2014

State Revenue Forecasting Accuracy

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July 3, 2014

Preliminary DRAFT Results

Prepared for the Annual Conference of the

International Symposium on Forecasting

June 29-July 2, 2014

Rotterdam

*** Not for Citation or Quotation ***

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Abstract

This paper examines forecasting accuracy of state revenue forecasting for 50 states using data published on the National Association of State Budget Officer's (NASBO) website (www.nasbo.org). The data shows four categories of revenue: sales tax, corporate income tax, personal income tax, and all other (as a residual from total taxes). It shows some evidence that forecast bias reflects a hedge against uncertainty; however, there is also evidence that there is a counterbalancing preference to find the money needed to provide the services demanded.

State Revenue Forecasting Accuracy

That there is revenue forecast underestimation bias is well established (Blackley & DeBoer, 1993; S. Bretschneider & Schroeder, 1985; S. I. Bretschneider & Gorr, 1987, 1992; S. I. Bretschneider, Gorr, Grizzle, & Klay, 1989; S. I. Bretschneider, Straussman, & Mullins, 1988; Burkhead, 1956; Grizzle & Klay, 1994; Heinemann, 2006; Klay & Grizzle, 1992; Rodgers & Joyce, 1996; Voorhees, 2006; Williams, 2012) and it is frequently associated with political motivation. Williams (2012) shows that disaggregating revenue into components and horizons helps understand the characteristics of bias in New York City's revenue forecast. Williams' findings include that forecast bias may be different for different revenue types and that forecast bias exacerbates over longer horizons.

This paper examines forecast accuracy and bias among the 50 US states from 1993 through 2011 decomposing revenue into four parts, examining the influence of horizons, and examining potential explanatory factors that may be associated with revenue forecast bias. While it is understood that political motivation may influence forecast revenue forecast bias, what that influence is and how it affects bias is unclear. Forecast bias itself has subtle implications. Underforecasting revenue provides those responsible for managing the system a hedge against risk. However, it also legitimizes the preferences of those who wish to stem government growth or cut its size because lower estimates of revenue inhibit voluntary program growth.

Overall, there are many contradictory expectations. Those wishing to avoid taxes may wish to stem government growth and therefore prefer underestimation; but underestimation can lead to the belief that taxes must be raised, even when revenue is actually adequate. Those preferring to maintain or grow government services have similarly contradictory preferences: when there is a perception of adequate or surplus revenue, government services can be maintained or grow. However, when there is adequate revenue, policy makers will not intentionally grow revenue sources and they may even reduce taxes. Conditions that lead to intentional growth in revenue sources also lead to the view that perhaps government should shrink. These contradictory conditions leave it unclear who, other than risk averse managers, will prefer what level of underestimation.

Hypotheses

The most general hypothesis of this paper is that there is forecast bias and that the direction of the forecast bias is for underforecasting. This expectation is consistent with the vast majority of the literature cited and much more written elsewhere.

> **Hypothesis 1a:** There is a negative coefficient on an appropriate measure of forecast bias.

Williams (2012) shows that forecast bias is found with a various New York City revenue types when total revenue is decomposed. He shows that examining forecast detail provides deeper insight into bias.

> **Hypothesis 1b:** There is a negative coefficient on an appropriate measure of forecast bias with respect to Corporate Income Tax (CIT), Personal Income Tax (PIT) and Sales Tax (STax).

Williams (2012) shows that where there is forecast bias, it exacerbates over time, that is, there is a negative slope associated with the horizon. His literature review explains that this finding is common in in forecast methods literature that looks at forecast results over various horizons (Makridakis et al., 1982; Makridakis et al., 1993; Makridakis & Hibon, 2000).

Hypothesis 2: There is a negative coefficient on the measure of forecast horizon.

Michael Brogan (2012) shows that there is a linkage between forecast errors and the political cycle. He examines features such as political party of the governor (Democratic), term year of the governor (number of years remaining), an interaction between governor's party and party division in the legislature, and the share of vote received by the elected governor. He examines a complex "Democratic factor," which also has an effect and has an interaction effect with divided government. He finds a weak direct effect for party division in the legislature. These effects reflect a variety of possible political factors, which are included in this study. These findings suggest that bias will, in part, be explained by political party and electoral politics:

Hypothesis 3a: When the forecast is made by a Democratic administration (governor), there is an effect on the revenue forecast bias.

Hypothesis 3b: When the forecast is made by a third party administration (governor), there is an effect on the revenue forecast bias.

Hypothesis 3c: When the forecast is made in a state where there is a divided legislature, there is an effect on revenue forecast bias.

Hypothesis 3d: There is a relationship between revenue forecast bias and the governor's share of the vote in the most recent gubernatorial election.

