconomic variations in demand, often are not included in time series models, because of lack of data, lack of analysis software, or both.

Cross-sectional models typically provide more opportunities for testing policy sensitivity. However, parameters and confidence intervals estimated in cross-sectional models may be biased significantly, if serial autocorrelation is present. Combined time series and cross-sectional models offer the

possibility of providing policy sensitivity and controlling for temporal estimation biases simultaneously. Simultaneous time-series and cross-sectional regression analysis are applied to transit ridership forecasting, assuming only first-order, serial autoregressive processes are involved (1). Three types of temporal variability are included in this analysis:

1. First-order serially autoregressive impacts;
2. First-order seasonally autoregressive impacts; and
3. Permanent, temporary, and lingering impacts of incidents over time.

Quarterly transit ridership data are used to demonstrate how alternative model formulations can be evaluated in terms of descriptive ability (overall goodness of fit), serial autocorrelation (parameter estimation bias), and predictive ability (forecast error).

First, some of the basic statistical and econometric principles required to conduct an exploratory analysis of this type are described. Second, various transit ridership model variations formulated to test these ideas using original data collected in Orange County, California, are compared and contrasted. Finally, some of the policy and research implications derived from a comparative evaluation of the various model results are reported.

DATA

The data used in this analysis were taken from the Orange County Transit District (OCTD) aggregate, or system-wide, transit ridership forecasting model. Variations on the temporal model discussed here were tested by the author while employed by OCTD from 1986 to 1988. A version of the model discussed here was developed independently by the Center for Economic Research at Chapman College (2), and is now in use by OCTD for transit ridership forecasting purposes. The Chapman College model is used to forecast transit ridership in Orange County 5 years in advance for financial and service planning purposes. In addition, the model is used to comply with the requirements of the regional transportation planning process, as administered by OCTD, the Southern California Association of Governments, the Orange County Transportation Commission, the State of California Department of Transportation, and other responsible public agencies in the region.

OCTD has been in operation for close to 20 years, beginning in the fourth quarter of 1973, after the first Arab oil embargo occurred. Quarterly transit ridership data are de-

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rived from a unique, stratified random sample of driver trip sheets, and adjusted using method of fare payment and fare data. The accuracy of this data is good, with an expected annual statistical measurement error of not more than ± 2 percent at the 95 percent confidence interval (*3*). Vehicle service miles, a supply measure, is even more accurate, as the length of all bus runs driven is known, and measured to within the nearest 10th of a vehicle-mile in service. Average county-wide employment figures, used in this analysis both as a reasonable and a reliable proxy measure of demand, are derived from Chapman College's annual forecast of Orange County employment, and are equally reliable in measurement. Over half of all person-trips made on the Orange County transit system are work-related trips, with a large part of the remainder school and recreational activities.

All other data used in this analysis are temporal in nature, and are not subject to sampling or measurement errors, at least not in the same sense that the cross-sectional variables just described might be.

METHODOLOGY

A variety of models are described, tested, and compared in this analysis. The principal types of models used include cross-sectional models, first-order autoregressive models (*4*), combined time series and cross-sectional models (*5*), seasonally adjusted combined models, and incident impact models. Evaluation measures include the traditional cross-sectional measures of overall goodness-of-fit and the magnitude and direction of independent variable effects, as well as two measures of serial autocorrelation, Durbin-Watson's d (*6*), for models without lagged endogenous variables (*7*), and Durbin's h (*8*), for models with lagged endogenous variables (*9*).

Basic Cross-Sectional and Time-Series Models

A traditional cross-sectional transit ridership forecasting model is as follows:

$$\text{PAS}_t = b_0 + b_1 * \text{VSM}_t + b_2 * \text{EMP}_t + e_t \quad (1)$$

where

$\quad \text{PAS}_t$ = total transit ridership in time period t,
$\quad \text{VSM}_t$ = total vehicle service miles in time period t,
$\quad \text{EMP}_t$ = average service area employment in time period t,
$\quad\quad e_t$ = error in prediction associated with the observation of total transit ridership in time period t, and
b_0, b_1, b_2 = parameters to be estimated.

A slight modification of this equation results in the familiar double-log econometric regression model, which provides direct measures of the elasticity of demand for the dependent variable (total transit ridership) with respect to each independent variable (total vehicle service-miles and average quarterly employment). The double-log model has proven to be useful for public and private policy sensitivity analysis in a variety of cases, and will be relied on throughout the remainder of this analysis:

$$\ln(\text{PAS}_t) = b_0 + b_1 * \ln(\text{VSM}_t) + b_2 * \ln(\text{EMP}_t) + e_t \quad (2)$$

If a time series variable, such as quarterly transit ridership, is subject to serial autocorrelation of the error terms in prediction, the resulting parameter estimates may be severely biased, with overall goodness of fit measures and parameter standard error terms similarly biased by the existence of serial autocorrelation. A commonly used and powerful test of serial autocorrelation in regression analysis is Durbin-Watson's d:

$$d = \frac{\sum (e_t - e_{t-1})^2}{\sum (e_t)^2} \quad (3)$$

where

$\quad\quad d$ = Durbin-Watson's d, and
$\quad e_{t-1}$ = error in prediction associated with the observation of total transit ridership in the preceding time period, $t - 1$.

