

State Sales Tax Forecasting

Presentation to the FTA on Special
Topics in Sales Tax Forecasting
September 23, 2003

Frederick Church, Research Director
Ohio Department of Taxation

Agenda

Sales Tax Forecasting: Incorporating Wealth
Effects on Revenues

Sales Tax Forecasting: Accounting for
Behavioral Impacts of Temporary Rate
Changes

Why We Care About These Topics

- Increases in stock market wealth in the 1990s and losses in the current decade have affected consumer behavior and thus sales tax revenues
 - Gains in real estate wealth are also having an impact, but it is difficult to disentangle from refinancing impacts on cash flow
- Although most states have done their most recent budget balancing with cigarette tax increases, borrowing between funds, etc., there may be more temporary sales tax increases in the future

PART I:

Wealth Effects on Sales Tax Revenues

Quality of the Data

- Disaggregated dependent variable data is preferable, but effects can be shown with aggregated data
 - Ohio breaks its sales tax revenues down only into automotive and non-automotive
 - Regression analysis shows wealth effects in the aggregated non-auto sector

Independent Variables

- Household wealth is the desired variable, as from the Flow of Funds data, but:
 - household wealth is not available at the sub-national level
 - household wealth forecasts are available only from national forecasting firms, and the forecasts have wide confidence intervals

Independent Variables

- A shortcut is to use a proxy variable for household wealth like a stock market index
 - empirical evidence suggests that this is not bad for explaining sales tax revenue swings in the late 1990s and early 2000s
 - obviously time will tell how well it works going forward

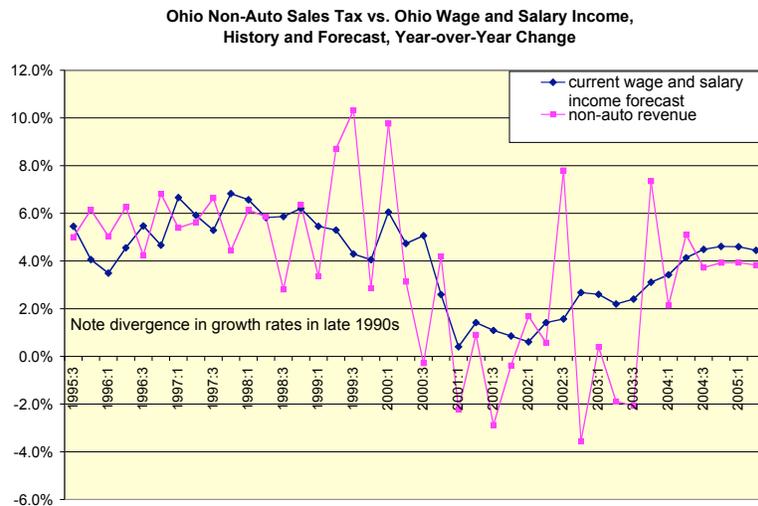
Independent Variables

- Stock market proxies also must be forecasted to use in sales tax revenue regression forecasts
 - one can use ARIMA forecasts
 - more importantly, one can do sensitivity analysis using different forecasts of the stock market index variable

Independent Variables

- How important is it that using a stock market proxy leaves out real estate wealth gains?
 - Depends on how well real estate prices correlate with stock market prices
 - Depends on whether consumer spending responds to real estate wealth gains in the same way (magnitude and time frame) that it responds to stock market wealth gains

Wealth Effects in Ohio?

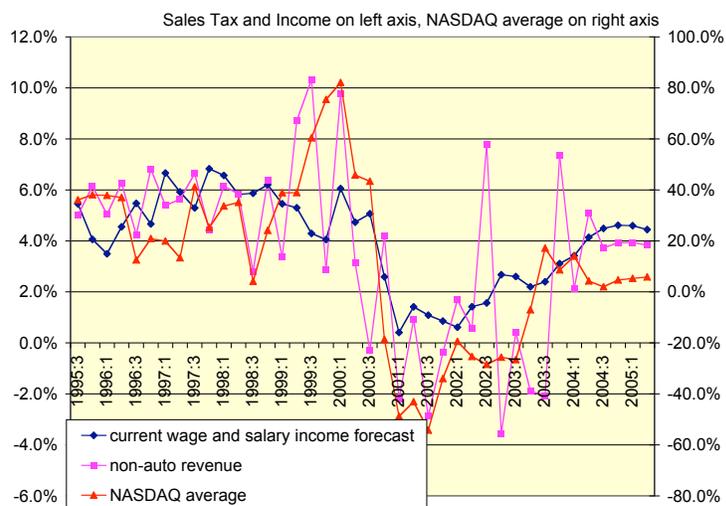


Wealth Effects in Ohio?

