Evaluating State Revenue Forecasting under a Flexible Loss Function

By

Robert Krol*
Professor
Department of Economics
California State University, Northridge
Northridge, CA 91330-8374
Robert.krol@csun.edu
818.677.2430

March 2011
(Revised June 2012)

Abstract

This paper examines the accuracy of state revenue forecasting under a flexible loss function. Previous research focused on whether a forecast is rational, meaning forecasts are unbiased and actual forecast errors are uncorrelated with information available at the time of the forecast. These traditional tests assumed that the forecast loss function is quadratic and symmetric. The literature found budget forecasts often under-predicted revenue and used available information inefficiently. Using California data, I draw the same conclusion using similar tests. However, the rejection of forecast rationality might be the result of an asymmetric loss function. Once the asymmetry of the loss function is taken into account using a flexible loss function, I find evidence that under-forecasting is less costly than over-forecasting California's revenues. I also find the forecast errors that take this asymmetry into account are independent of information available at the time of the forecast. These results indicate that failure to control for possible asymmetry in the loss function in previous work may have produced misleading results.

* I would like to thank Shirley Svorny, a referee, and the Editor Graham Elliott for helpful comments.

INTRODUCTION

Sound state government budget planning requires accurate revenue forecasts. The rational expectations approach has been used to evaluate the accuracy of state revenue forecasts.[1] A rational revenue forecast should be unbiased and forecast errors uncorrelated with information available at the time of the forecast. The research in this area often rejects forecast rationality.

Underlying any forecast is the loss function of the forecaster. The tests used by Feenberg, Gentry, Gilroy, and Rosen (1989) and others assumed forecast loss functions are quadratic and symmetric. This models the cost of over-predicting revenues as equivalent to under-predicting revenues. The literature finds a tendency for forecasts to under-predict revenues and use available information inefficently. However, systematic under-prediction of revenues can be rational if the costs of under-predicting revenues are less than those associated with over-predicting revenues. This possibility suggests the literature's rejection of revenue forecast rationality might be wrong.

This paper addresses these issues by conducting tests using data from California. California is an interesting case to examine for a number of reasons. First, it is a large economy with a gross state product of approximately $1.8 trillion dollars, almost 14 percent of the U.S. gross domestic product. Second, the state's general fund revenue reached a high of $102.5 billion dollars in fiscal year 2007/2008. Finally, given the state's progressive tax structure, revenues are volatile making forecasting a challenge.

Like the previous literature I first examine whether the revenue forecasts are unbiased and efficient assuming a symmetric loss function. I then adopt Elliott, Komunjer, and Timmermann's (2005) method to test rationality. Their approach uses a flexible forecast loss function where symmetry is a special case. This approach allows the researcher to estimate an asymmetry parameter to determine whether revenue forecasters view the costs associated with an under-prediction as being the same as an over-prediction of revenues. Within this framework it is also possible to test whether forecasters have successfully incorporated available information into their forecasts.

Revenue forecasting accuracy is important because forecast errors can be politically and administratively costly. An over prediction of revenues can force program expenditure cuts or unpopular tax increases during the fiscal year. Under-predicting revenues results in the underfunding of essential programs and implies taxes may be too high in the state. Both types of forecast errors require midcourse adjustments in the budget. In some situations, "unexpected" revenues that result from under-predicting might be a way to increase the discretionary spending power of the governor. Finally, both types of forecast errors generate bad press that can impact election results. Bretchshneider and Schroeder (1988), Gentry (1989), Feenberg, Gentry, Gilroy, and Rosen (1989), and Rogers and Joyce (1996) argue that the political and administrative costs associated with overestimating are greater than for underestimating tax revenues.

Using different states and time periods, Feenberg, Gentry, Gilroy, and Rosen (1989), Gentry (1989), Bretchshneider, Gorr, Grizzle, and Klay (1989), and Rogers and Joyce (1996) all find state revenue forecasters tend to under-predict. This is referred to as the "conservative bias" in revenue forecasting. In contrast, Cassidy, Kamlet, and Nagin (1989) and Macan and Azad (1995) do not find significant bias in state revenue forecasts. Feenberg, Gentry, Gilroy, and Rosen (1989), Gentry (1989), and Macan and Azad (1995) find forecast errors to be correlated with economic information available at the time of the forecast, suggesting forecasts could be improved with a more efficient use of economic data.

