FORECASTING WHEN THE DATA ARE ILL-BEHAVED – EXAMPLE USING THE KENTUCKY SALES TAX

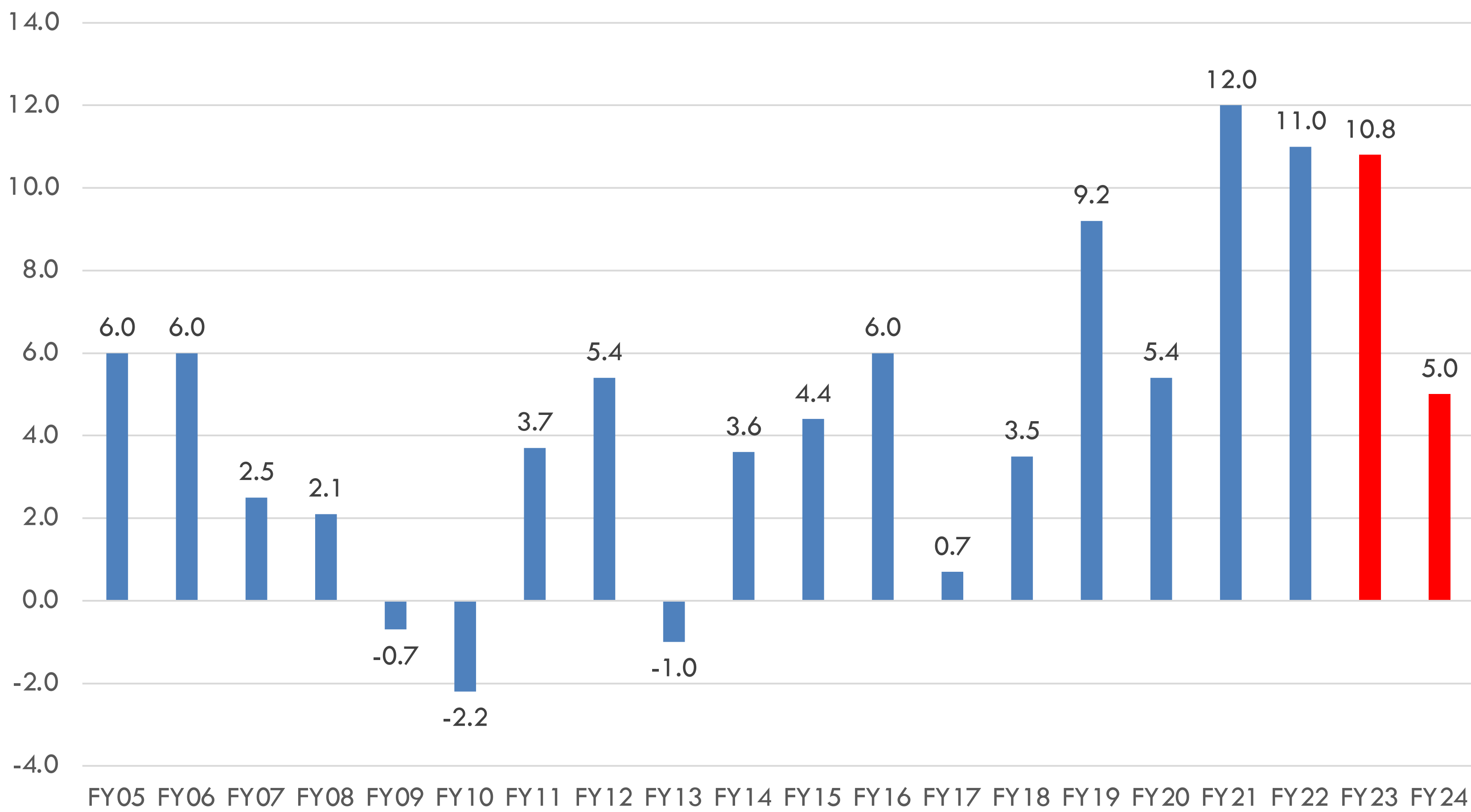
A presentation to the FTA Revenue Estimation Conference