- One can see year over year growth rates in non-auto tax revenue become much more volatile than wage and salary income growth rates about the 3rd quarter of 1998
- Statistically, there is a difference in the sales tax to income relationship even before that, but more subtle

Wealth Effects in Ohio?

Ohio Non-Auto Sales Tax vs. Ohio Wage and Salary Income, History and Forecast, Year-over-Year Change



Wealth Effects in Ohio?

- Simple visual analysis suggests that some of the volatility in non-auto sales tax growth rates may be explained by changes in a stock market variable (e.g. the NASDAQ index)

Wealth Effects in Ohio?

- Regression Analysis: several trials performed fitting historical model and then using historical model to do true forecasts of recent past
- The simple log-linear model ultimately selected had very small historical errors (e.g. FY 2000 error was -0.4%, or \$19.9 million on a base of \$5.092 billion)

Regression Equation

EViews Forecasting Equation

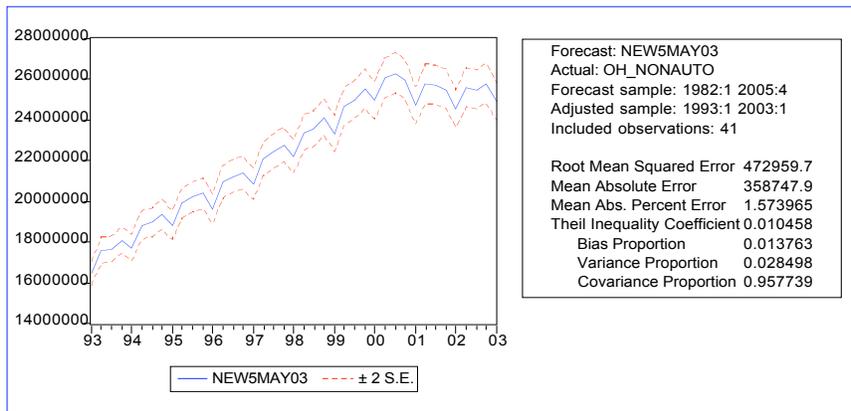
Dependent variable: LOG(OH_NONAUTO)
 Method: Least Squares
 Date: 5/23/2003 Time: 10:03
 Sample(adjusted): 1993q1 2001q4
 Included observations :36 after adjusting endpoints
 Convergence achieved after 5 iterations

Variable	Coefficient	Std. Error	t-Stat	Prob.
C	7.007488	0.769468	9.10693	0
LOG(OHWAGSAL_WEI	0.802576	0.070179	11.4362	0
LOG(NASDAQ)	0.040053	0.013884	2.88476	0.0071
@SEAS(1)	-0.043379	0.010227	-4.2414	0.0002
AR(4)	0.319058	0.11539	2.76504	0.0095

R-squared	0.98539	Mean dependent var	16.8973
Adjusted R-squared	0.983505	S.D. dependent var	0.1379
S.E. of regression	0.01771	Akaike info criterion	-5.1011
Sum squared resid	0.009723	Schwarz criterion	-4.8812
Log likelihood	96.81971	F-statistic	522.715
Durbin-Watson stat	2.742199	Prob(F-statistic)	0

Regression Equation

Note that the covariance proportion is almost 0.97, indicating an excellent fit



Wealth Effects in Ohio?

- First true test of the equation: FY 2003 revenues were \$5,431.7 million. Subtracting \$250 million to \$275 million for a law change that accelerated payments, revenues were \$5,156.7 million to \$5,181.7 million
- Model forecast was \$5,136.7 million, resulting in an error of 0.4% to 0.9%

Notes

- The model is actually quarterly, but the results have been aggregated to produce fiscal year totals
- Interest rates are not in the equation because all the interest rate variables used were statistically insignificant when wealth measures such as the NASDAQ or the S&P 500 were used

Notes

- When interest rate variables were used, the best fit was with a 6 quarter lag
- Obviously forecasting the NASDAQ is a problem, but one can do sensitivity analysis with different forecasts
- For example, an increase in the NASDAQ Index from 1500 to 2000 will increase non-auto sales tax revenues by 1.3%, or about \$18 million per quarter

PART II:

Temporary Sales Tax Rate Changes

Data Sources and Limitations

- Ohio does not have enough experience of temporary rate changes for us to use Ohio data as a starting point
- Nebraska does have enough experience, and they shared time series data with us