Values of d around 2 indicate the existence of no significant serial autocorrelation. Values of d close to 0 suggest positive serial autocorrelation, whereas values of d close to 4 suggest negative serial autocorrelation. If significant serial autocorrelation is identified, a lagged endogenous variable may be used to estimate an autoregressive time series regression model, on the basis of a normal first order autoregressive process, as follows:

$$\ln(\text{PAS}_t) = b_0 + b_1 * \ln(\text{PAS}_{t-1}) \quad (4)$$

where PAS_{t-1} is the total transit ridership in the immediately preceding time period, $t - 1$.

Such a model may still be biased by residual or higher order levels of serial autocorrelation. Durbin-Watson's d does not provide a reliable measure of serial autocorrelation in models that include lagged endogenous variables as independent variables. In such cases, Durbin's h may be used in place of Durbin-Watson's d, as a more reliable indicator of serial autocorrelation:

$$h = p * \left[\frac{T}{1 - T * \text{var}(b_.)} \right]^{1/2} \quad (5)$$

where

$\quad\quad h$ = Durbin's h;
$\quad\quad p$ = $1 - d/2$;
$\quad\quad T$ = total number of observations on which the regression model is based (not degrees of freedom), i.e., sample size; and
$\quad \text{var}(b_.)$ = variance of $b_.$, or square of the estimated standard error term for $b_.$, where $b_.$ is the parameter estimate of the first-order lagged endogenous variable [$\ln(\text{PAS}_{t-1})$], regardless of whether any other serially related exogenous or endogenous variables are included in the model.

A combined time series and cross-sectional transit ridership forecasting model would be as follows:

$$\ln(\text{PAS}_t) = b_0 + b_1 * \ln(\text{VSM}_t) + b_2 * \ln(\text{EMP}_t)$$
$$+ b_3 * \ln(\text{PAS}_{t-1}) + e_t \quad (6)$$

Other Types of Serial Processes

In addition to first-order autoregressive processes, many other types of serial autocorrelation are theoretically possible. Differenced models, in which the dependent variable is defined as the difference between ridership in time period t and ridership in some previous time period, $t - n$, may also be relevant in some cases, as are moving-average models, in which the dependent variable is hypothesized to be influenced by the weighted average of transit ridership over several time periods, which may include before and after time periods in estimation.

These analytically more complex types of models require the estimation of error terms in separate models are the use of instrumental variables in estimating final regression equations (4). Such models are usually neither necessary nor relevant in practice, often do not require direct estimation in any case, and are not further considered here. This implies that the temporal processes influencing aggregate transit ridership are relatively simple and straightforward, an assumption that will be tested explicitly as part of the development of the final recommended transit ridership forecasting model.

Seasonal Models

A second type of direct serial autocorrelation is seasonal autoregressivity. In this example, the length of seasonality is 4, because there are four quarters in each year. One formulation of such a seasonal model, which retains a first-order, lagged endogenous variable and cross-sectional variables as before, is as follows:

$$\ln(PAS_t) = b_0 + b_1 * \ln(VSM_t) + b_2 * \ln(EMP_t)$$
$$+ b_3 * \ln(PAS_{t-1})$$
$$+ b_4 * \ln(PAS_{t-n}) + e_t \qquad (7)$$

where n is the length of seasonality.

Alternatively, seasonality may be included in the model through the use of dummy variables. Each seasonal dummy variable tests for differences in transit ridership between that season and an arbitrary reference season, which may be any of the four quarters, as follows:

$$\ln(PAS_t) = b_0 + b_1 * \ln(VSM_t) + b_2 * \ln(EMP_t)$$
$$+ b_3 * \ln(PAS_{t-1}) + b_4 * SEA_1$$
$$+ b_5 * SEA_2 \ldots + b_x * SEA_{n-1} + e_t \qquad (8)$$

where SEA_x is 1 if the observed total transit ridership occurred in season n, and is 0 otherwise.

The choice of which alternative seasonal model formulation to use may be influenced by the length of seasonality. When the number of seasons (quarters, months, weeks, days, hours, etc.) is relatively small, collinearity between the first-order autoregressive term and the seasonal term will tend to be higher, suggesting the use of seasonal dummy variables. When the number of seasons is relatively high, the loss of efficiency in model estimation because of the necessary inclusion of $n - 1$ independent variables will tend to be higher, suggesting the use of a seasonally differenced term as an independent variable.

Incident Models

An incident is any event that disturbs the observed relationships between a dependent variable and any or all of its associated time-series and cross-sectional explanatory variables. Examples of incidents in the transit industry might include a large scale restructuring of transit services (the introduction of a new rail service, where before there was none, for example), significant fare restructuring, gas shortages, oil price increases, ambitious marketing programs, and perhaps the classic example, the transit work stoppage, or labor strike (10). Such incidents may have transit ridership impacts which are positive or negative, abrupt or gradual, temporary or permanent, in nature. A simple model of any or all of these types of effects is as follows:

$$\ln(PAS_t) = b_0 + b_1 * \ln(VSM_t) + b_2 * \ln(EMP_t)$$
$$+ b_3 * \ln(PAS_{t-1}) + b_4 * SEA_1$$
$$+ b_5 * SEA_2 + b_6 * SEA_3$$
$$+ b_7 * INC_s * e^{(s-1)*\delta} + e_t \qquad (9)$$

where

INC_s = 1 in time period s, during which the incident actually occurred and in all subsequent time periods as well, 0 otherwise;

s = time period, where s is measured in the standard time periods used in model construction, beginning with $s = 1$ in that time period during which the incident actually occurred; and

δ = exponential decay parameter, theoretically or empirically derived, which provides a measure of the (constant) rate at which an incident's effect changes over time (Table 1).