Pittsburgh, Pennsylvania October 25, 2022

Greg Harkenrider

Governor's Office for Economic Analysis. Office of State Budget Director

Sales Tax Growth Rates



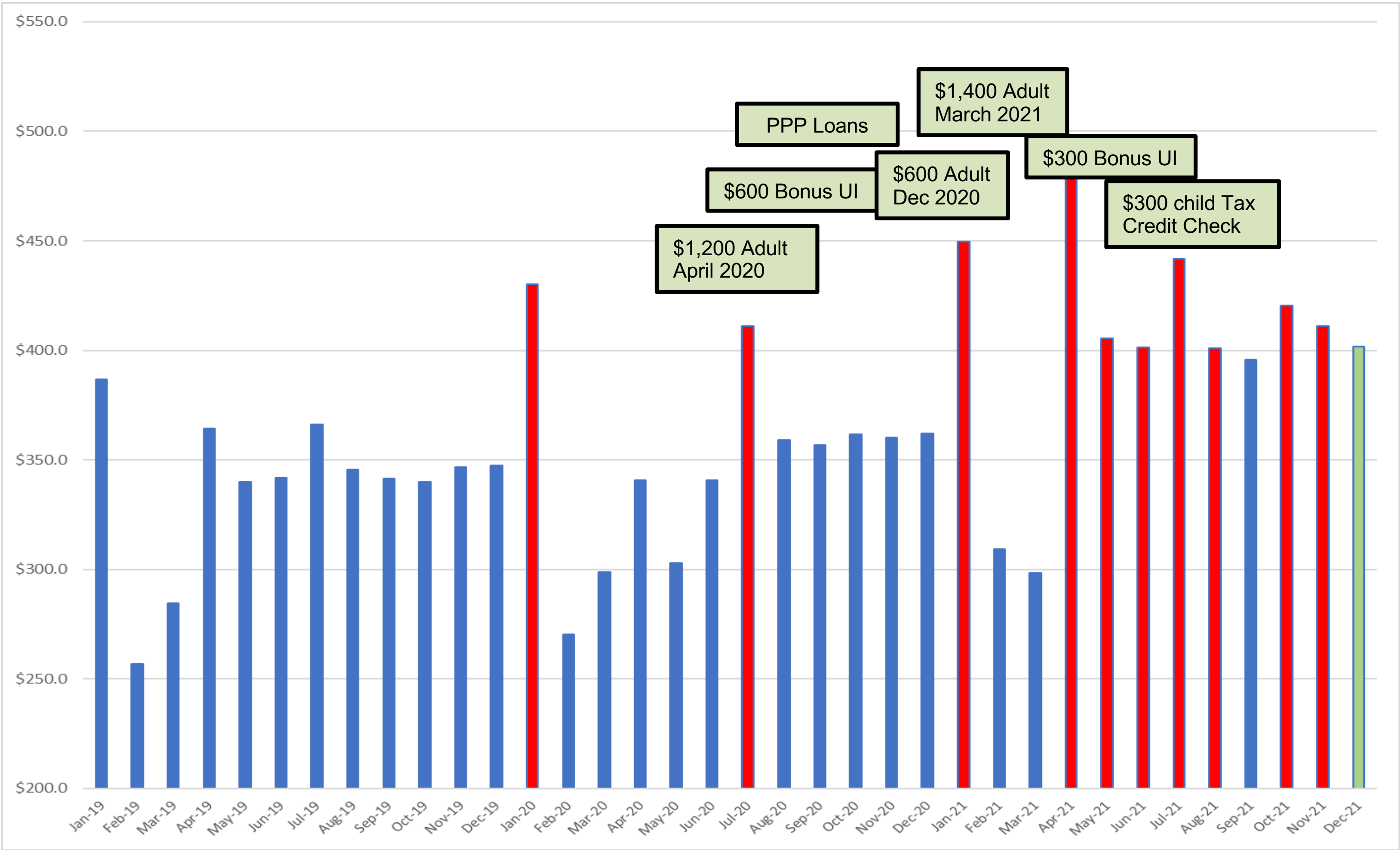
FY2021 General Fund Revenues

(FY21 revenue totals, $ million)

	FY21 Actual Receipts	FY21 Enacted Estimate	Difference from Enacted	Percent Change vs. FY20
Sales and Use	$4,561.0	$4,232.8	$328.2	12.0
Individual Income	5,143.8	4,813.0	330.8	7.9
Corp Inc & LLET	882.8	547.5	335.3	38.1
Coal Severance	56.1	52.4	3.7	-4.7
Cigarette Taxes	349.9	345.2	4.7	-1.4
Property	702.5	663.7	38.8	9.2
Lottery	289.1	286.1	3.0	6.5
Other	842.2	763.3	78.9	10.4
TOTAL	**$12,827.4**	**$11,704.0**	**$1,123.4**	**10.9%**

Monthly Sales Tax Collections

(Millions $, Influenced by Federal Stimulus efforts from CARES, CAA, and ARP)



FY2022 General Fund Revenues

(FY22 revenue totals, $ million)

	FY22				
	Full Year		Official		
	Actual	% Chg	Estimate	$ Diff	% Diff
Individual Income	6,047.5	17.6	5,424.7	622.8	11.5
Sales & Use	5,062.9	11.0	4,950.7	112.2	2.3
Corp. Inc. & LLET	1,186.6	34.4	970.5	216.1	22.3
Property	723.9	3.0	679.2	44.7	6.6
Lottery	295.0	2.0	319.3	-24.3	-7.6
Cigarettes	324.5	-7.3	334.7	-10.2	-3.1
Coal Severance	70.7	26.0	64.1	6.6	10.2
Other	991.5	17.7	1,013.9	-22.4	-2.2
General Fund	**14,702.5**	**14.6**	**13,757.1**	**945.4**	**6.9**

TEAM KENTUCKY

Dilemma We are Facing

- Underestimated the sales tax for two consecutive years, frankly tired of chasing it up
- Chosen composite forecasting for the sales tax
- Time series models have performed better in-sample, but …
- Is there a turning point coming, despite 12.8% growth in the first quarter?
- Structural models tend to do better during turning points vis-à-vis pure time series approaches

FY2023 General Fund Revenues

(FY23 revenue totals, $ million)