Hypothesis 3e: When the forecast is made in the first year or a new governor, there is an effect on the revenue forecast bias.

Hypothesis 3f: When the forecast is made in the first year after a governor's party change to Democrat, there is an effect on the revenue forecast bias.

Hypothesis 3g: When the forecast is made in the first year after a governor's party change to Republican, there is an effect on the revenue forecast bias.

Hypothesis 3h: When the forecast is made in the first year after a governor's party change to Third Party, there is an effect on the revenue forecast bias.

Hypothesis 3i: The number of years remaining until the next gubernatorial election is associated with revenue forecast bias.

Hypothesis 3j: When the forecast is made in the most frequent legislative election year, there is an effect on the revenue forecast bias.

Hypothesis 3k: An interaction between divided government and governor's party (Democratic) is associated with revenue forecast bias.

Hypothesis 3l: Brogan's Democratic factor is associated with revenue forecast bias.

Hypothesis 3m: An interaction between Brogan's Democratic factor and the governor's party (Democratic) is associated with revenue forecast bias.

These hypotheses set out the broad set of political influences on the forecast process. Many of the data are coded as indicators, valued 1 when the condition is met and 0 otherwise, from National Center for State Legislature data and data from *Party affiliations in the state legislatures : a year by year summary,* *1796-2006* (Dubin, 2007). Brogan's Democratic factor is included using a dataset and Stata command functions supplied by Brogan through personal contact and is lagged one period.

Larger states may have more resources for their revenue forecast effort. If underestimation bias reflects budget official risk aversion, then where risk is mitigated in other ways, then the use of bias as means of achieving risk avoidance may be less attractive. Thus, larger states may have a smaller forecast bias. Simonsen, Robins and Helgerson (2001), found that jurisdiction size may serve as a proxy for jurisdiction management capacity. Management capacity may mitigate uncertainty in that where jurisdictions have more capacity, they are more confident of their actual forecasts and therefore need less of a hedge against mistaken over-forecasting

> **Hypothesis 4:** When the forecast is made by a larger state (by population), the forecast under-forecast bias is smaller.

In real world revenue forecasting, accuracy is thought to interact with the business cycle; however, the exact relationship is not clear. Empirical forecast methods follow trends, so as the business cycle accelerates, an under-forecast bias should become more severe; while as it decelerates the under-forecast may become less severe or even reverse. However, actual forecasts may be made through a mixture of empirical and judgmental methods. Judgmental methods may anticipate or even over-anticipate accelerating or decelerating business cycles, thereby neutralizing or having the opposite effect of purely empirical methods. On the whole, while there is a potential impact of business cycle on forecast bias, the direction of impact is uncertain.

> **Hypothesis 5:** The acceleration or deceleration of the state economy (state GDP) will have an impact on forecast bias.

Unlike practices in developed nations, undeveloped nations are sometimes reported to exhibit positive forecast bias (Rubin, 1987). They are also frequently reported to engage in post-adoption budget modifications that may reflect matters associated with appropriations (Caiden, 1981; Caiden & Wildavsky, 1974; Omolehinwa & Roe, 1989). These observations lead to the possibility that there is a relationship between revenue effort (the degree to which taxing capacity is actually used) and forecast bias.

Hypothesis 6a: Positive forecast bias (or cancellation of negative bias) is positively associated with revenue effort.

The data for revenue effort are calculated from the U. S. Census Bureau Survey of State and Local Finance. Local revenue is included because the distribution of taxes between state and local levels differs from state to state. So a second element of this same factor is the share of the revenue that is actually attributable to the state. It is not clear whether this should result in a positive or negative bias.

Hypothesis 6b: State share of total state and local revenue is significantly associated with forecast bias.

The effect of revenue effort may be offset somewhat by receipt of transfer funds from the federal government.

Hypothesis 6c: Federal fund transfer is associated with forecast bias.

A more direct consideration of revenue capacity in the personal income of residents of the state.

Hypothesis 6d: Estimated real per capita personal income is associated with revenue forecast bias.

Another measure of revenue capacity which may also capture components of the business cycle is the per capita real GDP

Hypothesis 6e : State Per Capita Real GDP is associated with forecast bias.

Brogan finds a positive effect of the unemployment rate on budget accuracy. Unemployment is reasonably associated with forecast bias because it may capture components of the business cycle not otherwise identified with other variables or it may reflect another form of uncertainty.

Hypothesis 6f: The state unemployment rate has a positive association with forecast bias.

