Multivariate Time-Series Model of Transit Ridership Based on Historical, Aggregate Data: The Past, Present and Future of Honolulu

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Historical data on a small number of economic, demographic, and transportation variables from 1958 to 1986 were analyzed by multiple regression techniques to develop two models for forecasting transit ridership in Honolulu. A model predicting revenue trips and another for linked trips were consistent in their determination that the same five variables could account for 97 to 98 percent of the variance in bus ridership over this 29-year period. The four major variables were per capita income, employment, fares, and size of bus fleet, with a dummy variable included for strikes. The income elasticity for transit demand was found to be negative, indicating that mass transit is an inferior good. The model forecasts a continuing decline in bus ridership for Honolulu, mainly caused by this effect. The forecasting models for rapid transit ridership for Honolulu are examined, and alternative approaches to assessing demand elasticities are discussed. The advantages of using aggregate historical data and regression analyses for developing inexpensive forecasting models from time series data are emphasized.

Two multivariate models to forecast transit ridership for Honolulu using aggregate variables are presented and discussed with respect to different modeling approaches and their applications. The two models use the statistical technique of multiple regression that is widely used in economic forecasting and model construction in the other social sciences (*1,2*). This approach is most commonly used in transportation to study trends in time series data (*3–7*) and it is particularly useful for analyzing secondary sources of historical data (*8,9*). As such, it is well suited for long-range planning and it can be a valuable tool for transportation planners who have only limited resources available to them.

ELASTICITY OF TRANSIT DEMAND

The demand for transit (transit ridership), like that for any product, is related to two variables: price and income. The price relationship is best known. The demand for a product is inversely related to its price; or simply, the lower the price the higher the quantity demanded. Although the direction of this relationship is universal, the degree to which demand for a product changes with price—i.e., its price elasticity—varies considerably. If a given percentage change in price results in a proportionate or higher change in demand, the price elasticity is said to be elastic. If a percentage change in price results in a proportionally smaller change in demand (less than 1:1 ratio), the elasticity is said to be inelastic.

The concept of elasticity has important implications for transit operators. If the price elasticity of transit is elastic, then lowering fares (price) would increase ridership and revenues, whereas increasing fares would decrease both measures. If, however, demand is inelastic, lowering fares would increase ridership but decrease revenues, because the percentage increase in ridership would not be large enough to compensate for the drop in fares. Raising fares, on the other hand, would actually increase revenues despite decreasing ridership, because the ridership loss would be proportionally less than the fare increase.

The negative relationship between fare and ridership has been confirmed by many studies and the demand for mass transit is clearly inelastic (*5,6,10–13*). Fare elasticities for mass transit rarely are less than -0.70, with elasticities in the range of -0.20 to -0.60 being most common (*10–13,14*).

The second economic variable that must be considered in transit planning is income. Although income is recognized as an important variable determining choice of travel mode (*11*), only a few studies (e.g., *6,15*) have analyzed income elasticity with respect to transit ridership.

The income elasticity of most products is positive in that the demand for them increases with income. Some products, however, have a negative income elasticity in that demand for them decreases as income rises. Such products are called "inferior goods."

The income elasticity of a product is important for long-range planning purposes, because, if a product has a negative income elasticity and income is expected to rise, then long-run demand for that product can be expected to decline. This should be a matter of some concern to transit planners because transit may be an inferior good.

National demographic data on transit patronage suggest that fixed-route buses and trains are inferior goods (*16,17*),

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but few studies have calculated the income elasticity of transit ridership. Gaudry (*6*) found a negative income elasticity for transit in Montreal, but the effect of income in his ridership model was not significant. Gordon and Willson's (*8*) international analysis of rail transit, as well as other studies, provide indirect evidence that transit demand has a negative income elasticity (*12,15*).