It is possible that an incident may have one level of impact in the time period during which it occurs, and an entirely different level of impact in subsequent time periods. A good example of this is the effect of a work stoppage on transit ridership. It is common knowledge in the transit industry that work stoppages can affect transit ridership long after a strike has ended. While the strike is in progress, no transit service is provided at all, and thus no one may ride transit anywhere in the affected service area. Transit riders must then seek out alternative means of transportation (automobile, walking, etc.), or forgo their customary travel behavior. After the strike ends, individuals may choose to take one or more of the following actions for different types of trips:

1. They may revert immediately to their former customary travel behavior (i.e., get back on the bus);
2. They may permanently change their travel behavior (i.e., purchase a private automobile for their own personal use; or
3. They may delay changing their behavior, but ultimately wind up reverting to their former customary travel behavior

TABLE 1 NUMERICAL RELATIONSHIP BETWEEN DELTA AND INCIDENT EFFECTS

Value of delta (decay factor)	Effect of incident over time
Positive	Permanent, and increasing over time.
0	Permanent, and constant over time.
Negative	Temporary and lingering, that is, decreasing constantly over time.
Negative and very large i.e., negative infinity)	Temporary and abrupt, because the effect vanishes immediately, once the stimulus has been removed.

(e.g., to keep up their end of a carpool arrangement for a certain length of time).

Depending on the length and severity of the incident, individual travellers may wait longer or shorter periods of time before returning to their former customary behavior patterns. It is difficult if not impossible to model different kinds of temporal processes that occur simultaneously, explicitly in the context of time series analysis, just as the effects of separate incidents that occur at the same time cannot be isolated in a single aggregate forecasting model. It is possible to separate the temporary effect of one incident from the more or less permanent aftereffects of that same incident as follows:

$$\ln(PAS_t) = b_0 + b_1 * \ln(VSM_t) + b_2 * \ln(EMP_t)$$

$$+ b_3 * \ln(PAS_{t-1}) + b_4 * SEA_1$$

$$+ b_5 * SEA_2 + b_6 * SEA_3$$

$$+ b_7 * INC_s + INC_{s+1} * e^{(s-1)*\delta} + e_t \qquad (10)$$

where

INC_s = 1 in time period s only, when the incident actually occurred, 0 otherwise; and

INC_{s+1} = 1 in time period $s + 1$, immediately after the incident occurred, and 1 in all subsequent time periods, 0 otherwise.

The analytical results of each of these types of transit ridership forecasting models will be compared in the next section, with conclusions drawn concerning model validity, and their potential utility in public policy analysis. The primary data used in the model are shown in Figure 1. Orange County employment increased with few interruptions, from less than 500,000 in 1973 to well over 1,000,000 in 1989. OCTD transit service (VSM) expanded rapidly during the 1970s, but remained virtually constant during the 1980s. OCTD ridership nonetheless continued to increase in the 1980s, though at a much lower annual growth rate than in the 1970s.

RESULTS

Analytical results from a variety of model formulations are compared in terms of internal validity. Internal validity is composed of the statistical measures that explain the significance of estimated parameters, and the existence of measurement errors associated with collinearity or serial autocorre-
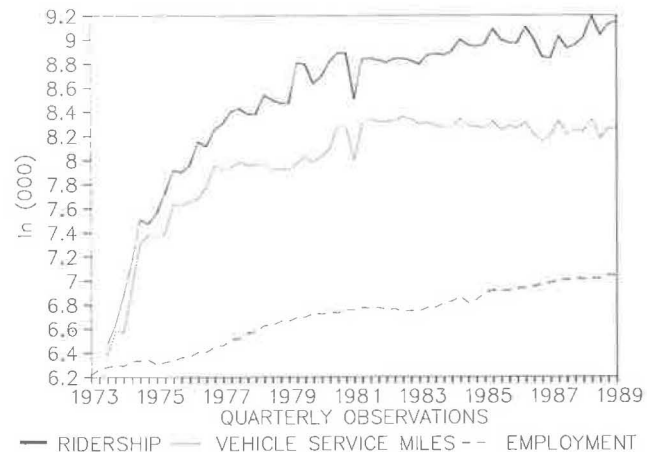

FIGURE 1 Orange County, California, trends.

lation. External validity could also be checked by comparing these model results with those from other transit ridership forecasting models, and actual transit performance in future time periods.

Basic Models

Table 2 presents results for basic cross-sectional, autoregressive time-series, and combined transit ridership forecasting models. All three models show significant serial autocorrelation in the distribution of error terms, indicating that model parameters may be biased in terms of magnitude, confidence level, or both. Parameter estimates for the simple cross-sectional and time series models are clearly too high by industry standards. Transit service elasticities generally range from +0.3 to +0.7, whereas the estimated parameter for VSM in Model 1.1 is greater than +1. The Model 1.2 results suggest that 90 percent of transit ridership is retained from one quarter to the next, but this is probably much too high as a measure of elasticity for individual transit riders. Model 1.3 is clearly preferred, with more appropriate parameter estimates for all three of the included variables. However, serial autocorrelation appears to be a slight problem even in Model 1.3.