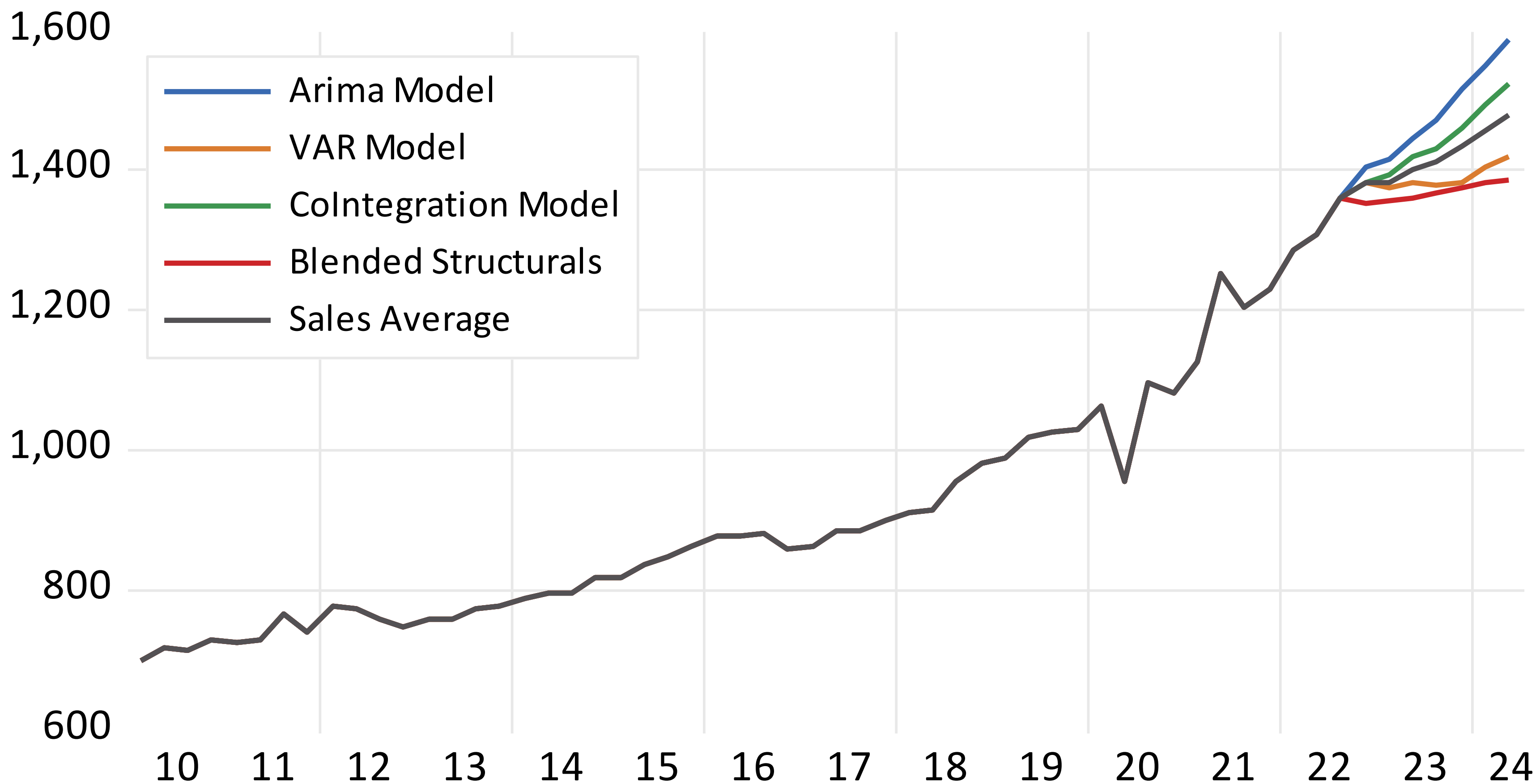
Table 1
General Fund Interim Forecast
$ millions

	FY23						FY23	
	Q1		Q2, Q3, & Q4		Full Year		Official CFG	
	Actual	% Chg	Estimate	% Chg	Estimate	% Chg	Estimate	$ Diff
Individual Income	1,368.9	8.4	4,399.8	-8.1	5,768.7	-4.6	5,342.3	426.4
Sales & Use	1,397.1	12.8	4,210.6	10.1	5,607.7	10.8	5,283.2	324.5
Corp. Inc. & LLET	337.2	16.0	1,056.6	17.9	1,393.8	17.5	909.8	484.1
Property	68.0	7.8	690.7	4.5	758.7	4.8	674.9	83.8
Lottery	75.0	7.9	262.0	16.2	337.0	14.2	335.0	2.0
Cigarettes	81.1	-3.4	231.4	-3.8	312.5	-3.7	318.6	-6.1
Coal Severance	22.1	72.2	72.8	25.9	94.9	34.3	76.6	18.3
Other	207.1	-48.7	636.1	8.3	843.2	-15.0	818.7	24.5
General Fund	**3,556.6**	**3.8**	**11,559.9**	**2.5**	**15,116.5**	**2.8**	**13,759.0**	**1,357.5**