I examine revenue forecasts for California's General and Special Funds, as well as revenue forecasts for sales, income, and corporate taxes for the period from 1969 to 2007. This time period includes six economic downturns that are always a challenge to revenue forecasters. Assuming the loss function is symmetric, the traditional tests reject the unbiased revenue forecast hypothesis 70 percent of the time. It appears state revenue forecasters tend to underestimate revenue changes. The null hypothesis is that there is no relationship between revenue forecast errors and economic data available at the time of the forecast was rejected in 75 percent of the cases examined.

These results are similar to Feenberg, Gentry, Gilroy, and Rosen (1989) and Gentry (1989) who find a systematic underestimation of revenues forecasts for New Jersey, Massachusetts, and Maryland.[2] They differ from Mocan and Azad (1995) who examine a panel of 20 states covering the period 1985 to 1992 but find no systematic under- or over-prediction in general fund revenues. All of the empirical tests find a correlation between forecast errors and information available at the time of the forecast. Based on these results, revenue forecasts do not appear to be rational. `

These results suggest revenue forecasts are not rational or efficient. Alternatively, they may reflect the higher cost associated with over-predicting revenues. Once the asymmetry of the loss function is taken into account, the results change dramatically. First, the estimated loss function asymmetry parameter indicates that underestimating tax revenues is less costly for the vast majority of forecasts evaluated than overestimating tax revenues. Second, rationality can be rejected in only one case. California forecasters appear to produce conservative tax revenue forecasts and use available information efficiently. These results call into question previous work evaluating tax revenue forecasting that conclude state tax revenue forecasts are not rational, systematically under-forecasting revenues. Instead, the "conservative bias" in revenue forecasting is a rational response to the forecast-error costs confronted by forecasters.

This paper is organized in the following manner. The first section defines rational forecasts and explains how the tests are implemented. The second section discusses the budget process in California and data issues. Section three presents the results.

DEFINING AND TESTING FORECAST RATIONALITY

A. Symmetric Loss Function

The rational expectations approach has been used to evaluate a wide range of macroeconomic forecasts. This approach typically assumes that the forecast loss function is quadratic and symmetric. It is popular in the forecast evaluation literature because it has the attractive property that the optimal or rational forecast is the conditional expectation which implies forecasts are unbiased (Elliott, Komunjer, and Timmermann, 2005, 2008).[3]

Rationality assumes that all information available to the forecaster is used. Complicating the analysis, the actual data used by the forecaster is not known by the researcher. Without this data, researchers test whether the observed forecast is an unbiased predictor of the economic variable of interest.

The first test examines forecasts of the change in revenues from one fiscal year to the next. Regression (1) tests whether the observed forecasted change in revenues is an unbiased predictor of the actual change in revenues.

(1) $$R_{t+h} = \alpha + \beta F_t^h + \mu_t$$

Here R_{t+h} equals the percentage change in tax revenues from period t to period t+h. In this paper the change is from one fiscal year to the next. F_t^h equals the forecasted h-period ahead percentage change in tax revenues made in period t. α and β are parameters to be estimated. μ_t is the error term of the regression. An unbiased revenue forecast implies the joint null hypothesis that α=0 and β=1. Rejecting this joint hypothesis is a rejection of the idea that the forecast is unbiased.

The second test for rationality requires that forecasters use available relevant information optimally. This notion is tested by regressing the forecast error in period t on relevant information available at the time of the forecast. This test is represented by regression (2).

(2) $$\varepsilon_t = \gamma + \eta_1 X_t + \eta_2 X_{t-1} + \nu_t$$

Where ε_t equals the forecast error in period t. X_t and X_{t-1} represent information available to the forecaster at time t and t-1.[4] η_1, and η_2 are parameters to be estimated. γ is the constant term to be estimated. ν_t is the error term of the regression. The joint null hypothesis is $\eta_1 = \eta_2 = 0$. Rejecting the null hypothesis indicates information available to the forecaster was not used and could have reduced the forecast error (See Brown and Maital, 1981).

B. Asymmetric Loss Function

Elliott, Komunjer, and Timmermann (2005) present an alternative approach for testing forecast rationality. A flexible forecast loss function allows the researcher to estimate a parameter which quantifies the degree and direction of any asymmetry present in the forecast loss function. Under certain conditions, a biased forecast can be rational.

In the context of this paper, the conservative bias found in the literature (and in this paper) reflects the higher costs associated with an optimistic forecast. Using the flexible forecast loss function, Elliott, Komunjer, and Timmermann (2005) examine IMF and OECD forecasts of budget deficits for the G7 countries. Once asymmetry is taken into account, the forecasts appear rational.

Capistrán-Carmona (2008) applies this approach to evaluate the Federal Reserve's inflation forecasts. Earlier work in this area rejected rationality (Romer and Romer, 2000). However, once the asymmetry of the loss function is taken into account, the Federal Reserve's inflation forecasts appear to be rational.