A few observations in each model indicate relatively high studentized residuals, identifying such observations as outliers. Heteroskedasticity (ordinary dependent variable autocorrelation) does not appear to be a problem in any of the

TABLE 2   BASIC CROSS-SECTIONAL, TIME SERIES, AND COMBINED TRANSIT RIDERSHIP FORECASTING MODELS

	Alternative Model Formulations[1]		
Model	1.1	1.2	1.3
Independent Variables	Cross-Sectional[2]	Time-Series[3]	Combined[4]
Intercept	-4.708	0.926	-2.888
$\ln(VSM_t)$	1.037 (0.043)		0.678 (0.095)
$\ln(EMP_t)$	0.740 (0.082)		0.511 (0.101)
$\ln(PAS_{t-1})$		0.896 (0.023)	0.304 (0.078)
Number of Observations	63	62	62
Degrees of Freedom	60	60	58
R^2	0.9808	0.9633	0.9820
Durbin-Watson's d	0.89		
Durbin's h		2.30	2.03

1.   The dependent variable in each case is $\ln(PAS_t)$.
2.   Basic cross-sectional model, including measures of supply and demand.
3.   Basic first order autoregressive time-series model.
4.   Combined cross-sectional and time-series model.

Note: Standard errors for all independent variables are given in parentheses next to each parameter estimate. All parameter estimates listed in this table are significant at the 0.05 level of confidence or higher, using a one-tailed test.

models. Serial autocorrelation is indicated when error terms tend to stay on one side or another of the origin (0), rather than bouncing back and forth randomly. All three models exhibit serial autocorrelation. An additional step would be necessary to correct for continued serial autocorrelation in the combined model. However, error models and instrumental variables are to be avoided because of complexity and inconvenience in spreadsheet applications. Analysts might refer to more sophisticated application techniques and computer software programs in such cases.

Seasonal Models

Table 3 presents results from combined cross-sectional and time series models with additional seasonally autoregressive terms introduced. There are two methods for incorporating seasonal autoregressivity into regression analysis, one using seasonally differenced variables, the other using seasonal dummy variables. Model 2.1 uses a seasonally differenced variable with the combined transit ridership forecasting model. Parameter estimates are generally lower for combined model variables, though Durbin's h is extremely high. This model is overdifferenced; collinearity between the seasonally and non-seasonally differenced variables has biased parameter estimates severely. Model 2.2 uses three seasonal dummy variables to account for ridership differences among quarters, with the fourth quarter as the implied baseline. Two of the three quarterly dummy variables are not significant, yet Durbin's h is less than 1.64, implying that serial autocorrelation in the distribution of error terms is no longer a significant problem in model estimation. Thus, Model 2.2 is preferred over Model 2.1.

Figures 2 and 3 show serial autocorrelation for Models 2.1 and 2.2. Figure 2 shows the effect of overdifferencing on error

terms in estimation. Figure 3 shows a notable reduction in serial autocorrelation, but two observations associated with incidents clearly act as outliers in model estimation. In both graphs, error terms in prediction are shown in relation to the dependent variable on the x-axis, and temporally with a linear time path.

Incident Models: Theoretical Tests

Table 4 presents results from the combined model with seasonal dummy variables and incident effects included. Model 3.1 assumes the effects of all three incidents, the 1979 gas shortage and the 1981 and 1986 work stoppages, to be temporary and abrupt, that is, that all effects vanish as soon as the incident is over. Model 3.3 assumes that the effects of all three incidents are permanent and abrupt, that is, that each incident has the same effect in all subsequent quarters that it has in the quarter in which it actually occurs. Model 3.2 assumes that the effects of all three incidents are temporary but lingering, with the rate of decay (delta) arbitrarily set at -1, which assumes a constant decline in parameter significance of 68 percent per quarter. Signs are as expected for every variable in all three models, although the 1986 strike effect is not significant for either extreme case, nor is the 1979 gas shortage effect significant under a permanent effects scenario. The temporary, lingering effects scenario (Model 3.2) provides the best overall goodness of fit, and the lowest Durbin's h value, with all variables significant and all signs as expected.

Incident Models: Empirical Tests

Table 5 presents results from the combined model based on empirically tested (or bootstrapped) best-fit identification of

TABLE 3 SEASONAL TRANSIT RIDERSHIP FORECASTING MODELS

| Model | Alternative Model Formulations[1] | |
	2.1	2.2
Independent Variables	Seasonal Difference Variable[2]	Seasonal Dummy Variables[3]
Intercept	-1.530	-2.252
$\ln(\text{VSM})$	0.467 (0.115)	0.535 (0.085)
$\ln(\text{EMP})$	0.521 (0.116)	0.430 (0.088)
$\ln(\text{PAS}_{t-1})$	0.106 (0.094)[@]	0.423 (0.071)
$\ln(\text{PAS}_{t-4})$	0.233 (0.077)	
SEA_1		0.022 (0.023)[@]
SEA_2		0.124 (0.025)
SEA_3		0.040 (0.024)[@]
Number of Observations	59	62
Degrees of Freedom	54	55
R^2	0.9739	0.9880
Durbin's h	7.92	1.30

1. The dependent variable in each case is $\ln(\text{PAS}_t)$.
2. Including a seasonally differenced measure of transit ridership as an independent variable, in addition to the first order autoregressive term.
3. Including three dummy variables representing relative transit ridership differences between the first and fourth, second and fourth, and third and fourth quarters of the year, respectively.