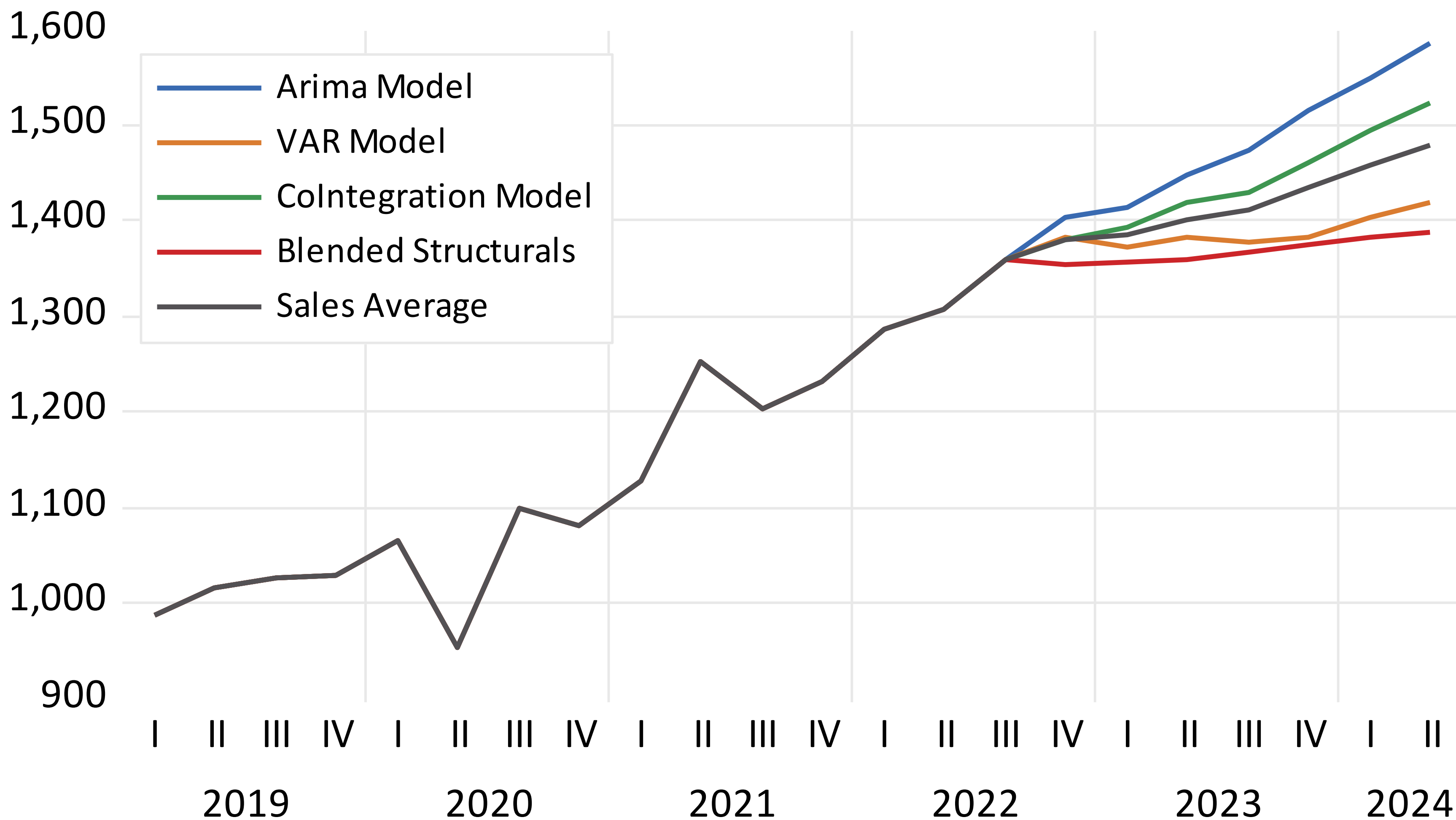
Lessons Learned from the Last 2 Years

- Time Series versus Structural Models
  - Don't disregard the various time series approaches (VEC, ARIMA, VAR, Cointegration)
  - Consider composite forecasting
- Difficulty in fitting dummy variables (inflation, fiscal stimulus, etc.) and populating dummies going forward
- Differenced data versus nominal or log specifications
- Consider the length of your estimation sample
- Turning points and time series models

Sales Tax Model Current Unofficial



Sales Tax Model Fall 2022



Model Specifications, Sales Tax

(Used in the latest Unofficial Estimates)

- Time Series for Estimation: 2010q1 to 2022q3
  - Have data back to 1990q1
  - Many law changes dating back that far
- All models use seasonally-adjusted data
- Arima {AR (1,3); 1st difference; MA (1,4,5)}
- Cointegration (Sales and Withholding)
- VAR (Sales and Wages & Salaries)
- Structural Models (SRTAFS_0 Nominal Retail Sales); (CDFHE_0 Consumer Spending Furniture and Durable Home); (DOMPURCH_0) Final Sales to Domestic Purchasers;

Advocacy for Time Series Models

(Suggest Blending for longer-term forecasting)

- Time series models have a place at the table during times where growth is faster than the underlying economy would predict
- Even ARIMA models can be used if the forecasting horizon is short; Avoid a-theoretical models for longer time horizons
- VAR models have a built-in check
- Still feel the need to blend in structural models

Aside: How to Blend?