This paper will apply this approach to the evaluation of California's tax revenue forecasts. Equation three is the flexible loss function used in this paper.

(3) $L(\varepsilon_{t+h}, \varphi) = [\varphi + (1 - 2\varphi)\ 1_{(\varepsilon_{t+h<0})}]\ |\ \varepsilon_{t+h}\ |^p$

$L(\varepsilon_{t+h}, \varphi)$ is the loss function, it depends on the forecast error and asymmetry parameter φ. $1_{(\varepsilon_{t+h<0})}$ is an indicator variable that takes on the value of one when the forecast error is negative and zero otherwise. Following Capistrán-Carmona (2008), the parameter p is set equal to two, implying a quadratic flexible loss function is quadratic. This also allows φ to be identified for estimation.

Capistrán-Carmona (2008) shows that the relative cost of a forecast error can be estimated as $\varphi / 1 - \varphi$. If φ were to equal 0.75, then under-forecasting revenues would be 3 times more costly than over-forecasting revenues. If φ equals 0.20, then the cost of under-prediction is one-fourth the cost of an equivalent over-prediction. The parameter φ has the following interpretation. When φ = 0 .5 the loss function is symmetric. When φ > 0.5, under-prediction is more costly than over-prediction. Finally, if φ < 0.5, then over-prediction is more costly than under-prediction (see Elliott, Komunjer, and Timmermann, 2005). A conservative bias is rational if state revenue forecasters perceive under-predicting tax revenues to be less costly than over-predicting tax revenues, φ would be significantly less than 0.5.

In order to derive the orthogonality condition associated with a rational forecast and to estimate φ, we assume that tax revenue forecasters minimize the expected loss function conditional on information available at the time of the forecast. This results in an orthogonality condition:

$$E[\omega_t (\varepsilon_{t+h} - (1 - 2\varphi) \mid \varepsilon_{t+h} \mid)] = 0. \quad (4)$$

In (4) ω_t is a subset of all available information. $(\varepsilon_{t+h} - (1 - 2\varphi) \mid \varepsilon_{t+h} \mid)$ is referred to as the generalized forecast error. The actual forecast error is adjusted for the degree of asymmetry and the absolute size of the forecast error. Under asymmetric loss, rationality requires that the generalized forecast error rather than the actual forecast error be independent of the information available to the forecaster. Tests using the actual forecast error result in an omitted variable problem that leads to biased coefficients and standard errors (Capistrán-Carmona, 2008).

The Generalized Method of Moments estimator (GMM) developed by Hansen (1982) is used to get a consistent estimate of φ.[5] When more than one variable from the information set is used as an instrumental variable in estimation, the model is over-identified and Hansen's J-test can be used to test if the orthogonality condition holds for these variables.

BUDGET PROCESS AND DATA

The California Constitution requires the governor to submit a budget to the legislature by January 10th during the preceding fiscal year. For example, Governor Brown submitted his 2011-2012 fiscal year budget on January 10, 2011. Included in the budget are revenue estimates for the 2011-2012 fiscal year for the general fund and special fund, including disaggregated revenue forecasts for various tax revenue categories. Following discussions with the legislature and the collection of additional data on the economy, a revised revenue estimate is made by May 14th. The legislature must approve the budget by a majority vote.[6] The governor is required to sign a balanced budget by June 15th.[7] Budget disagreements between members of the legislature and between the legislature and the governor may delay the final approval of the budget beyond June 15th.

While the exact information used in making the actual forecast is not available, I include past annual revenue forecast errors. In addition, to capture the behavior of the economy, I choose a set of national and state level variables that would be available to forecasters at the time of the revenue forecast. The data used to measure national economic conditions include final values for quarterly real GDP, the monthly consumer price index, and a monthly index that measures economic activity in the technology sector, which is important for California.[8] To measure the performance of the California economy I use final values of monthly unemployment, annual population, and quarterly personal income.[9]

The actual revenue data and revenue forecasts examined here come from the governor's budget proposal for each fiscal year.[10] Because data on the economy is provided on a calendar basis, and the frequency of the data used in the analysis varies from monthly to annual, it is necessary to make an assumption as to the data available at the time of the forecast. To ensure that the data is available to the forecasters when the forecast is made, I use lagged values of the data based on the official release dates of each variable included in the analysis.

