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A composite approach to forecasting state government revenues: Case study of the Idaho sales tax

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Abstract: Fiscal problems have led to increased reliance on economic and revenue forecasting by state governments in recent years. As a means of improving accuracy, many forecasters use alternative outlooks. Composite modeling goes a step further and allows analysts to systematically combine two or more forecasts. This paper examines the effectiveness of composite forecasting of sales tax revenues in Idaho. Base line projections are provided by an econometric model and a univariate time series model. The composite forecasts are found to outperform both base line forecasts. The combined forecasts are also found to be more accurate than the executive branch forecasts actually utilized from 1982 through 1985.

Keywords: Composite forecasting, Econometric modeling, State revenue forecasting, Univariate ARIMA analysis.

1. Introduction

Budgetary uncertainties have led state governments to rely ever increasingly on economic analysis in the 1980s. Because of the magnitude of the fiscal problems facing many states, forecasting has assumed a more central role in the policy making process. As a result, revenue forecasts are closely examined and accuracy is essential for planning purposes. To improve accuracy, staff analysts assemble as much information about their respective state economies as possible, including formal and informal consideration of alternative forecasts.

There are a variety of relatively easy and inexpensive methods for generating forecasts. One method for systematically incorporating alternative projections of economic variables into a new forecast is by linearly combining them [see Granger and Newbold, (1977)]. This approach has been successfully applied to several distinct areas including the demand for money [Mizrach and Santomero, (1986)], automobile sales [Keen, (1984)], personal income [Falconer and Sivesind, (1977)], and the demand for postal services [Guy and Waldau, (1984)]. When competing forecasts are combined, the resulting composite may be more accurate than any of the individual projections utilized, especially when the components provide complementary prediction information [Falconer and Sivesind, (1977, p. 7)].

Although composite modeling offers a straightforward method of forecasting economic variables, it has not been used extensively in budget planning activities by state and local governments. The objective of this paper is to develop a composite

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predictor of sales tax revenues for the state of Idaho and to compare its accuracy to that of the individual components. Subsequent sections of the paper include descriptions of revenue forecasting in Idaho, the forecasting methodologies employed, empirical analyses conducted, and suggestions for further research.

2. Revenue forecasting in Idaho

Independent revenue forecasts are developed by the executive and legislative branches of the Idaho state government. State law requires the governor to propose a budget to the legislature each year. A major input to the executive budget is the fiscal year revenue forecast, developed by the Idaho Division of Financial Management (DFM). The legislature is not required to use the governor's budget or the DFM revenue forecast. When the Idaho Legislature convenes each January, the Joint Revenue Projections Committee, comprised of members from both the House of Representatives and the Senate, holds hearings on the state of the economy. Testimony is presented by industry and government experts regarding Idaho business and fiscal conditions, as well as prospects for the next fiscal year, which runs from July 1 to June 30. Materials presented at these public hearings are usually of a general nature with only a few presentations offering detailed analyses of the state revenue outlook.

Based upon the information gained at these meetings, the Projections Committee decides upon its own revenue forecasts for each of the 18 categories of taxes and fees administered by the state. These forecasts are based entirely upon the materials provided by the individuals who testified to the committee; in this sense, the committee's forecast is a judgmental consensus forecast. Votes are taken on each revenue category. Most of the debate centers around the forecasts to be adopted for the sales, personal income, and corporate income taxes. The Senate and House then vote separately on whether or not to adopt the recommendations of the committee. Both chamber votes are generally unanimously in favor of the committee forecasts. The total projected revenue is then used as the basis for determining agency budgets and additional revenue requirements.

The executive branch, through DFM, presents the only comprehensive report examining all 18 sources of funds collected by Idaho state agencies. Econometric forecasting is the most extensively employed prediction technique relied upon by DFM, although smaller revenue classes may be forecasted entirely judgmentally. The cornerstone of these efforts is the Idaho Economic Model (lEM), an 85 simultaneous equation model of the state economy. The IEM provides forecasts of important state variables such as eight classes of personal income, single and multiple housing starts, net migration, 25 employment categories, and the labor force. Subsets of these variables are used as forecast inputs to regression equations estimated for individual revenue categories. Most of the exogenous inputs to the lEM are obtained from The WEFA Group's PC-Mark IX model of the U.S. economy. State forecasts are published triannually and the lEM is used to inform public officials about recent special events, such as plant closures, when needed. Further details on the IEM are available from the Summer 1987 issue of *Idaho Economic Forecast.*