DEMAND ELASTICITY AND TRANSIT SERVICE

The service characteristics of transit systems provide the supply functions that contribute to transit patronage (i.e., ridership). The service characteristic that has been found to be most influential in predicting ridership is the quantity of service (*7,11,13*). Carstens and Csanyi's (*18*) analysis of bus ridership in 13 Iowa cities indicated that revenue ridership was highly elastic in terms of miles of service. The results of other studies are not as optimistic. Although Rose (*7*) reports that the service elasticity for ridership on the Chicago rail system is both positive and elastic (elasticity = 1.84), his demand measure was not limited to revenue ridership. In other U.S. cities that have been examined (*13,19*), the relationship between transit ridership and miles of service, though positive, is inelastic (0.21 to 0.87). Although Kemp's survey of 35 demonstration projects reveals that transit ridership is more sensitive to changes in service than it is to fares, it appears from his survey that the increased revenues resulting from service increases are not enough to offset their cost.

Other factors also contribute to transit demand, and service measures of transit supply appear to play only a minor role in mode choice when demographic variables, such as income and automobile ownership, are taken into account (*6,8,12,15,18*). Demographic factors may also influence the effects of other variables. Fare elasticity, for instance, appears to vary inversely with city population size (*12,18*).

AVAILABLE AND SELECTED MEASURES

Various historical data were available from the start of Honolulu's all-bus transit system in 1957 (trolley service ended in 1956) to the present, including revenue passengers and total annual ridership (*20–24*). The only service measure available for this span of time was size of bus fleet (number of buses). Although it is admittedly a crude measure of service, it is the sole service factor that is used in policy proposals about future bus operations.

Four of the historical variables that were available are also forecast by the Department of Business and Economic Development (DBED) through the year 2010 (*25*). These variables are per capita income, population, number of visitors (tourists), and civilian employment (actual number of jobs held). Per capita income was naturally included in the model for determining income elasticity. Because the other three variables were all highly correlated, it was decided to start the model with only one of them. Employment was chosen because it was closely related to transit demand both in theory and practice. Other relevant variables for which data were available included number of registered passenger vehicles, gasoline prices, and bus fare. Bus fare was another natural choice for the model variable but the fare structure for the bus system posed some of the same problems encountered by Bates (*3*). Nevertheless, the average fare calculated from official estimates of passengers in different fare categories was comparable to that reported in recent annual reports of the Honolulu bus system. A dummy variable was entered into the model to account for two strikes of over 1 month's duration.

BUS RIDERSHIP MODELS

Two models were constructed using the statistical technique of least squares multiple regression. The first of these was developed to predict annual passenger revenue-trips (R-TRIPS) and the second to predict annual linked trips (L-TRIPS), or initial boardings.

Revenue Trips Model

The revenue-trips model consisted of five variables: (a) the natural logarithm (ln) of the number of civilian jobs (JOBS), (b) ln of per capita income in 1982 dollars (INCOME), (c) ln of fare in 1982 dollars, (d) ln of the number of buses in the bus fleet (BUSES), and (e) a dummy variable for strikes (STRIKES).

The full model for annual revenue trips is expressed as follows, with all values given in $ millions:

$$\begin{aligned}\text{R-TRIPS} = & -118.9 + 52.2(\text{JOBS}) - 60.9(\text{INCOME}) \\ & - 27.8(\text{FARE}) + 7.9(\text{BUSES}) \\ & - 4.4(\text{STRIKES}) \qquad (1)\end{aligned}$$

On the basis of 29 observations, the model has an adjusted R^2 value of 0.97. The t-statistic values for the respective variables were 2.26, 4.26, 5.02, 5.37, 3.19, and 2.12. The first three variables are significant at the $p < 0.001$ level. The t-value for BUSES is significant at $p < 0.005$, whereas STRIKES has a probability $p = 0.05$. The goodness-of-fit between the model's estimates and the actual data is shown in Figure 1 (1967 and 1971 were strike years). The inclusion of other variables, such as tourists, registered passenger vehicles, and gasoline prices, did not significantly improve the model. As indicated by the formula, per capita income, fares, and strikes all have inverse relationships with revenue ridership, as would be expected. Numbers of jobs and buses, on the other hand, are positively related to revenue passengers.

A better understanding of the effects of these variables can be gleaned by looking at their elasticities, which yield direct estimates of their effects on ridership in standardized form. According to the model for revenue trips, the employment elasticity is 1.04, which means that each 10 percent increase in employment should result in a 10.4 percent increase in ridership. Increases in per capita income, on the other hand, have a negative effect on ridership. Given the model's estimated income elasticity of −0.98, a 10 percent increase in income should yield a 9.8 percent decrease in ridership.