States collect taxes from a variety of sources. There has been considerable researcher into revenue diversification and a standard measure of revenue diversification, sometimes labeled RD is:

$$RD = 1 - HHI_N$$

Where, RD is the measure of revenue diversification and HHI_N is the Normalized Hirschman-Herfindahl Index (Calabrese & Carroll, 2012; Carroll, 2005; Carroll & Stater, 2009; Hendrick, Jimenez, & Lal). There is no evidence that past research has specifically associated revenue diversification with forecast bias. However, there are two competing reasons why it is anticipated that it is. First, because a jurisdiction has limited management capacity, the forecasting of more revenue types is more difficult. As one of the principle explanations of underestimation bias is a hedge against risk, it stands to reason that where capacity is insufficient, underestimation bias will increase. Therefore, when revenue is more diverse, there is more underestimation bias. Alternatively, where there are fewer sources of revenue, despite accuracy gains through the use of increased resources used for the limited number of forecasts, there is may be more risk associated with each individual forecast, as there are fewer other revenue sources that might have cancelling errors. Thus, the perception of risk leading to an underestimation hedge could arise from a limited number of substantial revenue sources. Consequently, it is anticipated that revenue diversity may affect bias, but the direction of affect is not known.

Hypothesis 7: The measure RD is associated with revenue forecast bias.

The data for used with respect to Hypothesis 7 is categorized in 7 broad groups, for calculation of RD.

In an 2011 report on state revenue forecasting (Boyd, Dadayan, & Ward, 2011), other factors that are identified as potentially affecting revenue accuracy include the volatility of the revenue source, the value of a budget stabilization fund, and the use, by the state, of biennial budgeting. These factors are related to risk aversion. A more volatile revenue source can be expected to have a larger forecast error, so the risk averse decision maker may need to adjust the forecast by a larger share of the forecast to avoid overstating revenue. Two types of measures of volatility are used. First, there is a direct measure of volatility of the data, this measure is the coefficient of variation (CV) of the series for the five years preceding the forecast year. Second, Boyd et al. (2011) suggest that natural resource related industries contribute to some parts of revenue instability, so the share of the state GDP attributable to mining and the share attributable to farming are considered.

Hypothesis 8a: There is a negative association between the forecast error and the CV measure for each tax type, CIT, PIT, and Sales Tax.

Hypothesis 8b: There is a negative association between the forecast error and the mining share of state GDP.

Hypothesis 8c: There is a negative association between the forecast error and the farming share of state GDP.

Hypothesis 8d: The relative size of the budget stabilization fund is negatively associated with forecast bias.

Hypothesis 8e: States that budget biennially exhibit a larger forecast bias.

The conceptual opposite of a budget stabilization fund is debt. Debt creates obligations that must be met and weakens the ability to offset unplanned expenditures. Two measures of debt are the debt itself as ratio to the state's GDP and the state's bond rating. Because debt creates uncertainty it may increase the need to hedge; however it may also indirectly relate to revenue capacity as higher both in the past (having past need to borrow) and in the present (repayment of debt limiting other uses of revenue). So the expectation is that a higher debt to state GDP ratio is associated with increased bias.

Hypothesis 9a: The debt to state GDP ratio is associated with revenue forecast bias.

Bond rating measures debt, debt capacity and the general financial health of the state, which might include, for example, the tendency to have a surplus in previous years. A higher bond rating indicates more remaining debt capacity, thus it is associated with less need to hedge. However, it may also be associated with underestimation practices. To use bond rating in this analysis, an index is constructed ranging from 1 to 27 converting bond ratings for C- to AAA+ and averaged over Standard & Poor, Moody's and Fitch. Some Moody's ratings are adjusted. Missing values are dropped from the average.

Hypothesis 9b: The state's bond rating is associated with revenue forecast bias.

Consistent with the explanation of Hypotheses 6a-6f, state laws – commonly known as Tax and Expenditure Limitations (TELS) – that restrict taxes or expenditures may affect the perception of total available revenue in relationship to other factors such as prior tax rates. The National Conference of State Legislatures recognizes four types of TELS, three of which restrict taxes and one of which restricts expenditures in relationship to revenue. These include a requirement for a supermajority of the legislature to raise taxes; a similar requirement, but for a narrow set of taxes; a cap on some or all taxes; and a cap on the amount of expenditures linked to the amount of revenue available. Each of these types of limits may lead to an offset to the otherwise expected underestimation bias as the demand for services may lead to a requirement for more funds than the restricted funding sources provide. However, narrowing the supermajority requirement may mediate the effect somewhat.

Hypothesis 10a: A size of any supermajority requirement to raise taxes is associated with a positive coefficient.

Hypothesis 10b: The fact that the supermajority is narrowed is associated with a bias.

Hypothesis 10c: The presence of a tax cap is associated with a positive coefficient.

Hypothesis 10d: The presence of an expenditure cap conditioned on revenue is associated with a positive coefficient.