Note: Standard errors for all independent variables are given in parentheses next to each parameter estimate. All parameter estimates listed in this table are significant at the 0.05 level of confidence or higher, using a one-tailed test. Those parameter estimates marked with an @ are not significant at the 0.05 level.
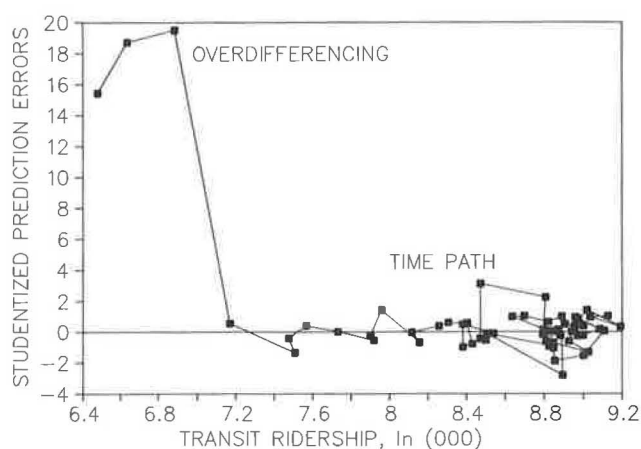

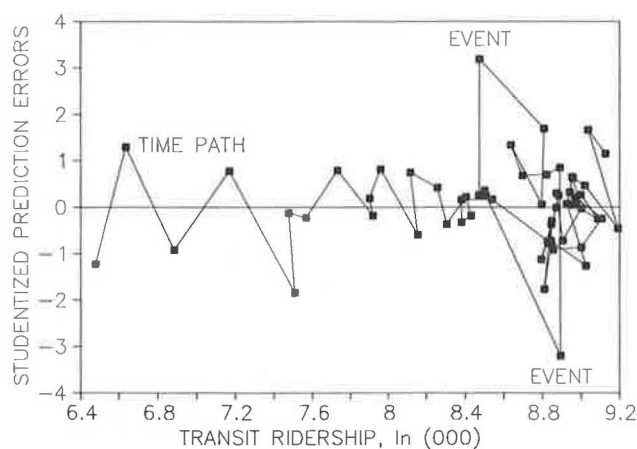FIGURE 2 Serial autocorrelation, Model 2.1.

FIGURE 3 Serial autocorrelation, Model 2.2.

decay parameter values for each incident. Model 4.1 assumes exponential decay parameters to be the same for all incidents, whereas Model 4.2 relaxes this restriction, allowing all decay parameters to vary independently. Both of these models have higher R^2 values, but also greater serial autocorrelation measures, than Model 3.3. Without any guidance on how to combine these two model evaluation measures into one unique qualifier, modelers will have to choose between them when ambiguous results are achieved, as in this case.

Incident Models: Abrupt and Lingering Effects Separated

Table 6 presents analytical results with temporary (abrupt) and lingering (permanent) effects of each incident modeled separately using independent variables for each such effect. Model 5.1 includes all available observations in estimation, whereas Model 5.2 excludes the first two observations in the temporal sequence of quarterly OCTD ridership that has oc-

TABLE 4   INCIDENT-RELATED TRANSIT RIDERSHIP FORECASTING MODELS:
THEORETICALLY DERIVED COMBINED EFFECTS

	Alternative Model Formulations[1]		
Model	3.1	3.2	3.3
Independent Variables	Temporary, Abrupt Effects[2]	Temporary, Lingering Effects[3]	Constant, Permanent Effects[4]
Intercept	-1.853	-2.458	-4.500
$\ln(VSM)$	0.441 (0.072)	0.549 (0.067)	0.689 (0.077)
$\ln(EMP)$	0.380 (0.070)	0.462 (0.069)	0.783 (0.137)
$\ln(PAS_{t-1})$	0.504 (0.060)	0.408 (0.056)	0.271 (0.067)
SEA_1	0.033 (0.019)	0.032 (0.018)	0.032 (0.019)
SEA_2	0.113 (0.020)	0.108 (0.019)	0.111 (0.021)
SEA_3	0.033 (0.019)	0.032 (0.018)	0.048 (0.020)
$GAS79_{a,l}$	0.217 (0.053)	0.234 (0.049)	0.038 (0.032)@
$STR81_{a,l}$	-0.253 (0.056)	-0.192 (0.049)	-0.146 (0.027)
$STR86_{a,l}$	-0.073 (0.054)@	-0.091 (0.050)	-0.020 (0.029)@
Number of Observations	62	62	62
Degrees of Freedom	52	52	52
R^2	0.9932	0.9935	0.9923
Durbin's h	0.42	0.16	1.61

1.   The dependent variable in each case is $\ln(PAS_t)$.
2.   Assuming that the exponential decay parameter for each independent lingering effect variable is equal to negative infinity. In essence, each incident affects transit ridership only in that quarter in which the incident actually occurs. Immediately thereafter, the incident's effect on transit ridership reduces to zero, and remains there.
3.   Assuming that the exponential decay parameter for each independent lingering effect variable is equal to -1.0.
4.   Assuming that the exponential decay parameter for each independent lingering effect variable is exactly equal to zero. In essence, each incident affects transit ridership permanently by a given percentage, beginning in that quarter in which the incident actually occurs, and continuing forever after.

Note: Standard errors for all independent variables are given in parentheses next to each parameter estimate. All parameter estimates listed in this table are significant at the 0.05 level of confidence or higher, using a one-tailed test. Those parameter estimates marked with an @ are not significant at the 0.05 level.