Because the fare elasticity was −0.56, each 10 percent decrease in fare is expected to yield a 5.6 percent increase in

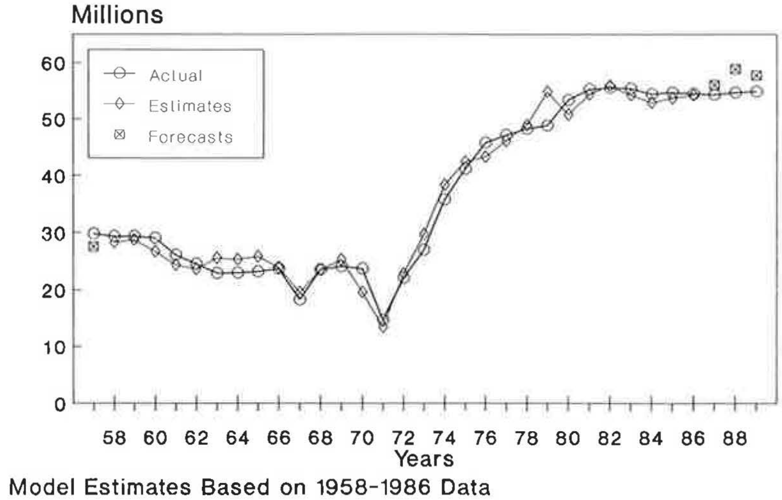

FIGURE 1 Actual and estimated annual revenue trips with forecasts for 1957 and 1987 to 1989.

ridership. Because Honolulu's bus system has had only a few small fare increases over the past 33 years, fares have continually declined in real dollars, helping to maintain ridership. But, because the fare elasticity is inelastic, the decline in fares produced decreased revenues.

The service elasticity, based on the number of buses, is 0.25. Hence, a 10 percent increase in number of buses can be expected to increase ridership only 2.5 percent. Of course, number of buses is only a crude measure of service, as stated earlier. Vehicle-miles of service would provide a more sensitive measure of service and, given past research, would likely produce a higher service elasticity than that found here (*7,19,26*). Nevertheless, for the years in which mileage data are available (1970 to 1989), the correlation between miles of service and number of buses is quite high, $r = 0.93$.

Linked Trips Model

Honolulu, like other cities, offers free bus passes to the elderly and handicapped, and free riders constitute just over 20 percent of all initial boardings. A second model was developed, therefore, to predict the total number of annual linked trips (revenue passengers plus free riders). Linked trips were derived from total annual trips by applying the correction factor for transfers used in the forecasting methodology for the Honolulu Rapid Transit Development Project (*27*), which was based on a 1986 on-board survey of bus riders.

The same five factors were found to predict linked trips as accurately as they did revenue trips. Adding other variables to the model, such as tourists, registered passenger vehicles, gasoline prices, and the percentage of free riders, did not improve it.

The model for annual linked trips (L-TRIPS) is as follows:

$$\text{L-TRIPS} = -118.3 + 38.2\,(\text{JOBS}) - 44.1\,(\text{INCOME}) - 36.0\,(\text{FARE}) + 10.6\,(\text{BUSES}) - 4.1\,(\text{STRIKES}) \quad (2)$$

Again, the model is based on 29 observations, with all coefficients given in \$ millions. The respective t values are 2.30, 3.17, 3.71, 7.09, 4.38, and 2.02. The adjusted R^2 value for the model is 0.98. As before, the effects of INCOME and FARE are all significant at the $p < 0.001$ level; the effect of STRIKES is only marginally significant at $p < 0.06$. In the present model, however, the t value for BUSES is significant at the $p < 0.001$ level, whereas JOBS has a probability of $p < 0.005$. Although the directions of the effects are the same in the second model as they are in the first, the coefficients derived from the two models differ, as do the elasticities.

The employment elasticity in the linked trips model is only 0.64, compared to 1.04 in the revenue trips model, indicating that employment does not have as strong an effect on total linked trips. Likewise, per capita income, with an elasticity of -0.59, has less of a negative effect on linked trips than it does on revenue trips. These differences are consistent with the fact that a substantial portion of the added trips in the linked trips model are attributable to elderly passengers using free bus passes.