Visual Inspection of the Data

- Begin with auto sales tax because effects seem to be visible to naked eye

Goal of Modeling Process

- Capture “pure” shifting of purchases between time periods due to tax rate changes
- We also ran models to test the longer-run impact of a temporary tax rate increase, but that is another topic

Choice of Modeling Technique

- Search of the literature suggested an “interrupted time series” model
- Essentially an ARIMA model with dummy variables for the rate changes (i.e. “transfer function” model)
- Dummy variables are of the “ramp” type

Choice of Modeling Technique

- Interrupted time series model, dummy variable choices
 - “pulse” goes on for one time period and then goes off
 - “step” goes on and stays on
 - “ramp” goes on for K time periods, then goes off

Estimation Period

- The hypothesis to test is that consumers shift purchases between time periods to avoid the tax
- So, the behavioral “ramp” dummy variable should be turned on before a rate increase (decrease) actually occurs, and then turned off after the increase (decrease) has been in effect a little while

Estimation Period

- We ran monthly models on the Nebraska data with different (small) numbers of months before and after rate changes to eliminate time periods that were too long or too short
- We settled on a model that had shifting behavior for two months before and two months after a tax rate change

Regression Design

Variable	Value 2 months before increase	Value 2 months after increase	High0

Regression Results

Dependent Variable: MV_SALES
Method: Least Squares
Sample(adjusted): 1992:05 2003:01
Included observations: 129 after adjusting endpoints
Convergence achieved after 7 iterations
Backcast: 1991:05 1992:04

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	95.811	7.433	12.890	0.000
@TREND	1.001	0.075	13.285	0.000
HIGH	-19.985	7.058	-2.832	0.005
LOW	22.940	8.418	2.725	0.007
AR(1)	0.571	0.075	7.659	0.000
AR(4)	-0.225	0.080	-2.800	0.006
MA(12)	0.317	0.104	3.054	0.003
R-squared	0.86478465	Mean dependent var	188.152491	
Adjusted R-squared	0.85813472	S.D. dependent var	43.5934513	
S.E. of regression	16.419477	Akaike info criterion	8.48754934	
Sum squared resid	32891.1054	Schwarz criterion	8.64273296	
Log likelihood	-540.44693	F-statistic	130.044072	
Durbin-Watson stat	2.0733916	Prob(F-statistic)	0	

Regression Results

- The tax rate variables have the expected signs (negative for high and positive for low) and are statistically significant
- The coefficients are also quite similar in absolute value, which supports the hypothesis that spending is being shifted between periods

Applying the Regression Results

- Calculate the coefficients on the tax rate variables as a percentage of the dependent variable
- Apply the percentages to Ohio estimated auto tax revenues for the months just before and after the tax rate changes

Applying the Regression Results

Estimated Revenue Impact on Ohio Over FY 2003 - 2005 Budget Period

	value	pct
Mean of dependent variable (MV sales)	188.15	
coefficient on "high" tax rate var	-19.99	-10.62%
coefficient on "low" tax rate var	22.94	12.19%
 <i>Ohio Revenue Impacts</i>		
	estimate	estimate doubled
Ohio estimated MV tax revenues, last 2 months of FY 2003	\$166.379	
Estimated gain due to shifting	\$20.29	\$40.57
Ohio estimated MV tax revenues, first 2 months of FY 2004	\$188.813	
Estimated loss due to shifting	(\$20.06)	(\$40.11)
Ohio estimated MV tax revenues, last 2 months of FY 2005	\$167.000	
Estimated loss due to shifting	(\$17.74)	(\$35.48)

Applying the Regression Results

- Estimated Ohio impacts range from shifting \$20 from FY 2004 into FY 2003 to shifting \$40 million from FY 2004 into FY 2003, depending on whether one believes that the impact should be doubled due to the fact that the Ohio tax rate change is 1.0%, rather than the 0.5% modeled

Applying the Regression Results

- Actually the final impact also involves cash flow lags in collecting auto sales tax revenue, since some of the increased activity at the end of FY 2003 actually results in higher FY 2004 tax collections
- This means that the shifting of tax revenue is somewhat less than the shifting of purchases between years

Notes

- If you had disaggregated data on non-auto sales tax revenues that allowed you to isolate “big-ticket” items like furniture and appliances, you could try the same analysis there

Notes

- We have also estimated full “transfer function” models
 - structural model with ARIMA errors
 - uses actual tax rate values instead of “high” and “low” dummy variables
 - coefficient on tax rate is negative and statistically significant

Closing

- What we have shown is only a fraction of the models we estimated to arrive at our “final” estimates
- We realize that our estimations are rough
- We welcome any suggested improvements