While DFM develops detailed analyses, as Bretschneider, Gorr, Klay, and Grizzle (1989) note, the traditional rivalry between the two elected branches of state government causes the Projections Committee to scrutinize the executive forecast. This rivalry has become even more politicized during the 1980s due to budgetary strains and the fact that Democratic governors have faced overwhelming Republican majorities in both chambers of Idaho's bicameral legislature [for detailed discussions of the tax climate and budget difficulties faced in recent years, readers are referred to Duncombe and Kinney (1984), and Fullerton (1987a)]. The revenue forecast is a key element in determining the Governor's budget and thus influences fiscal policy initiatives of each session. Not surprisingly, the executive forecasts are not always adopted. In 1988, the Joint Revenue Projections Committee selected higher projections for eight of the 18 revenue classes.

As with many other state governments in the U.S. [see Bretschneider, Gorr, Klay, and Grizzle (1989)], it is hard to overstate the importance of the sales tax to Idaho revenues. Fiscal year 1989 (FY89) executive branch revenue projections estimate that the sales tax will support approximately 40% of the programs funded out of the

\$666 million General Account [Idaho Division of Financial Management (1988, p. 19)]. Gross sales tax collections are also earmarked to help finance city and county revenue sharing, county government functions, and water pollution control programs. Budgetary uncertainty over the past six years has led to five rate changes [see Fullerton (1987b)] and most public officials agree that the sales tax is the workhorse of Idaho public finance. Despite the introduction of two new personal income tax brackets in 1987, it is anticipated that gross sales tax collections will continue to be the single largest source of revenue in the Gem State [Idaho Division of Financial Management, (1988, pp. 20-25)].

3. Composite forecast models

Composite forecasting models are simply combinations of two or more different forecasts. By incorporating the information provided by several forecasts, the analyst attempts to reduce uncertainty concerning future values of the variables of interest [Keen, (1984, p. 47)]. The combined forecast variance will generally be smaller than that of any single forecast considered [Granger and Newbold (1977, p. 270)].

The most popular approach used to create composite forecasts is a linear combination. Reinmuth and Geurts (1979) propose determining the combination weights by regressing the actual values of the dependent variable(s) against the *n* different forecasts. In equation form, the model can be expressed as

$$A_t = \mathrm{Co} + c_1F_{1t} + \ldots + c_nF_{nt}\,, \qquad (1)$$

where A_t is the actual value of the forecast variable in period *t* and *Fit* is the ith forecast of *A* for the same period.

When the individual forecasts are unbiased, the constant term is expected to be zero and the sum of the slope coefficients is expected to equal one. If this is the case, it allows the modeler to save two degrees of freedom as he can avoid estimating the constant term and residually calculate one of the slope coefficients. This is useful when the number of forecast observations is small, a likely situation for many public sector forecasting experiments. Bates and Granger (1969) demonstrate that restricting the regression equation in this fashion provides weight estimates that are efficient within the class of linear forecast combinations.

Bias in any of the component forecasts does not represent a serious problem in calculating the combination weights. Unrestricted linear regressions that include constant terms can be used to calculate the weights for the individual forecast series [Granger and Ramathan (1984, p. 201)]. It should further be pointed out that Clemen (1986, p. 34) shows that even in cases where bias exists in the component forecasts, the weights constructed using the restricted coefficient method may provide forecasts that are superior to those of the unconstrained least squares composite weights. Both approaches are easily implemented and understandable.

For the work at hand, two forecasting methodologies are tested for their ability to predict sales tax revenues. The first utilizes a single equation econometric model that is run as a satellite to the IBM. The second employs ARIMA univariate time series analysis to accomplish the same objective. ARIMA models are very useful for forecasting seasonal time series such as quarterly sales tax receipts [see Pankratz (1983)].

In the econometric model, sales tax revenues are modeled as

$$TAX_t = b_o + b_1WSD_t + b_2PC_t + b_3Q_1 + b_4Q_2 + b_5Q_3 + U_t\,, \qquad (2)$$

where *t* denotes quarters 1, . . . , *T*, TAX_t stands for sales tax receipts, WSD_t for Idaho wage and salary disbursements, PC_t for the implicit price deflator for personal consumption expenditures, Q_i for the dummy variables for quarters one through three, and U_t for the disturbance term. The expected signs of the coefficients on WSD and *PC* are positive and negative respectively. Wage and salary disbursements are indicative of the level of disposable income in Idaho. Because wage and salary payments are directly related to payroll employment, they also reflect consumer sentiment in the state. The personal consumption price deflator provides a measure of retail price movements. The dummy variables account for seasonal variation in retail sales.