The fare elasticity (-0.61) and service elasticity (0.28) for the linked trips model changed relatively little from those found for revenue trips. All of the elasticities calculated are long run and relatively inelastic, indicating that increases in bus ridership cannot be expected in the foreseeable future.

Although there are differences in the elasticities of the two models, they do not lead to sharply divergent predictions. In fact, the forecasts from each model tend to parallel each other (see Figure 2). Furthermore, the signs of the coefficients of both models are consistent with what would be expected from the theory of consumer behavior and the literature on travel demand elasticities.

BUS RIDERSHIP FORECASTS

The two models were tested against actual ridership in 1957 and years 1987 through 1989. These tests are shown for the first model in Figure 1, where they are labeled forecasts. The

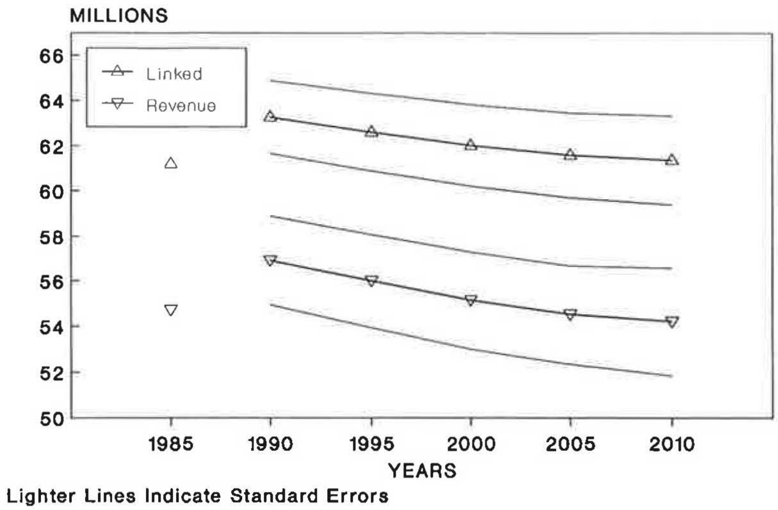

FIGURE 2 Forecasts of annual revenue trips and linked trips with current fares and buses.

goodness-of-fit for the models was further tested by calculating the mean absolute percentage error (MAPE) between model estimates and actual ridership for all years in the series (*2*). The MAPE was 5 percent in each case, confirming the high level of accuracy of the models. Both models, however, tend to overestimate current ridership, which has declined in the last few years. This recent downturn in ridership marks a significant trend ($z = 3.44$, $p < 0.001$), according to the change-point test (*28*), that is not predicted by the model.

Even so, the models do predict declining future ridership on Honolulu's bus system. Using DBED projections of per capita income and employment, the models forecast a reduction both in revenue trips and linked trips, holding fares and size of bus fleet constant.

The forecasted decreases in ridership are partially caused by the high negative income elasticity. Because the service elasticity is relatively inelastic, it would appear that significant increases in ridership can only be gained through substantial increases in bus fleet size. However, this result assumes that the bus fleet has been used in a way that maximizes service per bus and that number of buses is an adequate measure of service. If buses have been used inefficiently in the past or number of buses, per se, is a poor measure of service, the prediction may not be as dire. Because there is some evidence that recent decreases in ridership may be associated with less efficient use of the bus fleet (e.g., reassigning buses from urban trunk lines to express service for suburban commuters), improving service could offset declining ridership to some degree.

Decreases in real fare can be expected to continue to increase ridership, but at the expense of declining revenues. This process, unfortunately, increases the gap between revenues and costs. Although increases in employment have a positive effect on ridership, these expected gains tend to be counterbalanced by the income effect.

RAPID TRANSIT MODELS

The ridership forecasts for the proposed rapid transit system for Honolulu are derived from a model described by Brand and Benham (*29*), sometimes referred to as an incremental model (*27*). The Brand and Benham model has been empirically verified in a Maryland study, in which it proved quite useful for directly comparing the outcomes of different transit alternatives. However, there are some problems with the application of the model to Honolulu. Brand and Benham (*29*) cautioned that long-run elasticities should be used in any application of the model and that the elasticities used should be appropriate for the study area.