TABLE 5 INCIDENT-RELATED TRANSIT RIDERSHIP FORECASTING MODELS:
EMPIRICALLY DERIVED COMBINED EFFECTS

| | Alternative Model Formulations[1] | |
| Model | 4.1 | 4.2 |
Independent Variables	Equal Exponential Decay Parameters[2]	Varying Exponential Decay Parameters[3]
Intercept	-3.529	-4.237
$\ln(VSM)$	0.714 (0.064)	0.772 (0.059)
$\ln(EMP)$	0.609 (0.073)	0.694 (0.067)
$\ln(PAS_{t-1})$	0.265 (0.054)	0.229 (0.048)
SEA_1	0.034 (0.016)	0.032 (0.014)
SEA_2	0.105 (0.017)	0.095 (0.016)
SEA_3	0.041 (0.017)	0.039 (0.015)
$GAS79_{a,l}$	0.159 (0.031)	0.200 (0.039)
$STR81_{a,l}$	-0.191 (0.031)	-0.157 (0.024)
$STR86_{a,l}$	-0.094 (0.036)	-0.129 (0.033)
Number of Observations	62	62
Degrees of Freedom	52	52
R^2	0.9946	0.9957
Durbin's h	0.27	1.47

1.   The dependent variable in each case is $\ln(PAS_t)$.

2.   Assuming that the exponential decay parameter for each combined abrupt, lingering effect variable is equal to -0.20. This assumption maximizes goodness of fit (R^2), given that the exponential decay parameters for all incident variables must be exactly identical. Derived through iteration.

3.   Assuming that the exponential decay parameter for the 1979 gas shortage variable is equal to -0.68, for the 1981 work stoppage variable is equal to -0.06, and for the 1986 work stoppage variable is equal to -0.21. These assumptions maximize goodness-of-fit (R^2), given that exponential decay parameters for incident variables are allowed to vary independently. This solution was arrived at through an iterative process, beginning with marginal adjustments in the exponential decay parameters for each of the three incident variables sequentially, and ending when no further exponential decay parameter adjustment yielded an increase in R^2. The iterative order in which adjustments were made did not affect the final outcome in this example. Failure to converge to a unique solution, independent of the path taken, might have indicated model specification problems, which were not in evidence here.

Note: Standard errors for all independent variables are given in parentheses next to each parameter estimate. All parameter estimates listed in this table are significant at the 0.05 level of confidence or higher, using a one-tailed test.

TABLE 6 INCIDENT-RELATED TRANSIT RIDERSHIP FORECASTING MODELS:
ABRUPT AND LINGERING EFFECTS SEPARATED

	Alternative Model Formulations[1]	
Model	5.1	5.2
Independent Variables	All Observations Employed[2]	First Two Observations Removed[3]
Intercept	-4.215	-4.532
$\ln(VSM)$	0.725 (0.072)	0.824 (0.072)
$\ln(EMP)$	0.707 (0.077)	0.707 (0.071)
$\ln(PAS_{t-1})$	0.262 (0.060)	0.207 (0.055)
SEA_1	0.040 (0.014)	0.030 (0.013)
SEA_2	0.101 (0.015)	0.094 (0.014)
SEA_3	0.039 (0.015)	0.038 (0.013)
$GAS79_a$	0.187 (0.041)	0.192 (0.036)
$STR81_a$	-0.227 (0.044)	-0.197 (0.039)
$STR86_a$	-0.073 (0.042)	-0.068 (0.037)
$GAS79_l$	0.110 (0.042)	0.119 (0.037)
$STR81_l$	-0.131 (0.025)	-0.152 (0.024)
$STR86_l$	-0.151 (0.037)	-0.154 (0.033)
Number of Observations	62	60
Degrees of Freedom	49	47
R^2	0.9962	0.9957
Durbin's h	1.56	0.89

1. The dependent variable in each case is $\ln(PAS_t)$.
2. The empirically derived exponential decay parameters which provided the best overall goodness-of-fit in Model 5.1 were -infinity for the 1979 gas shortage lingering effects variable, -0.040 for the 1981 work stoppage lingering effects variable, and -0.32 for the 1986 work stoppage lingering effects variable.
3. The empirically derived exponential decay parameters which provided the best overall goodness-of-fit in Model 5.2 were -1.1 for the 1979 gas shortage lingering effects variable, -0.051 for the 1981 work stoppage lingering effects variable, and -0.32 for the 1986 work stoppage lingering effects variable.

Note: Standard errors for all independent variables are given in parentheses next to each parameter estimate. All parameter estimates listed in this table are significant at the 0.05 level of confidence or higher, using a one-tailed test. Those parameter estimates marked with an @ are not significant at the 0.05 level.

curred since 1973. In this case, Model 5.2 has lower serial autocorrelation, but also a lower R^2, than Model 5.1. Figure 4 shows serial autocorrelation for Model 5.1, the theoretically least restricted, and thus preferred, model, with full incident effects, and all observations included. Although serial auto-
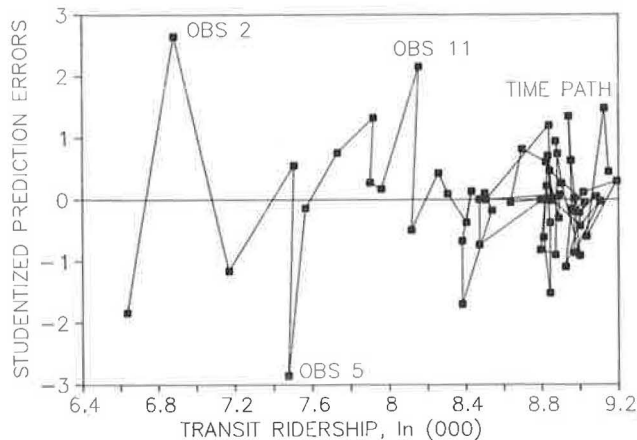