Ordinary least squares is used to estimate the parameters, except in cases where autocorrelation correction is necessary. For the latter case, an autoregressive moving average exogenous (ARMAX) nonlinear least squares correction technique is used [see Pagan (1974), and Challen and Hagger (1983)]. The structural parameters and the ARMA coefficients are jointly estimated.

As mentioned above, the second forecast component methodology tested in the well known Box-Jenkins univariate ARIMA technique. The general form of the ARIMA equations estimated here is

$$T_t = [Q_o + Q(B)Q^s(B)U_t] \\ /[(1- B)^d (1 - B^s)^D P(B)P^s(B)], \qquad (3)$$

where T_t represents the stationary working series calculated for the quarterly sales tax observations, Q_o the constant term, B the backshift operator, B^S the seasonal backshift operator, $Q(B)$ a moving average polynomial of order q, $Q^s(B)$ a seasonal moving average polynomial of order q^s, U_t the error term, d the degree of regular differencing required to induce trend stationarity in the working series, D the degree of seasonal differencing required to induce stationarity in the working series, $P(B)$ an autoregressive polynomial of order p, and $P^s(B)$ a seasonal autoregressive polynomial of order p^s.

4. Empirical analysis

4.1. *Data and experiment design*

Data on sales tax collections are available starting in 1967 from the Idaho State Tax Commission publication *Quarterly Sales Tax Report.* Presently, the sales tax rate is five percent, although, it has varied in recent years. A four percent rate was chosen as appropriate for this study because the five percent rate was initially only a temporary rate enacted to prevent a budget shortfall in FY87 [see Fullerton (1987b)]. Accordingly, the four percent rate is applied against all taxable sales in the sample. A time series plot of the rate-adjusted data is presented in Exhibit 1. Observations on the regressors used in the econometric specification are available from 1970 and can be found in *Idaho Economic Forecast* (1978-1987).

The sample test period is divided into two sub-periods, from the first quarter of 1978 through the fourth quarter of 1981, and from the first quarter of 1982 through the fourth quarter of 1985. Forecast data from the first sub-period, 1978: 1-1981: 4, are used to calculate the combination weights. Those weights are then used to calculate the composite forecasts for the second sub-period, 1982: 1-1985:4. Seven quarters is the maximum forecast horizon utilized in the test period. That corresponds to the length of forecast required for budget purposes by the Idaho State Legislature each winter. The models were fitted 16 times for each sub-period in order to develop the forecasts with the maximum amount of historical data available at those points in time. The number of forecasts for 1- through 7-steps-ahead are thus 16, 15, 14, 13, 12, 11, and 10 respectively.

4.2. *Econometric and univariate models*

Developing a composite forecast model as described in this article is a straightforward exercise; however, a large number of regressions and ARIMA models must be estimated and tested. Only a small subset of the modeling results are presented below. Readers who wish to obtain further results not reported may contact the author. The data included in the paper are adequate for purposes of highlighting the results of the modeling experiment and illustrating the methodology.

Results from the 16 forecast regressions in sub-period two, the composite test period, are presented in Exhibit 2. Numbers in parentheses are the individual parameter t-statistics. The estimated coefficients are all of the expected signs and are statistically significant. The seasonal dummies are significant and those associated with the third quarter are positive, reflecting increased retail sales associated with the school year and harvest activities. The coefficient estimates are roughly equivalent across all equations indicating that parameter heterogeneity is not a problem. Twelve of the equations are corrected for serial correlation. All of the models estimated have coefficients of variation greater than 0.95.