Unfortunately, no long-run elasticities derived specifically for Honolulu are used in making Honolulu's ridership projections (*27*). Although the incremental model used for these projections uses some of the same actual and projected demographic data that were tested in the models (fare, employment, population, and visitors), the long-run elasticities of these variables for transit in Honolulu have not been taken into account by project planners (*27*). Instead, the model arbitrarily assigns an elasticity of unity to population and employment changes to estimate their combined effects on transit ridership. Summed to form a single variable, the percentage change in population plus employment between the base (1985) and target (2005) years is used as a growth factor for forecasting transit ridership, aside from the affects of service variables. As such, the model essentially assumes that transit ridership will grow in the future, provided that population and employment increase.

Although it is likely that improvements in transit service will increase ridership, findings do not support the assumption of growth that is embedded in the model now being used (*27*). The models indicate that transit ridership does not simply grow with increases either in population or employment. In both models, the income elasticity was opposite in sign and almost equal in magnitude to the elasticity for employment. That, as explained earlier, is mainly why the models forecast declining bus ridership as employment and income increase in the future.

The analyses also challenge the propriety of combining employment and population data into a single variable. Because these two variables are highly intercorrelated, they cannot simply be added together, or summed. Doing so falsely mag-

nifies their effects. Any linear combination of these factors that does not remove their common variance is statistically invalid. If their shared variance is removed, the added predictive value of population data, once employment values are known, is trivial.

Of course, the two models presented cannot be directly applied to forecasting ridership for the proposed rapid transit system. However, they do point to some deficiencies in the present model. The general trends for transit found in both models may be better estimates of future transit ridership. Related analyses, in which Gordon and Willson's (*8*) light-rail model was applied to Honolulu, also support this view (*30*). Thus, the potential improvements in transit service afforded by a rapid transit system may operate within the context of decreasing transit ridership and they may have to be sufficient to overcome this downward trend.

PROBLEMS IN ELASTICITY ESTIMATION

Studies attempting to measure the elasticity of transit demand have used a variety of research approaches and analytical techniques. For example, many studies of fare elasticity have used data from quasi-experimental demonstration projects in which fare is directly manipulated as an independent variable, or from "natural experiments" in which the effects of fare changes on transit ridership are observed (*4,12,31*). Another common research method is the cross-sectional analysis of travel behavior in some specified area at a given point in time using direct observation or survey methods (*11,12*). The third major approach in transportation research is the multivariate time series study, which, like cross-sectional research, attempts to determine the influence of a number of independent variables on travel behavior (*4–8*).

There are advantages and disadvantages to each type of research, including costs in terms of time and effort involved in data collection and analysis, data accuracy, and the reliability and generalizability of the results.

Some of the problems associated with different kinds of studies of transit demand are worth mentioning. The natural experiment, for example, cannot clearly differentiate between the effects of the independent variable and possible effects of extraneous variables, which may include seasonal variations, secular trends, and variations in supply and service adjustments that may occur during the same period of time (*11*). True quasi-experimental designs are able to overcome this problem of identification by measuring all relevant variables to see if a change in some extraneous variable is likely to account for, or contribute to, the observed change in the dependent variable.

A second type of problem is more common, even when a valid quasi-experimental design is used. Often data are collected only for two points in time that are separated by a relatively brief interval—typically a few months at best (*11,12,18*); however, see the report by Lassow (*31*). In such cases, the time interval between the before and after (or pre- and posttreatment) measures of ridership provide only short-term elasticities (*4*) that may not accurately reflect long-term elasticities, and therefore may not meet long-term planning needs (*11*). The heart of the problem is the shrinkage ratio, which, when calculated in this way represents a point elasticity, and it is not possible to estimate long-term elasticity from a single point on a demand curve (*7,32*).

Cross-sectional studies suffer from a similar problem: because data are collected for a single point in time, they do not provide an estimate of long-term elasticity (*7,32,33*). Still, cross-sectional models are widely used, despite this drawback, because they usually take into account a broader number of variables (*34*), and the elasticities derived from such models often agree with expectations (*6,11*). However, they have been faulted for failing to provide an estimate of error of the parameter values used in the models, and there is no reason to believe that elasticities derived from current conditions will hold true outside the range of these initial conditions (*11*). Finally, because cross-sectional models are usually derived from survey research, they are, typically, quite expensive to conduct, and they are prone to various sources of error common to this methodology (*19*).