Data

The primary data for this study is extracted from National Association of State Budget Officers (NASBO) spring and fall Fiscal Survey of the States from 1991 through 2012, focusing on fiscal years 1993 through 2011. These data are supplemented with a variety of data that have been discussed with respect to specific hypotheses and with a list of governors and party affiliation as found on the National Governor's Association website, population data published by the United States Census Bureau, and state level gross domestic product (GDP) as published by the Bureau of Economic Analysis or the Federal Reserve Bank of St. Louis FRED data series.[1]

The GDP data are in two partial series; however this is a more substantial concern for level than it is for year-to-year changes, which could be computed for all periods as the year in which the series changes, 1997, both forms of the series are available. Modeling does not include an indicator for this change as it is collinear with time fixed effects. Changes in changes are computed to account for acceleration or deceleration in economic activity and included as an independent variable.

[1] Websites accessed include www.nasbo.org over several weeks in the spring of 2013; www.nga.org on Sept. 8, 2013; http://www.bea.gov/iTable/iTable.cfm?reqid=70&step=1&isuri=1&acrdn=1#reqid=70&step=1&isuri=1 on Sept. 8, 2013; and www.census.gov on Sept 8, 2013; and FRED http://research.stlouisfed.org/fred2/ accessed in the spring of 2014.

The governor data were essentially ready to use, except that party changes for several governors were traced to determine to which party they belonged in the analysis years.

The census data on state population is available in multiple tables, none of which are ready to use; however, they are generally made usable by deleting irrelevant details and combining data by decade.

The NASBO semi-annual reports contain tables showing revenue in four categories, total revenue and corporate income tax (CIT), personal income tax (PIT), and sales tax. For periods beginning in 2006, the data are reported from the spring of the year before the fiscal year, through the fall of the year after the fiscal year. Beginning in 1993 through 2005, 4 periods, ending in the fall just after the fiscal year ends are reported. For 1992, only two fall reports are available. For 1998, the first spring report is missing.

For all these periods there is at least one report before the end of the fiscal year and at least one report after the end of the fiscal year. The last available report is treated as the actual. For those years where comparison is available, there is some evidence of modest updating by some states when more than one post-fiscal-year-end report is available; however most states report the same or nearly the same data in post-fiscal-year-end periods. The pre-fiscal year end reports are treated as forecasts, although some are a combination of partial forecast and partial actuals.

The values are aggregate annual amounts; however, it is likely that most states forecast more granularly and sum to annual numbers. Horizons are calculated in months to the end of the fiscal year for which the totals are aggregated; however the exact number of months is unknown. For spring reports the assumed that the period begins in July and for fall reports, it is assumed that the period begins in January. This assumption allows calculation of months to the end of the fiscal year, which varies among the states and the slope of the horizon; however it may introduce a small error in the size of the intercept or, for no intercept models, for certain indicator variables. Because, as will later be seen, the actual size of slopes is very small, this error will also be very small.

For a small number of observations, either the forecast or the actual is imputed by substituting a value from another period. For a small number of observations, instances a gap of two periods leads to some weighted averaging. For 113 of these instances, the imputed value is the "actual," and the forecast that is used as the imputed actual is dropped from the analysis. Regression models include controls to detect the effect of this imputation.

Forecast Error Measure

This paper follows Williams (2012) evaluating forecast bias with the model:

$$\left(\widehat{\frac{F-A}{(F+A)/2}}\right) * 100 = \alpha + \sum_{i=1}^{k} \beta_i x_i + \varepsilon \qquad (1)$$

The dependent variable is the symmetric percent error.[2] This model is updated to reflect the current set of hypotheses, which focus on a much broader range of explanatory variables as discussed in the hypotheses. Two sorts of models are estimated. One set focuses on multiple horizons and is estimated with OLS using fixed effects for states and years created through dummy variables. For this approach, there is one model for each of the three tax types. The other focuses on each of three horizons forming panels using states and years to form panels. For this approach, there is one model for each of three horizons, with respect to each of three tax types. Because of the complexity of data and the models, Hypotheses 1a and 1b, cannot be evaluated with these models because the intercepts will be affected by the continuous variables which reach zero well outside realistic range of the data. Instead, they are examined with simple descriptive data as shown in Table 1

[Table 1 Here]

Table 1 shows that roughly 58% to 63% of the errors are negative for the aggregate of all tax types, the total of all tax types, and for corporate and personal income. For sales tax, the errors are negative 52%

[2] For estimation purposes, the data are retained in ratio form, but results are represented in percentage form.

of the time. For the total, aggregate, and each tax type, the average of all errors is negative ranging from -0.6% (PIT) to -4.5% (CIT). While these descriptive results are not dispositive, they are consistent with hypotheses 1a and 1b, except with respect to sales tax, which is marginal.