ARIMA modeling requires a stationary working series prior to estimation and diagnostic checking. As can be seen in Exhibit 1, the rate-adjusted sales tax data are seasonal and have a positive nonlinear trend in the mean of the series. To straighten the time trend of the series, a logarithmic transformation is necessary. Regular dif-

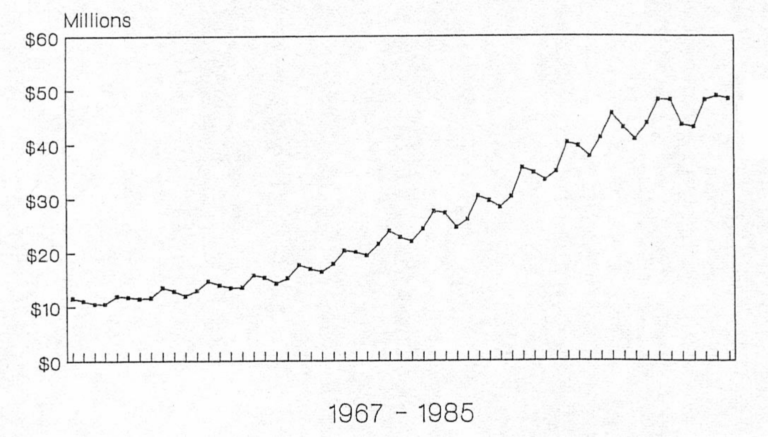

Exhibit 1. Quarterly sales tax collections.

Exhibit 2
Econometric model fitting results

Forecast origin	Constant	WSD	PC	Q1	Q2	Q3	MA(l)	AR(l)	MA(4)
1981:4	10.14 (8.51)	15.21 (20.96)	-16.54 (- 6.94)	-2.76 (- 8.36)	-1.61 (- 4.92)	1.64 (5.01)	0.52 (2.86)		
1982:1	10.45 (10.14)	15.30 (23.30)	-16.96 (- 8.05)	-2.84 (8.85)	- 1.65 (- 5.01)	1.64 (5.00)	0.47 (2.68)		
1982:2	10.45 (11.38)	15.34 (25.20)	-17.04 (- 8.89)	-2.84 (- 8.96)	-1.63 (- 5.12)	1.65 (5.09)	0.46 (2.69)		
1982: 3	9.77 (11.50)	14.98 (25.66)	-15.73 (- 8.70)	-2.90 (- 8.96)	-1.69 (- 5.23)	1.70 (5.24)	0.48 (2.75)		
1982:4	9.87 (12.26)	15.01 (27.14)	-15.90 (-9.44)	-2.86 (- 9.05)	1.63 (-5.17)	1.77 (5.61)	0.43 (2.58)		
1983:1	9.17 (10.73)	14.69 (24.24)	-14.72 (- 8.08)	-2.67 (-7.66)	-1.62 (-4.55)	1.77 (4.98)			
1983: 2	8.79 (11.18)	14.54 (25.40)	-14.14 (- 8.28)	-2.67 (- 8.03)	-1.51 (- 4.53)	1.79 (5.27)	0.41 (2.57)		
1983 : 3	7.95 (5.73)	14.15 (13.18)	- 12.65 (-4.01)	-2.70 (- 9.13)	-1.57 (-4.81)	1.89 (6.40)		0.43 (2.65)	
1983: 4	8.29 (6.94)	14.17 (14.98)	-12.99 (-4.74)	-2.63 (- 8.35)	1.44 (-4.13)	2.01 (6.56)		0.34 (2.22)	
1984: 1	8.57 (10.70)	14.39 (23.54)	- 13.68 (-7.62)	-2.74 (7.93)	- 1.50 (- 4.25)	2.01 (5.69)	0.39 (2.50)		
1984:2	8.95 (10.75)	14.44 (22.43)	-14.04 (-7.44)	-2.74 (-7.52)	- 1.66 (- 4.55)	1.95 (5.24)	0.40 (2.45)		
1984:3	8.48 (8.72)	14.41 (18.95)	- 13.66 (-6.15)	-2.74 (- 6.37)	-1.67 (- 3.88)	2.25 (5.23)			
1984:4	8.55 (8.82)	14.39 (19.16)	- 13.66 (-6.20)	-2.75 (- 6.57)	-1.68 (-4.02)	2.25 (5.38)			
1985 : 1	8.55 (8.99)	14.39 (19.27)	- 13.65 (- 6.24)	-2.80 (- 6.88)	- 1.68 (- 4.05)	2.25 (5.41)			
1985 : 2	8.65 (9.17)	14.31 (19.27)	-13.52 (- 6.20)	-2.82 (- 6.90)	- 1.84 (- 4.55)	2.30 (5.56)			0.29 (2.01)
1985:3	8.60 (9.26)	14.35 (19.52)	- 13.58 (- 6.29)	-2.81 (-7.02)	- 1.83 (- 4.58)	2.34 (5.84)			0.31 (2.10)