Time series models, using regression analysis, are generally less data intensive and can use data that already exist. Several useful forecasting models, incorporating various combinations of these factors, have been developed in recent years. These models, however, have been designed to model rail ridership (*5,7,8,35*), whereas the majority of mass transit is provided by bus systems. There are two limitations to this type of modeling, according to some planners. The first is that they usually consider only a small number of variables (*34*).

Two problems come into play to limit the number of variables that can be used in regression or time series models. The first problem is the availability of information over a sufficiently long period of time to validate the model. The second problem is multicollinearity (*35*), which means in essence that the independent variables of interest may be so highly correlated that they cannot be used together (*2*). This problem limited the variables used in the models and it raises concerns about the incremental model now used to forecast rapid transit ridership for Honolulu (*27*). Three of the four variables predicted by DBED (i.e., employment, population, and tourists) are so highly intercorrelated only one of them can be used in a given model; entering the others into the model did not improve its predictive ability.

The second criticism of time series regression models is that the aggregate data on which they are usually based do not provide a sufficient level of detail to meet the needs of transit operators (*6*).

The number of variables used in a model is irrelevant if the model is soundly based on economic theory and the model is a good historical predictor. As for the second point, different levels of detail are required for daily operations, project planning, and long-term planning. Long-term planning requires a look at long-term trends, and therefore requires a level of analysis commensurate with this objective. This result is best achieved by using historical data at the aggregate level. Aggregate data have the added advantage of having smaller sampling errors (*19*).

CONCLUSIONS

The economic definition of demand, which states that the quantity demanded of a good is inversely proportional to its price, has been used. Transportation planners sometimes lose

sight of this principle, tending to view demand as simply a volume of customers. In keeping with an economic perspective, income would be expected to have considerable influence on demand for transit. This was confirmed by the model, which indicates that the income elasticity for mass transit is negative and, therefore, that mass transit is an inferior good.

Most attempts to measure transit demand rely on cross-sectional studies. This usually entails expensive surveying techniques to collection information on age, sex, income, etc., and using that data to estimate the potential ridership of a particular system. Although every forecasting method has problems associated with it, cross-sectional studies seem to be particularly ill suited for meeting long-term planning needs, because they can provide only short-term elasticities. Ben-Akiva and Morikawa (*19*) have recently indicated how some of the shortcomings of cross-sectional surveys can be compensated for by combining this approach with results from aggregate analyses. Even so, the time and expense of surveys still make them prohibitive. Time series analysis provides an indirect, less costly way of observing consumer behavior by using statistical records of behavior. However, this method, like other nonexperimental methods, suffers from the identification problem. This problem can be overcome by gathering historical data on the major variables likely to affect transit demand and then by using the least squares multiple regression technique to get a fairly good and inexpensive estimate of their relative influence.

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DISCUSSION

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In the introductory section of this paper on empirical research in forecasting transit demand in Honolulu, the authors state that this approach is "well-suited for long-range planning." I would argue that the formulation and variable selection embodied in this model limits its application, at best, to relatively small variations in the existing structure and provision of bus service.

LONG-RANGE PLANNING LIMITATIONS

The Department of Transportation Services (DTS) of the city and County of Honolulu is currently involved in the preliminary engineering stage of the planning and design of a rapid transit system. The model structure outlined by the authors, with size of bus fleet as its only service-related variable, inherently lacks the ability to reflect the improved level of service and corridor capacity provided by this proposed investment. At a practical design level, the model is not sensitive, for example, to variations in alignment or station location. Even at a conceptual level, the unique opportunity for the capture of significant levels of additional (or the latent demand of) non-home based and visitor tripmaking by the rail system cannot be addressed by this approach. Extending this methodology to the analysis and evaluation of a rapid transit system would certainly be neither possible nor appropriate.