FIGURE 4 Serial autocorrelation, Model 5.1.

correlation is acceptable (barely), and the independent effect of all three incidents has been accounted for successfully, three new observations appear as outliers, all three occurring relatively early in OCTD's history. These three observations cannot be modeled easily as incidents, although they may be related to the 1973 oil crisis, or major service expansions. The primary reason for this inability to model such incidents is lack of data. OCTD did not begin operations until 1973. It is thus impossible to know exactly what equilibrium transit ridership would have been in Orange County before start-up in 1973. Without prior data, it is dangerous and sometimes highly inaccurate to try to model the aftereffects of specific incidents.

Another method of dealing with outlier observations is to eliminate them from the analysis. In the case of time series analysis, however, observations cannot be plucked at random from the data base. A continuous stream of data is required. This suggests that observations could be modified in value to conform to model predictions (a somewhat dubious practice), or entire segments of data including outliers could be eliminated from the beginning or end of the contiguous time series. Model 5.1 was reestimated with the first 2, 5, and 11 observations eliminated. With the first two observations removed, R^2 decreased, but so did Durbin's h. It was felt by the author

that the loss in R^2 was more than made up for by the reduction in serial autocorrelation in Model 5.2. Removing additional observations from the data resulted in additional reductions in R^2, and also increasing serial autocorrelation in relationship to Model 5.2, and are not further considered.

The effects of incidents on transit ridership using Model 5.2 as the basis for comparison are shown graphically in Figure 5. The 1979 gas shortage is shown to have a large, abrupt, and temporary effect on transit ridership, which virtually disappears once gasoline is no longer in short supply. The 1981 work stoppage was prolonged. No service was provided to patrons during this strike. The result was a large decrease in transit ridership, which did not return to normal for a long time. The 1986 work stoppage was much shorter, and limited service was provided to patrons by trained supervisorial and management personnel under a well-kept secret contingency plan during the strike. The result was a similar loss in ridership to the 1986 work stoppage, which rebounded toward normal levels of patronage much more quickly. Note that the abrupt effect of the 1986 work stoppage was smaller than might be expected, presumably because this strike occurred at the very end of a quarter.

Role of Pricing in Determining Orange County Transit Ridership Trends

The economist in the audience will have noted already the absence of a pricing variable in any of the forecasting models so far presented. This omission was not accidental, but the result of preliminary model testing that found pricing variables to have no significant effect on transit ridership in Orange County, once the effect of incidents had been included. Figure 6 shows pricing trends for automobile (average gasoline price) and transit (average bus fare) over the 15-year study period. Inclusion of a transit price variable in the first and second series of models (Tables 2 and 3) produced significant price elasticities varying around -0.3, the industry standard. However, serial correlation remained a problem in these models. When transit pricing was included in the incident impact models (Tables 4–6), the elasticities dropped to a range of about -0.03 to -0.06, and were no longer found to be significant. Similarly, gasoline prices were not found to have a significant
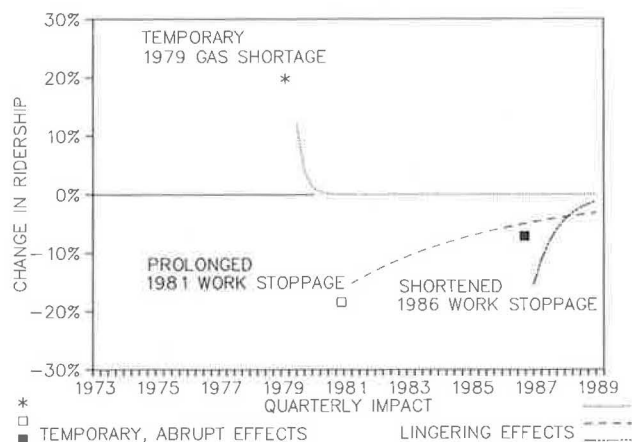
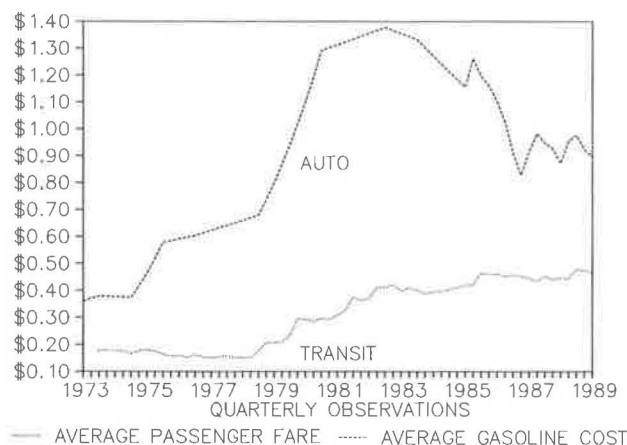**FIGURE 5   Effects of incidents on transit ridership.**

FIGURE 6   Trends in pricing.

independent effect on transit ridership in any of the models considered here.