For regressions that test whether forecast errors are independent of available information, the measure used depends on the time frame for which the data is available. For the January forecast using monthly data, I include the percentage change in the variable of interest between October - August and August - June of the preceding year in the regression.[11] For data available on a quarterly basis, I include the percentage change in the variable of interest between third - second quarters and second - first quarters of the previous calendar year in the regression. For the one annual variable population, I use the growth rate from the previous calendar year.

For tests of the May forecast, when data is available on a monthly basis, I include the percentage change in the variable of interest between February (of the current calendar year) – December (of the previous calendar year) and December (of the previous calendar year) – September (of the previous calendar year) in the regression. For data available on a quarterly basis, I include the percentage change in the variable of interest between fourth quarter (of the previous calendar year) - third quarter (of the previous calendar year) and third - second quarters of the previous calendar year in the regression. For the annual variable, population, I use the growth rate from the previous calendar year.

Political factors may also influence revenue forecasts. I include three political dummy variables to take this into account. The first dummy variable equals one if the governor is Republican and is zero otherwise. This captures Republican control of the executive branch and a divided government.[12] The second dummy variable equals one in an election year and is zero otherwise. The third political dummy variable equals one during the first year of a governor's term and is zero otherwise (see Feenberg, et al. (1989), Gentry (1989), Bretschneider and Gorr (1992), and Macan and Azad (1995)).

EMPIRICAL RESULTS

A. Summary Statistics

Revenue forecasts for the general fund, special fund, sales tax, income tax, and corporate tax are evaluated for the period 1969 to 2007.[13] There can be some advantages to examining both total general fund revenues and the components. The uncertainty or variability associated with some component revenues may be different from general fund revenues. As a result, the bias may differ for these individual revenue components. Revenues with greater uncertainty may have greater bias. The economic factors that have the strongest influence on individual revenue components may differ from those that influence the total general fund revenues, affecting the efficiency tests. For example, the sales tax might be relatively more sensitive to inflation (Gentry, 1989).

Figure 1 illustrates the forecast error for each revenue category over the sample period. The revenue error is calculated as the actual percentage change in a revenue category from one fiscal year to the next minus the government's forecasted change in that revenue category over the same period.[14]

We can draw three observations from Figure 1. First, forecast errors appear to be largest during recessions. It should come as no surprise that business cycle turning points make revenue forecasting difficult. Second, and also not surprising, the January forecast errors are generally larger than the May forecast errors. The additional five months of data on the economy improves forecasts. Third, the forecasted revenue tends to be less than actual revenue during expansions and greater than actual revenues during recessions. In other words, budget forecasters tend to under predict changes in revenues.

This can also be seen from the revenue forecast error summary presented in Table 1. In all cases except the January sales tax forecast, the errors are positive. The general fund forecast error is significantly different from zero. While the average percentage change in general fund revenues was 8.3 percent over the entire sample period, the average January forecast error was 2.4 percent. The May forecast error is half that amount.[15] Also, the mean percentage change and standard error differ between the various revenue sources. The income tax had the highest mean growth while the sales tax had the lowest. The variability is highest for the special fund and lowest for the general fund and sales tax. These differences make testing for bias and efficiency using the general fund and components of interest. The degree of asymmetry may also differ between the different revenue categories.

B. Symmetric Loss Function

Both regressions 1 and 2 assume the loss function is symmetric. They are estimated using ordinary least squares. Because the regression error term is likely to follow a serially correlated moving average process, the standard errors are estimated using the approach suggested by Newey and West (1987).[16]

Table 2 presents results testing whether California's revenue forecasts are unbiased. Included are the regression 1 parameter estimates and the p-value for the test of the joint null hypothesis that the intercept coefficient equals zero and the slope coefficient equals one. Test results are provided for the general and special funds, along with sales, income, and corporate taxes. The test is conducted for both the January and May revenue forecasts.

For the January forecast, the null hypothesis of an unbiased forecast is rejected in each case with p-values of .054 or less. The value of the slope coefficient β is less than one in each case, suggesting a tendency to under predict revenues.[17] The unbiased forecast hypothesis fares better for the May forecast. It is rejected with a p-value that is less than .05 for only the sales and income tax. In these two cases, the slope coefficient β is greater than one.

Table 3 presents Regression 2 results testing whether California's revenue forecasts efficiently incorporate information that is available at the time of the forecast. P-value estimates test the joint null hypothesis that current and lagged values of state or national variables have no impact on the forecast error. As stated above, the state economic variables included in the analysis are unemployment, population, and personal income. The U.S. economic variables included in the analysis are real GDP, the consumer price index, and the technology index. All variables are expressed as growth rates.