- Subjective Methods
  - Averaging or weighted averaging (but how do you determine the weights?)
  - Let the "decider" help determine the weights
    - Decider could be either the chief revenue estimator; or
    - The consensus forecasting group who oversees the process
- Objectively
  - Restricted Least Square where the restriction is that the coefficients must add to 1(Use the forecasts you wish to blend as the regressors to predict the withheld historical observations in-sample)
  - Weight by the MSE or AIC, SIC methods

Restricted Least Squares Method

- Withhold 8 to 12 quarters of data from the estimation sample.
- Get the forecasted values for each equation
- Then forecast the 8 to 12 quarters you withheld
  - Dependent Variable is Sales Tax
  - Independent Variables are your forecasted values you wish too blend
- You must restrict coefficients to equal 1
- Sales = c + B_1(F1) + B_2(F2) + 1-B_1 -B_2 (F3)

Lesson 2 – Dummy Variables

- Considered dummy variables for inflation and for federal fiscal policy
- Problems:
  - Don't fit statistically if your model dates back very far
    - No variation in the dummy until COVID period)
    - Coefficients insignificant
  - How do you populate the dummy variable going forward?
    - Example: Fiscal Stimulus. How do we know which present and future quarters will be 1 or Zero?
  - Quickly get Dummy Paralysis if you try to account for all exogenous possibilities that require dummy variables

Lesson 3 – Differenced Data

Null Hypothesis: SALES_SA has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=3)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.560400	0.9828
Test critical values:	1% level	-3.959148	
	5% level	-3.081002	
	10% level	-2.681330	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations
and may not be accurate for a sample size of 15

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SALES_SA)
Method: Least Squares
Date: 10/21/22 Time: 11:49
Sample (adjusted): 2019Q1 2022Q3
Included observations: 15 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SALES_SA(-1)	0.075009	0.133850	0.560400	0.5855
D(SALES_SA(-1))	-0.611567	0.257786	-2.372387	0.0352
C	-43.52620	147.0470	-0.296002	0.7723

R-squared	0.323966	Mean dependent var	25.29898
Adjusted R-squared	0.211293	S.D. dependent var	61.82121
S.E. of regression	54.90291	Akaike info criterion	11.02587
Sum squared resid	36171.95	Schwarz criterion	11.16748
Log likelihood	-79.69400	Hannan-Quinn criter.	11.02436
F-statistic	2.875288	Durbin-Watson stat	2.436106
Prob(F-statistic)	0.095458		

Dependent Variable in Levels

Dependent Variable: SALES_SA
Method: Least Squares
Date: 10/21/22 Time: 11:24
Sample: 2010Q1 2022Q3
Included observations: 51

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-48.60816	24.39196	-1.992795	0.0519
SRTAFS_0	0.168530	0.004232	39.82638	0.0000

R-squared	0.970033	Mean dependent var	907.8747
Adjusted R-squared	0.969422	S.D. dependent var	174.1502
S.E. of regression	30.45310	Akaike info criterion	9.708679
Sum squared resid	45442.17	Schwarz criterion	9.784437
Log likelihood	-245.5713	Hannan-Quinn criter.	9.737628
F-statistic	1586.140	Durbin-Watson stat	0.512677
Prob(F-statistic)	0.000000		

Dependent Variable in Logs

Dependent Variable: LOG(SALES_SA)
Method: Least Squares
Date: 10/21/22 Time: 11:26
Sample: 2010Q1 2022Q3
Included observations: 51

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.117167	0.245936	-8.608624	0.0000
LOG(SRTAFS_0)	1.032749	0.028495	36.24306	0.0000

R-squared	0.964038	Mean dependent var	6.794574
Adjusted R-squared	0.963304	S.D. dependent var	0.179926
S.E. of regression	0.034467	Akaike info criterion	-3.859210
Sum squared resid	0.058210	Schwarz criterion	-3.783452
Log likelihood	100.4099	Hannan-Quinn criter.	-3.830261
F-statistic	1313.559	Durbin-Watson stat	0.422920
Prob(F-statistic)	0.000000		