The Chapman forecasting model developed for use by OCTD used a transit/automobile price ratio variable that was significant, had a value of -0.3, and was associated with significant serial correlation and parameter biases (*1*). Why does pricing seem to have little if any effect on OCTD transit ridership at the aggregate level of analysis? A review of secular trends in the characteristics of OCTD transit patrons may reveal part of the answer (*11–13*). As Table 7 shows, OCTD patrons increasingly are captive riders making nondiscretionary trips. In 1987, 58 percent of all trips made were work trips, 70 percent of riders were regular users of the system, and 80 percent of patrons had no car available to them to make the trip. Captive riders have low price elasticities of demand for nondiscretionary trips, and virtually zero cross-price elasticities for competitive modes that, like the automobile, are out of reach for them, at least in the near term (*14*). Flat fare systems such as the one used in Orange County often contribute to this lack of price sensitivity on the part of transit patrons (*15*).

Ironically, OCTD financial planning staff recommended implementing a 25-cent fare increase in 5-cent increments over 5 years, to minimize potential transit ridership losses. Taking inflation into consideration, such a policy constitutes maintaining a constant fare over time in real dollars, for which the price elasticity of demand should indeed be 0. These results also reconfirm the notion that OCTD transit ridership increased in 1979 in response to a temporary shortage of gasoline, rather than to a more permanent increase in its price.

CONCLUSIONS

Cross-sectional models are generally evaluated on the basis of theoretical validity, conformance with theoretical expectations concerning the magnitude and direction of change, and overall model goodness-of-fit. Individual parameter estimation error terms and confidence intervals may be significantly biased, if serial autocorrelation of the error terms in prediction is present, for time series dependent variables. In order to prevent temporally related biases from introducing major errors into forecasting models and procedures, various

TABLE 7   SECULAR TRENDS IN OCTD RIDER CHARACTERISTICS

OCTD Rider Characteristics	Year of On-Board Survey			
	1976[1]	1979[1]	1982[2]	1987[3]
Regular Rider[4]	52%	63%	70%	70%
Trip Purpose				
Work	35%	46%	46%	58%[5]
School	35%	25%	26%	18%
Shopping	10%	11%	10%	7%
Recreation	7%	5%	4%	5%
Other	13%	13%	14%	12%
Age				
Under 16	12%	10%	8%	8%
16-64	79%	80%	82%	83%
Over 65	9%	10%	10%	9%
Female	58%	58%	57%	54%
Low Income[6]	74%	55%	51%	45%
No Car Available for Trip	76%	71%	74%	80%
Ethnicity				
White	not asked	not asked	64%	46%
Hispanic			21%	34%
Asian			8%	7%
Black			5%	6%
Sample Size	not available	10,669	21,866	approx. 17,000

1.   DMJM and COMSIS Corp., 1981.
2.   TRAM, 1983.
3.   NuStats, Inc., 1988.
4.   Rides five or more days per week.
5.   This figure may be high, in that the 1987 system-wide on-board survey sampled bus trips in the a.m. only, rather than all day.
6.   Annual household income less than $15,000, *in current dollars.*

techniques are available. Generally, explicit representation of the underlying theoretical temporal processes, through the use of time series transformation of the dependent variable, are required to reduce serial autocorrelation, absent the use of indirect estimation methods that are not discussed here. Ostram (4) provides an introduction to indirect estimation techniques, for those who might be interested.

Time series methods include the use of serial and seasonal autoregressive terms, differenced or integrated equations, moving average models, etc. If the independent variables used in the model are influenced by temporal processes, these should be considered, particularly if such "independent" temporal processes are related to those endogenous temporal processes that are known or hypothesized to influence the dependent variable.

Models of the type discussed in this paper may provide more reliable measures of policy sensitivity, as well as more accurate forecasts of future conditions with respect to the dependent variable. These improvements can be tested empirically using ex ante or ex post comparative evaluation measures. Ex ante evaluation requires making a forecast, and waiting for the forecast period to expire before comparing forecast and actual results. Ex post evaluation, or backforecasting, is done by excluding some of the most recently available data from model estimation, and comparing this model

output with actual results. Technically, only information on exogenous variables that was available before the backforecast time period should be used in making ex post backforecasts, for the sake of methodological consistency. The model discussed here will probably increase in utility to planners and policy analysts as time series analysis techniques and data become more readily available and understood. Random samples of time series data can be used to lower data collection costs, as long as such data are sampled systematically (16,17). The use of such techniques in research and development seems to be increasing. Periodic updating, testing, and evaluation of such time series model results as are in use by practicing planners will enhance understanding and ability to use these versatile methods in the future. Practical advantages of this class of methods should include more accurate forecasting ability, although this must await further testing of applications in the field for verification.

In terms of policy, the effects of incidents on transit ridership can be modeled quite accurately to determine temporal variations in the lingering effects of such incidents. The ability to measure past responses to incidents should help planners and decision makers in preparing for anticipated future shocks to transit performance, whether positive or negative in nature. It would be useful to know if the results reported here for incidents can be duplicated partially or wholly in other parts

of the country, with similar or different types of transit markets in operation. A 1966 transit strike in New York City resulted in permanent regular ridership losses of only 2.1 percent for work trips, 2.6 percent for shopping trips, and 2.4 percent for all other trips, on the basis of an ex post travel behavior survey (*18*). Are the measured results for Orange County reported here much greater because of differences in sampling procedures, differences in modeling procedures, differences in the timing of work stoppage occurrence, differences in the spatial configuration of transit markets, or other factors? Additional study using data from multiple transit agencies might assist in answering some of these questions.

ACKNOWLEDGMENTS

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