STRUCTURAL CONCERNS

Within any mathematical modeling framework (i.e., regression, cross-classification, logit), the inclusion and representation of an explanatory variable must be based on a logical and understandable hypothesis. The authors describe, in some detail, their basis and hypothesis for including each of the four model variables (employment, income, fare, and bus fleet size). However, no discussion is provided to substantiate the use of a natural logarithmic transformation for all of the variables. The net effect of this transformation is to reduce the variation and sensitivity of the changes in each variable over time. Unfortunately, the authors do not include any summaries of observed data for any of the 29 data points (years), and, therefore, it is not possible to examine the properties of the data either before or after their transformation. Even without such information or discussion, use of the natural logarithmic transformation would seem to seriously undermine the analysis.

From a statistical point of view, the authors indicate a rather substantial R^2 value for both forms of the model (i.e., revenue and linked trips). However, it would be beneficial to understand the relative contribution of each variable to the value of this statistic. Beyond employment, does each of the additional variables (income, fare, and size of bus fleet) add to the explanatory power? To what extent are the variables intercorrelated? Alternatively, if the dependent model variable were specified, for example, as annual trips per employee, then would the formulation and statistical results of the regression be of considerably more value?

CAUSAL RELATIONSHIPS

Beyond the mathematical properties of the model, and notwithstanding the limitations apparent for long-range forecasting, the choice of the four model variables themselves provides some concern as well. Although a measure of employment level is certainly an important factor in the choice of trip destination, the choice of mode (specifically, transit) is substantially affected by the density of that employment and the corresponding cost and supply of parking. With only total employment as a key model variable, these additional factors are not considered.

The use of income in the model reflects a level of transit usage that decreases as income increases. However, the 1986 On-Board Rider Survey indicated a rather substantial level of "choice" riders. That is, the choice to use transit in Honolulu goes well beyond the lack of an automobile or, simply, the relative tradeoff between time and cost. In fact, the system carries an atypical number of relatively higher-income passengers.

The single service variable, size of bus fleet, measures the quantity, not the quality, of service. Essentially, regardless of how buses are allocated to the system, the model responds with an identical result. This is because the variable is insensitive to the level of service provided by the competing transit and highway systems.

Finally, the use of fares as the only cost variable ignores the tradeoff between transit fare and automobile (operating and parking) costs.

CONCLUSIONS

Although the empirical research conducted by the authors may be appropriately applicable to generalized policy planning for the existing bus system in Honolulu, particular care needs to be taken in extending the conclusions suggested by the model beyond the explanatory capabilities of the model. Clearly the model cannot be applied in a setting that contemplates the construction of a rapid transit system.

Authors' Closure

We are happy to see that our paper stirred such concern about mass transit ridership forecasts for Honolulu, as evidenced by the immediate response to it (*1*). While our model expressly deals with Honolulu's bus system, we believe that our findings have implications for the fixed-guideway rapid transit system that is proposed for parts of the city.

LONG-RANGE PLANNING NEEDS AND GOALS

We agree with the discussant that our approach is best suited for general policy planning and that it is not applicable at the

project level. But his criticisms fail to distinguish between the goals and data needs of long- and short-term methodologies, which we discussed.

The goals of long-range planning are to understand the variables that affect demand for a product and to estimate how changes in these variables will affect future demand. Our models do this by determining the relative influences of key variables on mass transit ridership (demand) in Honolulu and by showing the consequences of future trends (*2*) on transit ridership. As we would not try to deduce from these trends where to place a bus stop, neither would we try to deduce where to put a particular train station. This is a question for the practical design level of project planning, as Davidson acknowledges. From a long-range planning perspective, however, the question is not where to build a train station but whether any should be built at all. The plans for the Honolulu rail transit system ignore significant, local (*3,4*) and national (*5*) transit trends, while their model gets lost in details (*6*).

It is not common practice to publish summaries of raw data and the discussant's complaint that we did not do so not only ignores the fact that the data sources were cited, but that the data are the same as those used by, and (in some cases) come from, the Honolulu Department of Transportation Services (DTS). Because the discussant quotes findings from an unpublished DTS survey, he surely must have ready access to all the data we used in constructing our models.