Differenced Dependent Variable

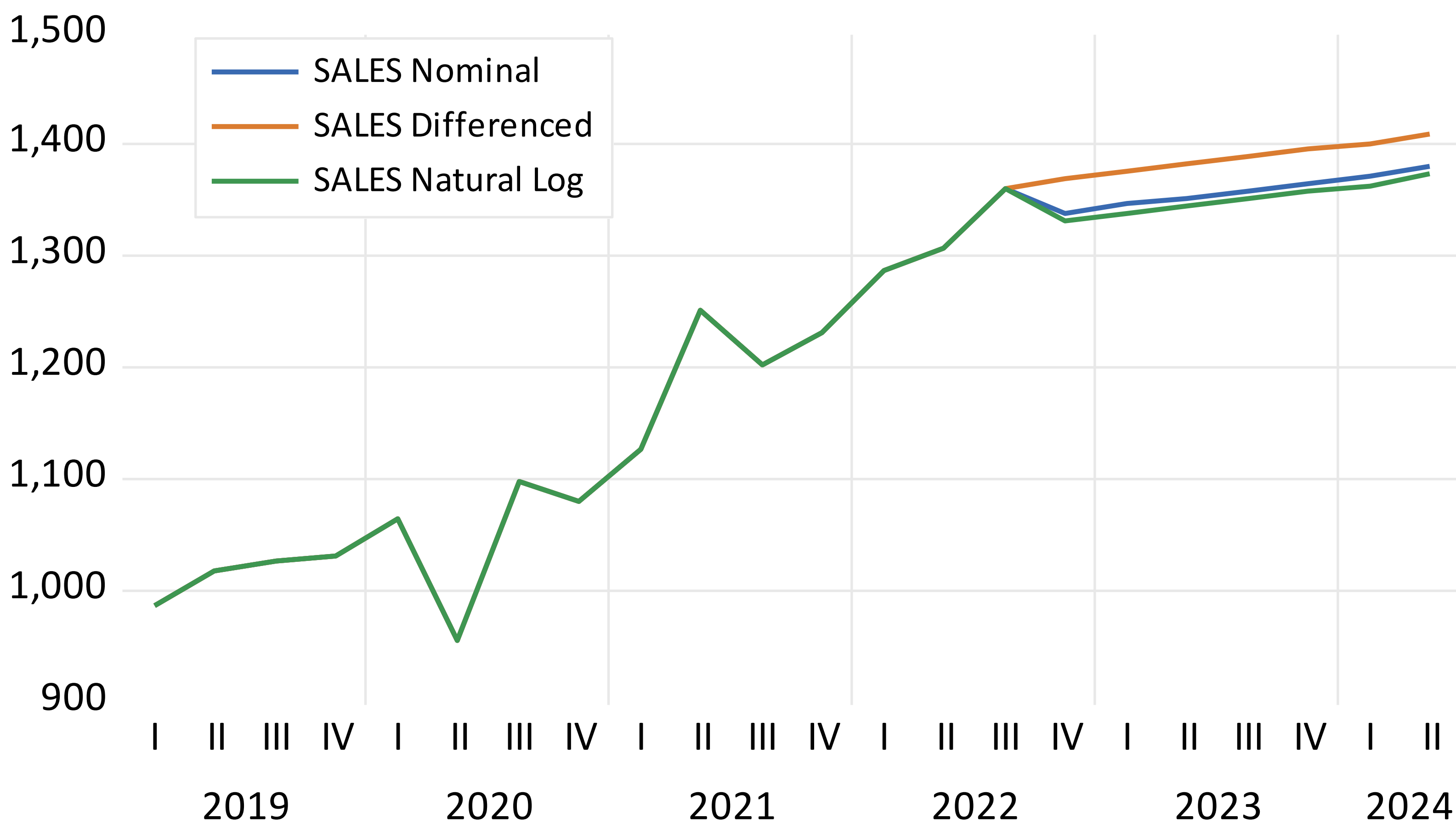
Dependent Variable: D(SALES_SA)
Method: Least Squares
Date: 10/21/22 Time: 11:30
Sample: 2010Q1 2022Q3
Included observations: 51

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.374759	3.380882	-0.110847	0.9122
D(SRTAFS_0)	0.170679	0.018326	9.313535	0.0000

R-squared	0.639021	Mean dependent var	13.15730
Adjusted R-squared	0.631654	S.D. dependent var	35.92105
S.E. of regression	21.80103	Akaike info criterion	9.040218
Sum squared resid	23288.96	Schwarz criterion	9.115975
Log likelihood	-228.5255	Hannan-Quinn criter.	9.069167
F-statistic	86.74193	Durbin-Watson stat	2.470990
Prob(F-statistic)	0.000000		

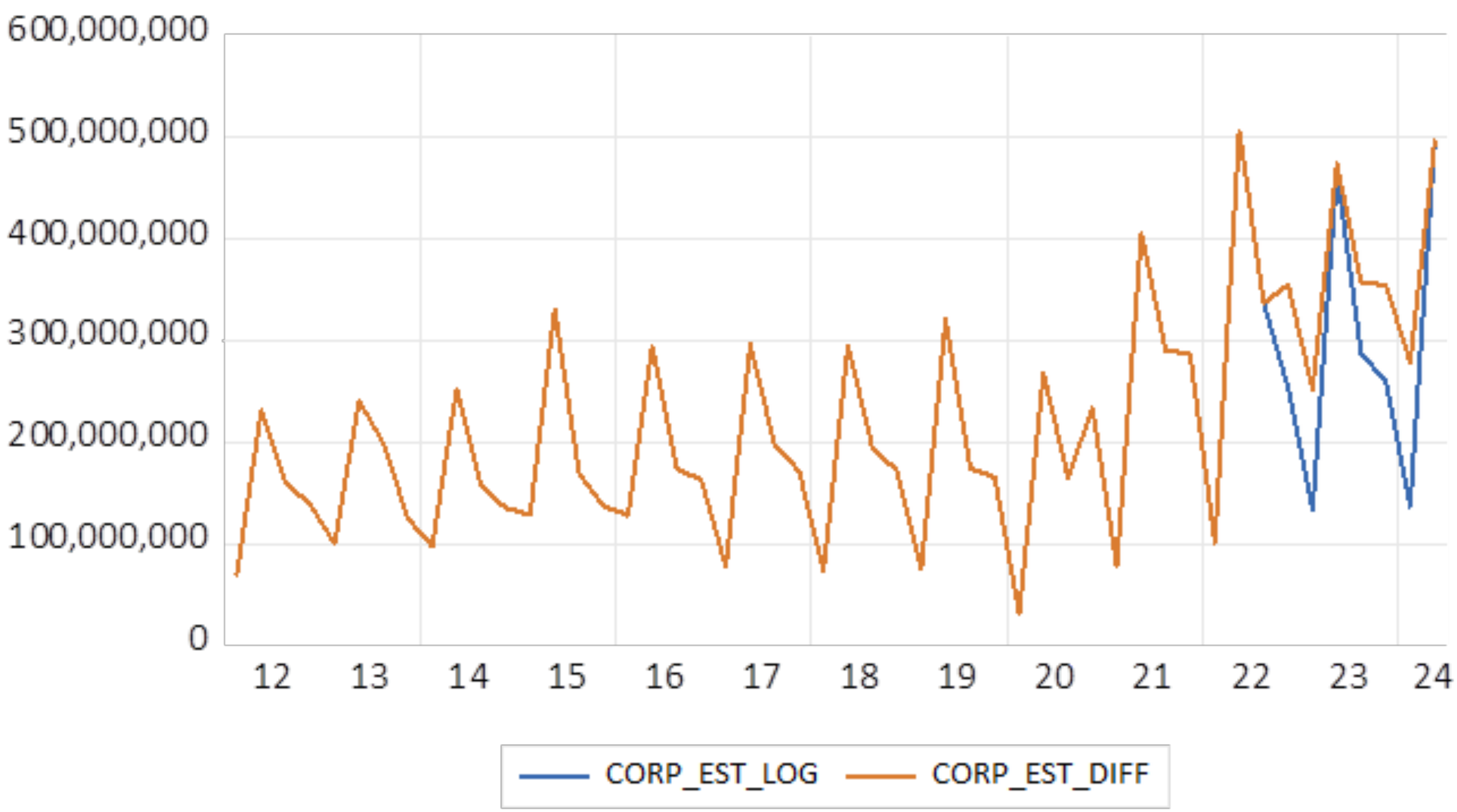
Differencing Data or Not?