Regression Models

Because of the large number of regression models and the large number of variables, results are grouped to display. All regression coefficients for a particular x variable are displayed in a 4 column (all horizons, and each of horizons 1 through 3) by 3 row (tax type CIT, PIT, and Sales) block. These blocks are shown in four tables, Strong Evidence, Variables with Interaction, Weak Evidence, and No Evidence. These tables report twelve separate regressions: three using {OLS with robust standard errors} and fixed effects through dummies for states and years for multiple horizons; and the remaining nine using XTReg with robust standard errors with fixed effects through panels for states formatted yearly. For the OLS models, the F values are 4.9 for Sales Tax, 10.42 for CIT, and 15.87 for PIT, all have p-values < 0.001. For the panel data, the Wald Chi^2 range from 1136.26 to 165662.66, all with p-values < 0.001. Explained variance ranges from 6.66% to 31.15%. All rho values are <.06.

Variables marked no evidence have no significant coefficients in 12 regressions. The variables with interaction are displayed in a separate table to assist discussion. Variables marked strong evidence have a substantial number of significant coefficients with multiple tax types and horizons; and where there is a prior expectation of a direction, all or nearly all coefficients have the expected sign. The three coefficient of variation variables are considered together. The variables marked weak evidence have fewer substantial coefficients, with one exception where the results have inconsistent directional coefficients.

[Table 2 Here]

Table 2 shows the variables with strong evidence of association. The first block examines hypothesis 4 that the state population, as a proxy for forecasting capacity, is positively associated with the forecast error. The variable LN Population is the log of the state population. Although not significant except once for individual horizons, it is highly significant for each of the tax types when examined in the multi-horizon model and it has the expected sign with all significant coefficients and four of the remaining seven. The anticipated implication of is that when there is a larger population, there will be more capacity to forecast and the need to under-forecast to hedge against uncertainty will be reduced.

The second block, examines hypothesis 5 that there is an associated between the acceleration or deceleration of the state GDP (at the time the forecast is made) and forecast error. It shows that the coefficients for all twelve models are negative, with significant coefficients for 9 of twelve models. The variable measures the change in the change of the state GDP, thus a positive value implies accelerating growth while a negative value implies deceleration, not necessarily actual decline. The negative coefficient implies that when there is a positive change at the time of the forecast, there will be underestimation and it implies the opposite for negative change at the time of the forecast. These results suggest the need for further investigation.

The third block examines hypothesis 6a that the state and local revenue effort is positively associated with forecast error. This positive association is anticipated because, where there is insufficient revenue to meet demand for services, overestimation of revenue can provide flexibility for more spending. Ten of twelve coefficients have the anticipated sign and six are significant at each of the three horizons. The all horizon models have the anticipated sign, but are not statistically significant. Although these results could be stronger, the finding is particularly interesting in that it helps explain why poor jurisdictions exhibit different forecast biases than elsewhere.

The fourth block examines hypothesis 6f that unemployment is associated with forecast bias. There are 9 negative coefficients, of which 6 are significant. These results are opposite the anticipated result from Brogan, who found positive coefficients with some significant t values.

The fifth through seventh blocks examine hypothesis 8a, that the lagged 5 period coefficient of variance (CV5) for the three tax types is negatively associated with forecast error.[3] This hypothesis is related to the view that high revenue variability increases the need to hedge against uncertainty; this concern arises not only where the forecast revenue has high variability, but also where other revenues have high variability. Block 5 (the first of these three blocks) examines CV5 for sales tax. All 12 coefficients are negative and 11 are statistically significant. Block 6 examines CV5 for PIT. Here 10 of 12 coefficients are negative, but only the 4 associated with the PIT forecasts are statistically significant. A potential explanation of these less significant findings is that fewer states have PIT revenue, so the models for Sales Tax, CIT and all horizons include a substantial number of zero values for this variable. In block 7, the results for CV5 for CIT are as expected with respect to the CIT forecast, but are mixed with respect to the other forecasts, with two significant negative coefficient's and four negative coefficients, two of which are significant. This inconsistency may relate to the relatively low contribution that CIT makes to most states' revenue; of these three revenue types, the average contribution of CIT for all states excluding Alaska and New Hampshire (which rely heavily on CIT) is 8.5%.

[Table 3 Here]

Variables with Interaction

Following Brogan, the divided legislature variable is interacted with two other variables, the Democratic Governor variable and the Democratic Factor variable. The statistical significance for the direct effects for Democratic Governor and Democratic Factor are very slight. For Divided Legislature, there are 4

[3] Where the tax type is not present, the coefficient of variance is assumed to be zero.

statistically significant positive coefficients, two with corporate income tax and two with personal income tax. For the Divided Legislature * Democratic Governor interaction, all coefficients are negative, but only three are statistically significant, one with corporate income tax and two with sales tax. For the Divided Legislature * Democratic Factor interaction, there are 5 statistically significant negative coefficients including all the corporate income tax models and one personal income tax model. There is one significant positive coefficient with sales tax. There is no discernable pattern with respect to horizons. In general these results are very mixed and would not be remarkable except for the Divided Legislature * Democratic Factor interaction.