Exhibit 3
ARIMA Model fitting results

Forecast origin	MA(l)	AR(2)	SMA(4)	Q_{14}
1981: 4	-0.22 (- 1.94)	-0.34 (- 3.11)	-0.63 (- 4.06)	11.46
1982:1		-0.37 (- 2.91)	-0.70 (- 4.57)	10.15
1982:2		-0.37 (- 3.03)	-0.73 (-4.89)	11.20
1982:3		-0.34 (- 3.03)	-0.71 (-4.89)	10.15
1982:4		-0.36 (- 3.74)	-0.69 (-4.77)	11.07
1983 : 1		-0.34 (- 2.93)	-0.76 (- 5.31)	8.48
1983: 2		-0.34 (- 3.04)	-0.80 (- 6.06)	7.70
1983:3		-0.33 (- 3.06)	-0.76 (-5.77)	6.97
1983:4		-0.33 (- 3.11)	-0.75 (-5.74)	7.39
1984: 1		-0.33 (- 3.13)	-0.76 (- 6.09)	7.86
1984:2		-0.33 (3.18)	-0.77 (- 6.23)	7.69
1984: 3		-0.39 (- 3.58)	-0.79 (- 6.10)	10.81
1984:4		-0.37 (- 3.46)	-0.78 (- 6.10)	10.50
1985: 1	-0.17 (- 1.96)	-0.34 (- 3.27)	-0.79 (- 6.17)	11.62
1985:2	-0.15 (1.95)	-0.34 (- 3.29)	-0.78 (- 6.16)	10.81
1985:3	-0.18 (- 1.92)	-0.33 (- 3.26)	-0.78 (- 6.54)	11.73

ferencing or order one and seasonal differencing of order four are used to induce stationarity.

Results of the ARIMA modeling for sub-period two are reported in Exhibit 3. All 16 equations have autoregressive terms at lag two and seasonal moving average terms at lag four. Four equations have first order moving average terms in them. No equation has a statistically significant constant term. Numbers in parentheses are the calculated t-statistics. The last column of the table contains the Box-Pierce *Q* statistics estimated for 14 lags in the residuals. None of the *Q* statistics indicate that anything but white noise is present in the model residuals.

4.3. *Composite model and forecast results*

Individual tests for prediction bias for both methods were conducted by regressing the rate-adjusted sales tax collection data against the predicted values generated for each method in sub-period one. The data were grouped by the number of steps ahead forecasted, 1,2,..,7, prior to running the regressions for each forecast method. None of the constant terms for these tests is significantly different from zero at the five percent level. Consequently, it is assumed here that the forecasts are unbiased.

The appropriate composite forecast equation here is

$$A_t = c_o + c_1 F_{1t} + c_3 F_{2t}, \tag{4}$$

where F_{1t} is the econometric forecast at quarter *t* and F_{2t} is the ARIMA forecast at quarter *t.* Because the individual forecasts are unbiased, two degrees of freedom are saved by dropping the constant term and restricting the component weights to $c_1 + c_2 = 1$. This allows us to substitute $c_2 = 1 - c_1$ into (4) yielding:

$$(A_t - F_{2t}) = c_1(F_{1t} - F_{2t}). \tag{5}$$

This specification is run seven times, once for each step ahead forecasted.

Exhibit 4 presents the component weights for the forecast equation. The econometric predictions receive greater weights for all of seven forecast horizons, but there is no discernible pattern to the assignment of weights as the number of steps ahead forecast increases. Ashley (1983) has shown that there is no a priori reason to expect multivariate forecast models that rely on macroeconometric inputs to always perform better than univariate forecast equations. The evidence presented here does not indicate a consistent pattern of dominance by the econometric model. A more relevant issue is whether or not the ARIMA forecasts contribute additional information to the revenue predictions.

Exhibit 4
Component weights for the composite forecast equation.