(Forecasting Sales Tax, Structural Model, Using Nominal Variable, Natural Logs, and Differences)



Natural Logs versus Differences

(Corporation Income Taxes)

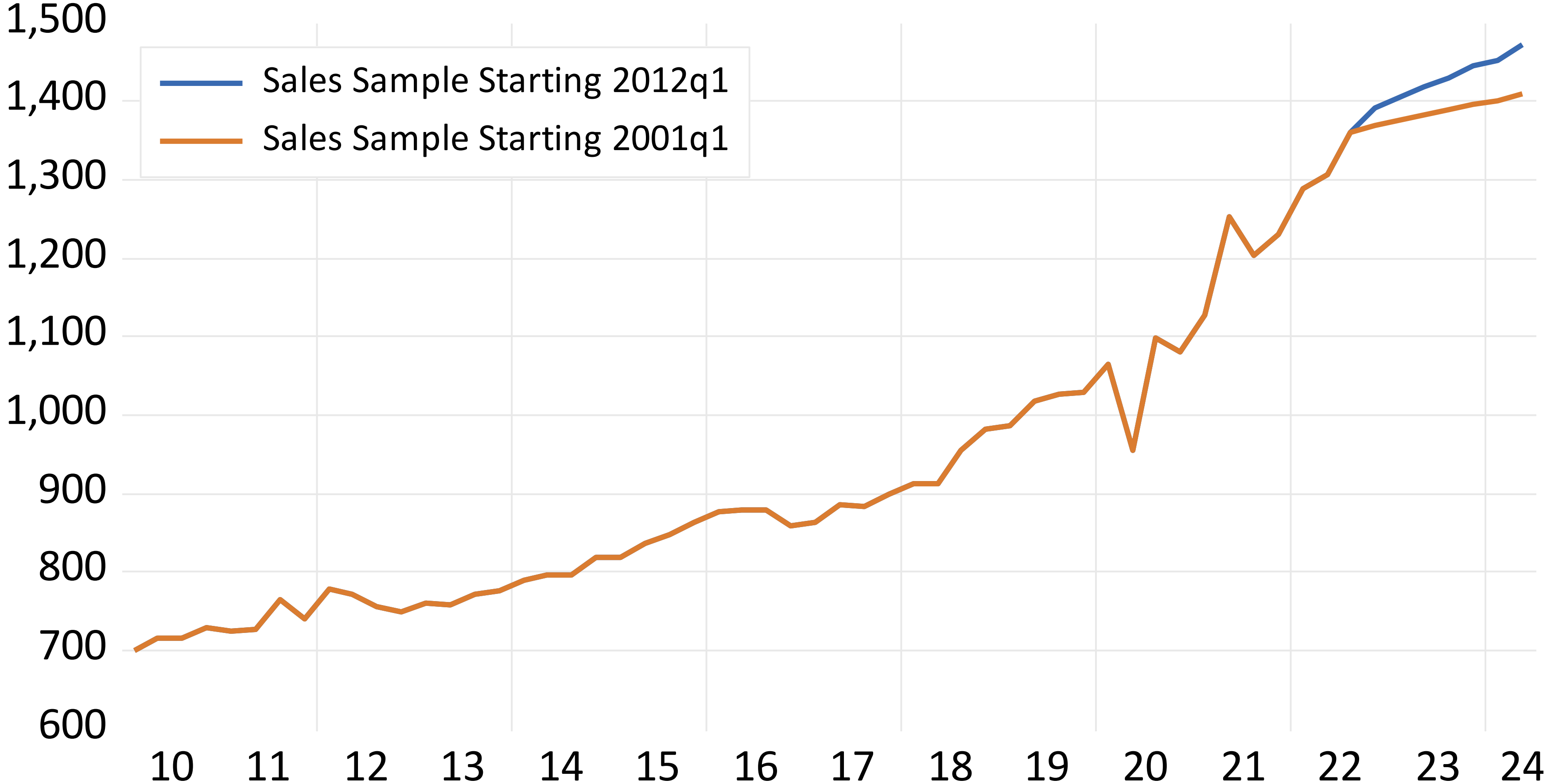


Lessons Learned 4 – Length of Sample

- The rule of thumb that you should always use the entire sample size when running a regression is not always true in time series modeling
- Factors to consider:
  - Tax Reform – Need to have a policy-neutral dependent variable
  - Major court cases or board of tax appeals rulings can affect a time series
  - Changes in the administration of a tax can corrupt a time series