[Tables 4 Here]

Weak and No Evidence

In general the results with respect to the other coefficients are either weak or non-existent. Table4 shows five hypotheses for which there are no statistically significant results. These include years to the next governor's election (Hypothesis 3i), which Brogan reported as significant (as "term year"), and Biennial Budget Indicator (Hypothesis 8e), which Boyd, Dadayan, & Ward suggest is significant. Also excluded are: Third Party Governor (Hypothesis 3b), Governor Change to Democratic (Hypothesis 3f), and Tax or Expenditure Cap (Hypothesis 10c).

[Table 5 Here]

Table 5 shows 19 hypotheses for which there is weak evidence. With the exceptions discussed next, these have no more than three of 12 coefficients that are statistically significant. Even with these, some have inconsistent signs with the coefficients. Four hypotheses reported in Table 5 have 4 or 5 significant coefficients. Of these, two (Hypothesis 6c, Federal Fund Transfer / State Revenue; and hypothesis 10d, Expenditure Cap as a Ratio to Revenue) are excluded because the results are inconsistent, The remaining two are: (1) Percent Vote for Governor (Hypothesis 3d), which has 11 of 12 positive coefficients with 4 statistically significant. Three of these are with models for corporate income tax. (2) Per Capital Real GDP (Hypothesis 6e), which has 9 of 12 positive coefficients, with 4 significant, distributed across all three tax types and differing horizons.

Discussion

The descriptive data shown with respect to hypothesis 1a and 1b are consistent with the view that underforecasting is common, although not ubiquitous. The regression analysis finds that most statistically significant independent variables are associated with uncertainty. Where there is greater capacity as suggested by population, uncertainty may be mitigated. The positive relation with revenue effort suggests that there is a counterbalancing bias favoring finding enough money to pay for the services demanded.

Table 1

	Highest	Lowest	Average	Total <0	Total	Share <0
CIT	6.5%	-15.7%	-4.5%	533	861	62%
PIT	3.8%	-7.1%	-0.6%	476	797	60%
Sales Tax	4.5%	-77.3%	-2.2%	449	860	52%
Total	6.5%	-77.3%	-2.5%	1458	2518	58%
Aggregate	3.1%	-12.0%	-2.2%	597	949	63%

Table 2

Strong Evidence											
				All Horizons		H1		H2		H3	
H	P	Tax	Symmetrical Ratio Error	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.
4	+	CIT	LN Population	0.058	***	0.003		0.005	**	0.003	
4	+	PIT	LN Population	0.017	***	-0.0002		0.001		0.0003	
4	+	Sales	LN Population	0.023	***	0.0003		-0.0001		-0.0002	
5		CIT	2Dif %GDP	-0.001	***	-0.001	***	-0.001	***	-0.002	***
5		PIT	2Dif %GDP	-0.0001		-0.0001		-0.001	***	-0.001	***
5		Sales	2Dif %GDP	-0.0004	***	-0.0002		-0.001	***	-0.001	***
6a	+	CIT	S & L Rev Effort	0.065		0.142	**	0.167	**	0.190	***
6a	+	PIT	S & L Rev Effort	0.034		0.076	***	0.127	***	0.115	***
6a	+	Sales	S & L Rev Effort	0.022		-0.066		-0.017		0.020	
6f	+	CIT	Unemployment Rate	-0.028	***	-0.012	**	-0.014	***	-0.010	
6f	+	PIT	Unemployment Rate	-0.003		-0.006	***	-0.001		0.003	
6f	+	Sales	Unemployment Rate	-0.007		-0.004	*	0.001		0.001	
8a1	-	CIT	Coef Var. 5 Period, Sales Tax	-0.010	*	-0.008	**	-0.013	**	-0.009	
8a1	-	PIT	Coef Var. 5 Period, Sales Tax	-0.008	***	-0.008	***	-0.004	**	-0.009	**
8a1	-	Sales	Coef Var. 5 Period, Sales Tax	-0.059	***	-0.071	***	-0.047	***	-0.078	***
8a2	-	CIT	Coef Var. 5 Period, PIT	0.011		-0.003		-0.007		-0.032	
8a2	-	PIT	Coef Var. 5 Period, PIT	-0.025	***	-0.019	**	-0.056	***	-0.053	***
8a2	-	Sales	Coef Var. 5 Period, PIT	-0.010		0.003		-0.009		-0.012	
8a3	-	CIT	Coef Var. 5 Period, CIT	-0.021	***	-0.017	***	-0.053	***	-0.053	***
8a3	-	PIT	Coef Var. 5 Period, CIT	0.003		0.002		-0.006	**	-0.008	***
8a3	-	Sales	Coef Var. 5 Period, CIT	0.009	**	0.007		0.008	***	0.007	