The null hypothesis is rejected with p-values less than .10 in 50 percent of the 30 regressions. The January forecast does worse than the May forecast. In the January case, available information is significant in 53 percent of the regressions. In the May forecast, available information is significant in 47 percent of the cases. The different results might reflect the more timely information available at the time the May forecast is made. It could also reflect problems with the loss function assumptions that underlie the tests. U.S. economic factors are significant 80 percent of the time. California economic factors have p-values near zero for all forecasts except for the special fund and the May sales forecast.

As noted above, political factors included are dummy variables that equal one in years when the governor is Republican, a gubernatorial election year, and the first year of a governor's term. The political factors do not appear to have a significant impact on forecast errors.[18]

These results raise an important question. Are the forecasts simply irrational and inefficient, or are the costs associated with optimistic forecasts greater than conservative forecasts. This issue is investigated further in the next section of the paper.

C. Asymmetric Loss Function

GMM estimates of the asymmetry parameter φ and its standard error are reported in Table 4. Also reported is the J-Statistic and p-value that test whether the forecaster's information is independent of the generalized error term. Since the econometrician does not know the exact information set used by the forecaster, it is common in the literature to use alternative information sets (Capistrán-Carmona, 2008, Elliott, Komunjer, and Timmermann, 2005 and 2008). Previous work used constants, lagged forecast errors, and variables that are likely to influence the forecast variable.

Rows A through C represent different combinations of instrumental variables used in the estimation in order to determine the robustness of the results. Each estimate is based on an alternative set of instrumental variables that were part of the information set used in the previous analysis. Set A includes a constant and forecast errors lagged 1 and 2 periods. Set B includes a constant, forecast errors lagged 1 and 2 periods, lagged CA unemployment, lagged CA personal income, and lagged CA population. Set C includes a constant, forecast errors lagged 1 and 2 periods, lagged tech pulse index, lagged CPI inflation, and lagged real GDP growth.

Each estimate of φ is significantly different from zero at the one percent level. In 24 of the 25 estimates of φ less than 0.5, the parameter estimate is significantly less than 0.5 at the one percent level. These results suggest forecasters operate under conditions where under-prediction is less costly than over-prediction. When φ is equal to .20, the cost of under-prediction is one-fourth the cost of an equivalent over-prediction. For the May general fund forecast, estimates of φ are higher but still significantly less than 0.5. Only the January sales tax revenue forecast and two corporate tax estimates fail to reject the null hypothesis that φ equals 0.5. These results support the idea that over-estimating the general fund, income tax, the May sales tax, and the special fund revenues appears to be more costly than under-forecasting tax revenues.

Gentry (1989), Batchelor and Peel (1998), and Capistrán-Carmona (2008) show the size of the bias is a function of the variability of the variable being forecast. Batchelor and Peel show the optimal forecast depends negatively on the expected conditional error variance. The optimal forecast ends up being less than the expected conditional mean in the case when over prediction is more costly. This suggests the conservative bias found in the revenue forecast should be larger for those revenue sources with greater forecast uncertainty.

In the context of this paper, the asymmetry parameter φ should be smaller for revenue series with larger forecast error variability. There is some evidence supporting this idea in this paper. The May forecast error variability is less than the January forecast error variability. In the cases where there was a conservative bias associated with each forecast, 55 percent of the time the bias was less for the May forecast. The special fund has the highest forecast error variability and the lowest asymmetry parameter values. The sales tax revenue has the lowest forecast error variability and high values for the asymmetry parameter. Income tax revenue forecast error variability is moderate and the asymmetry parameter lies between special fund and sales revenue values. Corporate forecast error variability is also moderate yet the asymmetry parameters are high. The general fund forecast error variability is low and so is the asymmetry parameter values. The last two results are not consistent with the idea that a lower asymmetry parameter value is associated with higher forecast error variability.

Overall, the general fund, the May sales revenue, income revenue, and special fund forecasts have asymmetry parameters less than 0.5. These results provide specific evidence and generally support the conclusion that tax revenue forecasters view an under-forecast as being less costly than an over-forecast.

The second question concerns whether forecasters use information about the economy efficiently, whether forecasts are rational. The test results under an asymmetric loss function are dramatically different from those under a symmetric loss function. In all but one model estimated, the generalized forecast error is independent of the variables included in the information set, suggesting that forecasters use information about the economy efficiently; the forecasts are rational.

These results differ from previous studies that failed to allow for asymmetry in the forecast loss function. California tax revenue forecasters tend to have a conservative bias, generally under-predicting revenues. In addition, they appear to efficiently incorporate information on the economy into their revenue forecasts.