Forecasting Differences due to Sample Size

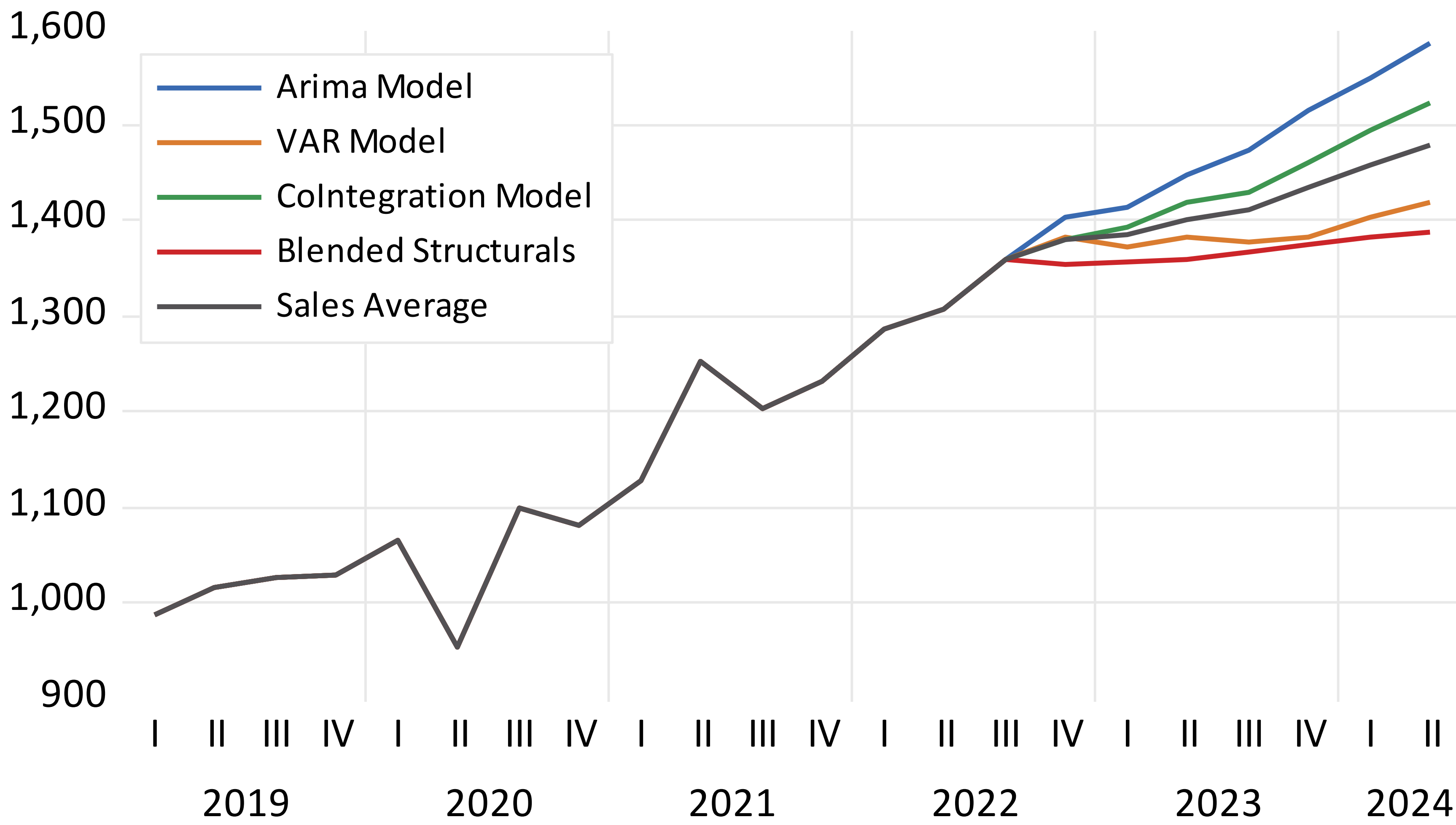
(Structural Model with US Retail Sales)



Lesson 5: Times Series and Turning Points

- While time series models may have predicted the past better than some other models, they do not capture turning points
- Structural models will better reflect the macro turning points projected by IHS Markit
- Still feel the need to blend given past forecasting errors

Sales Tax Model Fall 2022



Disaggregation of Past Errors

- Errors in IHS Markit forecasts that provide predicted values in structural models
  - Mitigated by composite forecasting
  - Made up over one-half of the error in structural models
- Errors in time series models
  - Smaller differences in sample
  - Could change around turning points
- True error was that we didn't trust the time series models enough to use objective weights

Conclusions

- Forecasting is difficult when the data are ill-behaved
- Consider composite forecasting or blended forecasts
- Don't completely rule out time series models if your goal is accuracy in the short run
- Differenced data is preferable for nonstationary dependent variables
- Don't let your preconceived beliefs dictate your weights or selection of models
- Time series models may overshoot in periods of turning points