Table 3

H	P	Tax	Variables with Interaction	All Horizons		H1		H2		H3	
3a		CIT	Democratic Governor	0.005		0.025		0.025		0.028	
3a		PIT	Democratic Governor	0.006		-0.004		0.019	**	0.011	
3a		Sales	Democratic Governor	-0.003		0.008		-0.005		-0.009	
3k		CIT	Dem Governor * Divided Leg	-0.004		-0.077	**	-0.025		-0.080	
3k		PIT	Dem Governor * Divided Leg	-0.012		-0.005		-0.009		-0.027	
3k		Sales	Dem Governor * Divided Leg	-0.017		-0.045	*	-0.022		-0.041	**
3c		CIT	Divided Legislature	0.032	*	0.052	**	0.044		0.063	
3c		PIT	Divided Legislature	0.020	**	0.013		0.006		0.026	**
3c		Sales	Divided Legislature	0.000		-0.006		-0.008		0.009	
3m		CIT	Div. Leg * Democratic Factor	-0.048	**	-0.052	*	-0.098	**	-0.102	*
3m		PIT	Div. Leg * Democratic Factor	0.006		-0.023	*	0.019		-0.007	
3m		Sales	Div. Leg * Democratic Factor	-0.003		0.014		0.017		0.036	**
3l		CIT	Democratic Factor	-0.006		-0.011		0.001		-0.013	
3l		PIT	Democratic Factor	-0.005		-0.003		-0.009	*	-0.012	*
3l		Sales	Democratic Factor	0.003		-0.003		0.003		0.002	

Table 4

				No Evidence							
				All Horizons		H1		H2		H3	
H	P	Tax	Symmetrical Ratio Error	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.
3b		CIT	Third Party Governor	0.062		0.048		0.074		0.018	
3b		PIT	Third Party Governor	0.029		**-0.023**		0.060		0.025	
3b		Sales	Third Party Governor	**-0.001**		0.034		0.025		0.017	
3f		CIT	Gov. Change to Democratic	0.041		**-0.004**		**-0.017**		0.023	
3f		PIT	Gov. Change to Democratic	0.009		0.010		**-0.015**		0.003	
3f		Sales	Gov. Change to Democratic	0.016		**-0.013**		0.023		0.026	
3i		CIT	Years to Next G. Election	**-0.005**		**-0.004**		0.003		**-0.001**	
3i		PIT	Years to Next G. Election	**-0.002**		**-0.003**		**-0.003**		**-0.001**	
3i		Sales	Years to Next G. Election	0.004		0.004		0.008		0.009	
8e	-	CIT	Biennial Budget Indicator	**-0.057**		**-0.012**		**-0.022**		**-0.019**	
8e	-	PIT	Biennial Budget Indicator	**-0.003**		0.010		**-0.004**		0.001	
8e	-	Sales	Biennial Budget Indicator	0.008		**-0.024**		**-0.012**		**-0.021**	
10c	+	CIT	TEL: Tax or Expenditure Cap	0.015		**-0.007**		0.019		0.014	
10c	+	PIT	TEL: Tax or Expenditure Cap	0.021		0.001		**-0.003**		0.004	
10c	+	Sales	TEL: Tax or Expenditure Cap	**-0.029**		**-0.020**		0.003		**-0.013**	