CONCLUSION

I first examine forecast rationality assuming a symmetric loss function using data from California. Regressions were estimated to test whether the revenue forecast is unbiased. Additional tests were conducted to determine if the actual forecast errors are uncorrelated with information available at the time of the forecast. The unbiased forecast hypothesis was rejected in seven out of ten cases. In addition, actual forecast errors are correlated with available economic data in 15 of the 20 cases.

Once the asymmetry of the loss function is taken into account, the results are significantly different. The estimate of the asymmetry parameter is consistent with forecasters facing an objective function in which under-predicting revenue is less costly than over-prediction. Furthermore, there is nearly no evidence against the rationality hypothesis. These results indicate that failure to control for possible asymmetry in the loss function in previous work may have caused researchers to misjudge the accuracy of state revenue forecasts.

While California's tax revenue forecasts appear to be conservative and rational, it would be a mistake to generalize this evidence for other states. Past research has drawn different conclusions using different states and periods. In addition, California is a state with a large budget and it may devote more resources to revenue forecasting than other states.

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Table 1

Summary Statistics of Revenue Forecast Errors

Revenue Category	Actual % Change	January Forecast	May Forecast
General Fund	.083*	.024**	.012***
	(.011)	(.012)	(.007)
Sales Tax	.072*	-.001	.003
	(.011)	(.010)	(.003)
Income Tax	.101*	.027	.022
	(.020)	(.021)	(.010)
Corporate Tax	.079*	.014**	.007
	(.019)	(.023)	(.011)
Special Fund	.075	.067	.058
	(.072)	(.053)	(.052)

The revenue forecast error equals the actual percentage change in revenue minus the forecasted percentage change in revenue. Significance levels for testing the null hypothesis the mean statistic is zero are * one percent level, ** five percent level, and *** ten percent level. The sample period equals 1969 to 2007.

Table 2

Test Results for Unbiased Forecasts Assuming a Symmetric Loss Function

Rev. Category	A	β	R bar squared	P-Value
General Fund				
Jan. Forecast	.059	.415	.152	.000
	(.010)	(.126)		
May Forecast	.016	.956	.622	.130
	(.008)	(.075)		
Sales Tax				
Jan. Forecast	.029	.588	.335	.001
	(.014)	(.129)		
May Forecast	-.001	1.06	.366	.050
	(.004)	(.039)		
Income Tax				
Jan. Forecast	.079	.298	.010	.008
	(.026)	(.262)		
May Forecast	.015	1.091	.766	.009
	(.017)	(.123)		
Corporate Tax				
Jan. Forecast	.063	.247	.020	.000
	(.019)	(.177)		
May Forecast	.011	.946	.660	.743
	(.015)	(.083)		
Special Fund				
Jan. Forecast	.068	.885	.443	.054
	(.050)	(.091)		
May Forecast	.059	.989	.460	.282
	(.049)	(.043)		

The P-Value is for testing the joint null hypothesis that the regression intercept equals zero and the slope equals one. The sample period equals 1969 to 2007.

Table 3

P-Values for Tests of Information Efficiency Assuming a Symmetric Loss Function

Revenue	CA Factors	U.S. Factors	Political
Gen. Fund			
Jan. Forecast	.000	.000	.540
MayForecast	.070	.004	.581
Sales Tax			
Jan. Forecast	.000	.000	.242
MayForecast	.136	.001	.146
Income Tax			
Jan. Forecast	.000	.000	.756
MayForecast	.000	.000	.427
Corp. Tax			
Jan. Forecast	.000	.088	.342
MayForecast	.002	.029	.126
Spec. Fund			
Jan. Forecast	.458	.410	.593
MayForecast	.608	.490	.145

CA factors include lagged state unemployment, population, and personal income. U.S. factors include lagged chained real GDP, the aggregate consumer price index, and a technology index. Political variables includes a dummy variable for Republican governor, election year, and first term of the governor. The sample period equals 1973 to 2007. The sample period for the political variables equals 1969 to 2007.