Steps Ahead	Econometric Weight	ARIMA weight
1	0.56	0.44
2	0.74	0.26
3	0.73	0.27
4	0.79	0.21
5	0.51	0.49
6	0.54	0.46
7	0.84	0.16

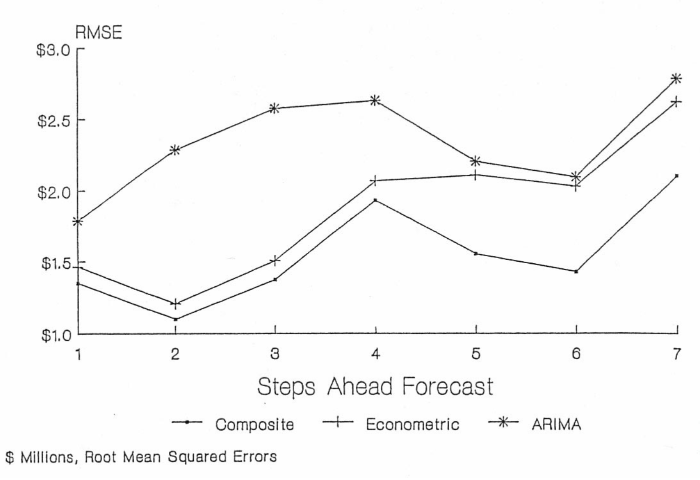

Exhibit 5. Model forecast errors.

Exhibit 5 illustrates the predictive performance of the three models. To evaluate each, the root mean squared error (RMSE) is used. The econometric predictions are more accurate than the time series extrapolations, but both individual models are outperformed by the composite forecasts at every step length. Compared to the econometric approach, the RMSE is reduced on. average by 15.4%. The degree of improvement is especially noticeable in quarters 5, 6, and 7, where the econometric forecasts are similar to the ARIMA projections in terms of accuracy. In the last three periods, the percentage improvement over the econometric model is 26.3, 29.7, and 21.7 respectively. This is a particularly interesting result because those are the quarters where any budget cutting typically occurs.

The value of the composite approach to Idaho sales tax forecasting is also illustrated in Exhibit 6. Data in column two of the table represent actual collections adjusted to a four percent tax rate for sample sub-period two. Column three contains the executive forecasts actually presented to the legislature in those years and described above. The entries in column five represent the fiscal year composite projections calculated from the last quarter of history available when the executive forecasts were estimated. In every case, the composite prediction is more accurate than that year's forecast. In fiscal years 1984 and 1985, the composite model errors were less than one percent.

5. Conclusion

Composite forecasting has proven useful in many business and federal government applications, but has not been extensively used by state and local public administrators. Because it is easy to apply and quickly implemented, composite modeling may prove very useful to government forecasters facing staff and budget limitations. Another consideration for less-populated states such as Idaho is that there are generally very few detailed and timely revenue forecasts available for comparison purposes. The few that are available should be used in an optimal fashion. The combined forecast's potential for improving accuracy

Exhibit 6
Rate adjusted sales tax collections and forecasts (millions of dollars).

Fiscal year	Rate adjusted collections	Executive forecast	Percent error	Composite forecast	Percent error
1982	194.478	209.857	7.9	199.563	2.6
1983	202.574	209.964	3.6	197.263	-2.6
1984	214.438	225.850	5.3	214.140	-0.1
1985	235.815	241.679	2.5	237.115	0.6

Source: Idaho Division of Financial Management and author's calculations.

makes it particularly useful during periods of fiscal uncertainty and sluggish economic growth.

The results reported here indicate that a composite model built with econometric and univariate ARIMA projections of Idaho retail sales tax receipts provides better forecasts than either single model. Predictions from these models seem complementary. Root mean squared forecast errors of the composite model were lower than those of either individual method, especially during the critical later quarter forecasts. The composite predictions also compare favorably with the executive forecasts presented to the Idaho legislature from FY82 to FY85.

It is worth noting that the Idaho sales tax series is relatively easy to model and forecast. In spite of the fact that both the econometric and ARIMA projections are very accurate, the composite predictions are superior at every step length forecasted. The combination of alternative forecasts may also prove beneficial when considering variables that are not easy to project. This speculation merits further investigation. Mizrach and Santomero (1986) provide evidence that composite forecasting is also useful when the structure of an economy is changing, a situation now being faced by the oil patch, agricultural, and high technology states throughout the U.S. Analysts facing structural and/or policy environment changes may also find composite modeling to be helpful. As a systematic means of combining different outlooks, the composite methodology appears to offer pubic sector analysts a sound approach to improving accuracy.

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