Table 5

Weak Evidence											
				All Horizons		H1		H2		H3	
H	P	Tax	Symmetrical Ratio Error	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.
2	-	CIT	Monthly Horizon	-0.002	**	-0.011	*	-0.010		0.006	
2	-	PIT	Monthly Horizon	0.00003		0.008		0.001		0.001	
2	-	Sales	Monthly Horizon	0.0001		-0.007		-0.001		-0.009	
3d		CIT	Percent Vote for Governor	0.001	*	0.002		0.004	***	0.004	**
3d		PIT	Percent Vote for Governor	0.0003		-0.0001		0.001		0.001	*
3d		Sales	Percent Vote for Governor	0.0004		0.001		0.0002		0.001	
3e		CIT	Change in Governor	-0.004		0.008		0.029		0.009	
3e		PIT	Change in Governor	-0.015	**	-0.011		0.005		-0.004	
3e		Sales	Change in Governor	-0.004		-0.001		0.008		-0.014	
3g		CIT	Gov. Change to Republican	0.100	***	0.070		0.009		0.064	
3g		PIT	Gov. Change to Republican	0.014		-0.006		0.003		0.000	
3g		Sales	Gov. Change to Republican	-0.012		-0.010		-0.016		0.002	
3h		CIT	Gov. Change to Third Party	-0.236	**	-0.135		-0.269		-0.205	
3h		PIT	Gov. Change to Third Party	-0.017		0.024		-0.038		0.007	
3h		Sales	Gov. Change to Third Party	-0.009		-0.018		-0.032		-0.035	
3j		CIT	Most Freq. Leg Election Year	0.035	**	0.031		0.021		0.038	*
3j		PIT	Most Freq. Leg Election Year	-0.002		0.005		0.008		0.001	
3j		Sales	Most Freq. Leg Election Year	0.002		0.015	*	0.007		0.009	
6b		CIT	State Share S&L Rev Effort	0.033		0.013		0.028		0.023	
6b		PIT	State Share S&L Rev Effort	-0.007		-0.018	***	0.003		0.003	
6b		Sales	State Share S&L Rev Effort	0.027	*	0.003		0.002		-0.002	
6c		CIT	Fed Trans/ State Revenue	0.022	*	0.005		0.011		0.009	
6c		PIT	Fed Trans/ State Revenue	0.002		-0.005		0.002		0.001	
6c		Sales	Fed Trans/ State Revenue	0.016	***	-0.010	**	-0.002		-0.009	*
6d		CIT	Est Real Per C Pers. Income	-0.039		-0.011		0.001		-0.005	
6d		PIT	Est Real Per C Pers. Income	-0.013		0.011	**	0.014	**	0.007	
6d		Sales	Est Real Per C Pers. Income	-0.015		0.002		0.007		0.006	
6e		CIT	Per Capita Real GPD	0.075	*	0.001		-0.003		-0.002	
6e		PIT	Per Capita Real GPD	0.019		-0.004		0.011		0.018	**
6e		Sales	Per Capita Real GPD	0.010		0.006		0.019	*	0.022	**
7		CIT	Revenue Diversity	-0.073	**	-0.030		-0.017		-0.015	
7		PIT	Revenue Diversity	-0.013		0.008		-0.027	***	-0.027	***
7		Sales	Revenue Diversity	0.026		-0.008		0.005		0.003	
8b	-	CIT	Share GDP from Mining	-0.061		-0.055		-0.061		-0.078	
8b	-	PIT	Share GDP from Mining	0.030		0.032	**	-0.011		0.011	
8b	-	Sales	Share GDP from Mining	-0.011		0.020		-0.012		-0.005	
8c	-	CIT	Share GDP from Farming	0.071		-0.009		0.024		-0.021	
8c	-	PIT	Share GDP from Farming	-0.098	*	-0.021		-0.035		-0.037	
8c	-	Sales	Share GDP from Farming	-0.029		-0.016		-0.021		-0.028	
8d	-	CIT	BSF/State Rev	-0.005		-0.017	*	-0.023		-0.029	
8d	-	PIT	BSF/State Rev	-0.029	**	-0.039	***	-0.018		-0.031	
8d	-	Sales	BSF/State Rev	0.004		-0.007		0.024		0.028	
9a		CIT	Debt over GDP	0.168	***	0.066		0.083	**	0.055	
9a		PIT	Debt over GDP	-0.012		0.026		0.007		0.011	
9a		Sales	Debt over GDP	-0.022		-0.021		-0.044		-0.030	

Weak Evidence											
				All Horizons		H1		H2		H3	
H	P	Tax	Symmetrical Ratio Error	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.
9b		CIT	Bond Rating Index	**-0.004**		**-0.002**		0.007		0.005	
9b		PIT	Bond Rating Index	**-0.002**		0.004		0.002		0.008	*
9b		Sales	Bond Rating Index	**-0.012**	*	**-0.010**	**	**-0.002**		**-0.004**	
10a	+	CIT	TEL: Supermaj. Size Required	0.052		0.010		0.056		0.048	
10a	+	PIT	TEL: Supermaj. Size Required	**-0.015**		0.003		0.047	***	0.028	*
10a	+	Sales	TEL: Supermaj. Size Required	**-0.014**		**-0.011**		0.019		0.005	
10b		CIT	TEL: Narrow Supermajority	0.070		0.003		**-0.075**	*	**-0.066**	
10b		PIT	TEL: Narrow Supermajority	0.088	**	0.032		**-0.026**		**-0.012**	
10b		Sales	TEL: Narrow Supermajority	0.655	***	0.088		0.064		0.060	
10d	+	CIT	TEL: Exp. Cap R to Revenue	**-0.003**		0.001		**-0.005**		**-0.004**	
10d	+	PIT	TEL: Exp. Cap R to Revenue	0.042	***	0.004	*	**-0.003**	*	**-0.003**	
10d	+	Sales	TEL: Exp. Cap R to Revenue	**-0.041**	***	0.007	***	**0.000**		0.004	*

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