Table 4

GMM Estimates of φ and Orthogonality Tests

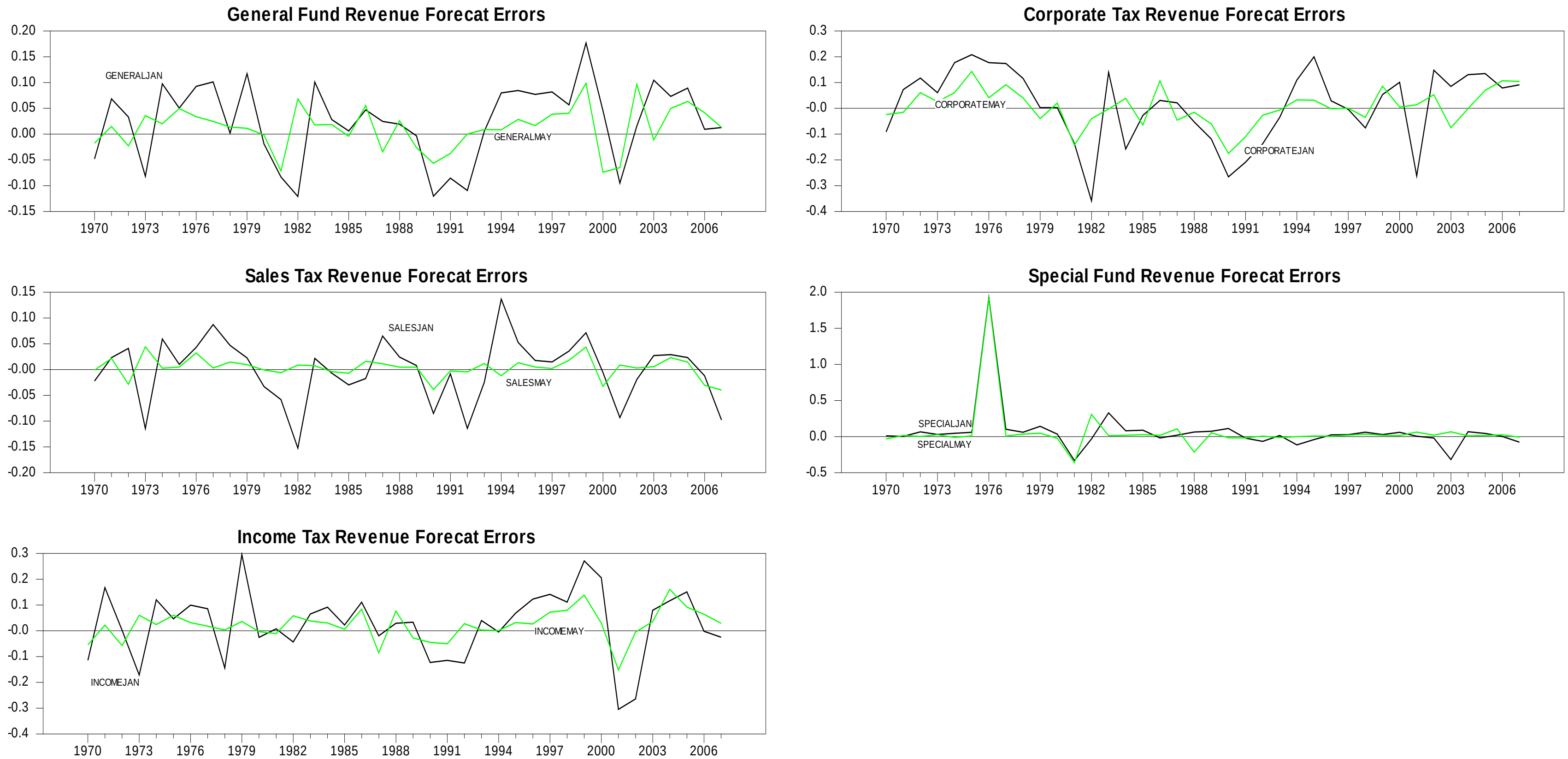
Revenue	φ	Standard Error	J-Statistic	P-Value
Gen. Fund Jan. Forecast				
A	.21	.011	5.33	.07
B	.21	.013	6.28	.51
C	.22	.009	5.97	.65
Gen. Fund May Forecast				
A	.31	.008	0.11	.95
B	.26	.007	6.22	.52
C	.39	.002	7.25	.51
Sales Tax Jan. Forecast				
A	.54	.013	2.23	.33
B	.61	.011	7.97	.34
C	.53	.012	4.74	.79
Sales Tax May Forecast				
A	.41	.010	0.78	.68
B	.43	.017	6.07	.53
C	.47	.0003	7.88	.45
Income Tax Jan. Forecast				
A	.33	.011	1.57	.46
B	.31	.008	4.74	.69
C	.44	.009	5.95	.65
Income Tax May Forecast				
A	.25	.008	0.27	.88
B	.23	.009	5.13	.64
C	.41	.0007	6.39	.60
Corporate Tax Jan. Forecast				
A	.44	.017	3.46	.18
B	.67	.011	7.90	.34
C	.48*	.010	7.64	.47
Corporate Tax May Forecast				
A	.35	.017	3.68	.16
B	.52*	.011	7.32	.40