RELIABILITY OF MODEL FORECASTS

A concern was raised that the data transformations we made could reduce our models' sensitivity to changes in their variables over time. The transformation we used is a standard statistical procedure to linearize regressors (*7,8*) and the almost perfect fit of our model's estimates with actual ridership over a 30-year span, shown in Figure 1 of our paper, attests to the fact that the model is quite sensitive to changes in these variables.

The question of sensitivity should rightly be asked about the DTS model. The DTS model uses the same aggregated employment and population data we used but it disaggregates them into 190 traffic analysis zones (TAZs) for a base year (1985) and a target year (2005). Population and employment within each zone are summed to form a composite variable, and the percentage increase in this composite between the base and target years is used as a growth factor. Transit ridership for the base year is multiplied by the growth factor to estimate ridership for the target year (*6*). Because there are few zones in which the composite decreases, transit ridership is predicted to grow, independent of service and cost. Apart from the potential error in disaggregating the data and the probable impropriety of using this composite, which we discuss in our paper, one might ask how sensitive such a model is to observed changes over time?

Three distinct ridership trends are clear in Figure 1 of our report: a 20.5 percent decrease between 1957 and 1970 (ignoring the strike years); a 150.5 percent increase between 1972 and 1982; and a 1.4 percent decrease from 1982 to 1988. During the same time periods, the employment-population composite increased 50.9, 17.2, and 9.9 percent, respectively. Given the importance assigned to this composite as a growth factor in the DTS model, it is unlikely that it would be able to predict these past ridership trends.

Another statistical criticism was made that we did not provide enough information for the reader to determine the relative contributions of the variables to the models. This is not true. The direction and magnitude of the effects of each variable are provided by the formulas and elasticities, whereas their t and p values indicate that each makes a unique, significant contribution to the model. If it was common practice to list the partial correlation coefficients, we would have included them as well, but doing so would convey basically the same information in different form (*7,8*).

The adjusted R^2 values for the models demonstrate their statistical reliability, and we also presented measures of error for each model. In contrast, DTS provides no measurements of model error, nor has it done a sensitivity analysis to see how the model is affected by different assumptions about population and employment growth. DTS has not even tested the model's basic assumption that population plus employment is a good predictor of ridership.

In order to test this assumption, we summed base year transit trips into and out of each TAZ and regressed these values on the composite population and employment data for each of the 190 TAZs in the base year. The results of this analysis produced an R^2 value of 0.10, which indicates that the composite accounts for just 10 percent of the zonal variation in transit trips. With such a weak association between these variables, it is difficult even to predict base year trips from the base year employment and population data. The error rate of the predicted values, in terms of their mean absolute percentage error (MAPE), was above 120 percent. Is it likely that this model can accurately predict the future?

MODELING AND CAUSAL RELATIONSHIPS

The problem of assigning causality is particularly difficult whenever nonexperimental methods are used, as we discussed at some length in our paper. This, as we explained, is why the explanatory variables we chose were based on economic theory. In the absence of a theoretical framework, any number or manner of variables might be included in a model. Several recent studies point to the importance of transit vehicle size on ridership (*9,10*), yet this variable is not included in the DTS model. How might this variable effect DTS's ridership projections?

We repeatedly noted that bus fleet size provides only a crude measure of service, but it may not be as crude as some would think. Although data on vehicle-miles of service only go back to 1970, from 1970 to 1989 (the last year of our model) the correlation between number of buses and miles of service is $r = 0.93$. Despite the suggestion to the contrary, we examined the affects of automobile costs and availability, but they do not add to the explanatory power of the model; nor does the number of visitors. The suggestion that income must not influence ridership because the bus system has an "atypical number of relatively higher-income passengers" falls under the rubric of the fallacy of composition: i.e., erroneously generalizing from the parts to the whole.

CONCLUSIONS

We certainly do not believe that our models would apply to new and innovative transit alternatives like those being pursued in California and elsewhere. Nor have we advocated that our models be used to forecast ridership for Honolulu's fixed-guideway system. They were intended to model fixed-route, fixed-schedule mass transit, in short, a bus system. Because a fixed-guideway system epitomizes these transit characteristics, however, our models may have more relevance for such a system that we credit them with having.

Our findings regarding the ridership trends of the Honolulu bus system are consistent with forecasts used by Gordon and Willson (*11*) in other cities.

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