C	.45	.001	7.22	.51
Special Fund Jan. Forecast				
A	.20	.016	3.48	.18
B	.04	.003	5.34	.62
C	.20	.007	4.84	.77
Special Fund May Forecast				
A	.11	.010	0.87	.65
B	.21	.009	5.63	.58
C	.24	.002	6.44	.60

The * superscript on a coefficient indicates a failure to reject the null hypothesis that the coefficient equals .5 versus the alternative hypothesis that the coefficient is less (or greater when $\varphi > .5$) than .5 at a one percent level. Each estimate is based on an alternative set of instrumental variables. Set A includes a constant and forecast errors lagged 1 and 2 periods. Set B includes a constant, forecast errors lagged 1 and 2 periods, lagged CA unemployment, lagged CA personal income, and lagged CA population. Set C includes a constant, forecast errors lagged 1 and 2 periods, lagged tech pulse index, lagged CPI inflation, and lagged real GDP growth.

Figure 1

Actual Percentage Change in Revenue Minus Forecasted Percentage Change in Revenue



Endnotes

[1] The main papers in this research area include Feenberg, Gentry, Gilroy, and Rosen (1989), Bretchshneider, Gorr, Grizzle, and Klay (1989), Gentry (1989), Cassidy, Kamlet, and Nagin (1989), Macan an Azad (1995), and Rogers and Joyce (1996).
[2] Gentry (1989) breaks down the New Jersey forecast into the six largest revenue components. He rejects rational forecasts for total revenue. While there is some variation among the revenue components results, rationality of the forecasts is rejected most of the time.
[3] Other properties include that a h-step ahead forecast error is uncorrelated beyond h-1 and the unconditional variance of the forecast error is a non-decreasing function of the forecast horizon.
[4] Additional lags can be used depending on the particular forecast examined.
[5] Also see Hamilton (1994) for a good discussion of GMM.
[6] Prior to 2010, a two-thirds majority was required for budget passage.
[7] The requirement that the governor must sign a balanced budget has only been in effect since the 2004-2005 fiscal year. Prior to that time, the governor was only required to propose a balanced budget in January.
[8] Hobijn et. al. (2003) construct an index that is designed to capture economic activity in the tech sector of the economy. The index includes information on technology employment, production, shipments, investment, and consumption. The data was downloaded from www.frbsf.org/csip/pulse.php.
[9] The CPI and state unemployment rate data were downloaded from the Bureau of Labor Statistics at www.bls.gov. Real GDP and state personal income were downloaded from the Bureau of Economic Analysis at www.bea.gov. Population data were taken from the California Statistical Abstract at www.dof.ca.gov/.
[10] Budget data was found in *California Budget* various issues and at http://dof.ca.gov/.
[11] For a forecast published in January 2007, the previous year is 2006.
[12] The California legislature has been controlled by Democrats over the time period covered in the paper except for the Assembly during the years 1996-7.
[13] Not all of the data series begin in 1969. As a result some of the regressions have shorter sample periods.
[14] In order to put things in a business cycle perspective, the NBER dates cyclical peaks during the sample period at 12/69, 11/73, 1/80, 7/81, 7/90, 3/01, and 12/07. Cyclical troughs occurred at 11/70, 3/75, 7/80, 11/82, 3/91, and 11/01.
[15] There are 26 Republican governor forecasts and 12 Democratic governor forecasts over the sample period. Given the small sample size, especially for Democratic governors, the distribution assumptions needed for statistical analysis of Democratic governors are not likely to hold. With this in mind, only for the May income tax revenue forecasts did the forecast of the Republican governors statistically differ from the forecast of Democratic governors at the one percent level.
[16] For either test or forecast, the error term will be a MA(1) process. Consider the December 2003 forecast for fiscal year 2004-5. The forecasters do not know the forecast errors for fiscal year 2003-4 or 2004-5, resulting in the MA(1) error term. The Newey-West procedure takes this correlation into account resulting in consistent standard errors.
[17] Batchelor and Peel (1998) show for certain classes of asymmetric loss functions, the intercept and slope coefficients of this regression can be biased downward increasing the chances of rejection.
[18] Cassidy, Kamlet, and Nagin (1989), Gentry (1989), Feenberg, Gentry, Gilroy, and Rosen (1989), and Macan and Azad (1995) also do not find evidence that political factors significantly influencing forecast accuracy. While Bretchshneider and Schroeder (1988) and Bretchshneider, Gorr, Grizzle, and Klay (1989) do find a significant relationship between forecast errors and political factors.