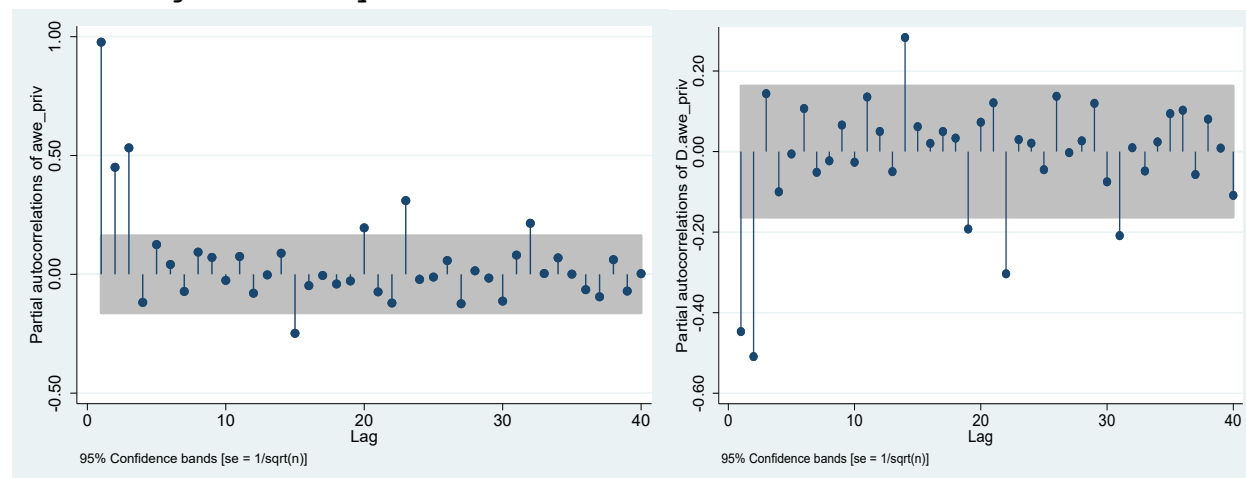


**Final Exam****Instructions**

- Answer the questions below on the answer sheet provided. Write only on the fronts of the pages.
  - Organize your answers logically. Use scratch paper to work them out ahead of time if needed.
  - Be NEAT! If it is too hard to read, it is wrong.
  - Be concise. You will lose points for saying incorrect things as well as for not saying correct things.
- 
1. Consider part 1 of the output provided. Interpret the PACs and Dickey-Fuller results. What do they imply for modeling average weekly earnings?
  2. Part 2 of the output gives results for a “baseline” model. Why would we think of this as the baseline model for a one-step forecast in this case?
  3. Consider the baseline model in part 2 of the output and the alternative model in part 3 of the output. Argue that the alternative model with a window size of 60 months is best.
  4. Suppose you want to know the confidence interval for the change in next month’s average weekly earnings associated with a change in the share of employment in leisure and hospitality. Should you use the output in part 3 or the output in part 4? Why?
  5. Using the information in part 5 of the output, calculate the 90% empirical forecast interval for March 2019 average weekly earnings. Why not use the coefficients from part 3 of the output?
  6. To keep work on question 5 simple, all variables are untransformed. Why would it make sense to take the log before modeling average weekly earnings? If we were working in logs what additional steps would you need to perform in the previous question?
  7. Out of sample validation is crucial to protect against over fitting. What is overfitting? Why is standard K-fold cross validation potentially troublesome in a time series context? What is rolling window estimation and validation? How does it avoid the trouble suffered by with K-fold cross validation?
  8. Suppose we want to explore models with alternative predictors and various lags. We used the GSREG package to do such things. Why did we use AIC, BIC, and out of sample RMSE to rank models with GSREG instead of the regular RMSE or R-Squared?
  9. How would we best go about making a forecast for average weekly earnings for horizons 2, and 3?
  10. What is a fan chart, and how would we make one for our forecasts?
  11. How would the baseline model above be used to make a dynamic forecast for horizons 1, 2, and 3? What are the advantages and disadvantages of this relative to the method in the previous question?
  12. How would a Vector Autoregressive Model (VAR) be used to make a dynamic forecast for horizons 1, 2, and 3?
  13. Briefly, what does Christopher Sims have to do with VAR models and what was his critique about?
  14. Rewrite the AR(1) model  $y_t = ay_{t-1} + e_t$  ( $e$  is white noise and  $0 < a < 1$ ) as an infinite MA model.
  15. What is the Wold Representation Theorem and why is it foundational for forecasting?

The Stata output below pertains to models of monthly average weekly earnings for private sector employees in Florida (awe\_priv). The baseline model is purely autoregressive. The alternative model includes the share of leisure and hospitality employment in total nonfarm employment (share\_lh). All models include month indicators.

## 1. Assessing Stationarity



### Dickey-Fuller Test for Average Weekly Earnings

Augmented Dickey-Fuller test for unit root				Number of obs	=	133
				----- Interpolated Dickey-Fuller -----		
	Test	1% Critical	5% Critical	10% Critical		
	Statistic	Value	Value	Value		
-----						
Z(t)	0.332	-4.029	-3.446	-3.146		
-----						

MacKinnon approximate p-value for Z(t) = 0.9964

### Dickey-Fuller Test for *Difference* in Average Weekly Earnings

Augmented Dickey-Fuller test for unit root				Number of obs	=	132
				----- Interpolated Dickey-Fuller -----		
	Test	1% Critical	5% Critical	10% Critical		
	Statistic	Value	Value	Value		
-----						
Z(t)	-3.625	-4.029	-3.446	-3.146		
-----						

MacKinnon approximate p-value for Z(t) = 0.0278

## 2. Baseline Model

Source	SS	df	MS	Number of obs	=	133
Model	8709.02717	23	378.653355	F(23, 109)	=	7.00
Residual	5898.44378	109	54.1141631	Prob > F	=	0.0000
				R-squared	=	0.5962
				Adj R-squared	=	0.5110
Total	14607.471	132	110.662659	Root MSE	=	7.3562

D.awe_priv	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
awe_priv						
LD.	-.6011393	.094644	-6.35	0.000	-.7887205	-.413558
L2D.	-.5196872	.1092459	-4.76	0.000	-.736209	-.3031654
L3D.	-.0015883	.1198929	-0.01	0.989	-.2392122	.2360356
L4D.	-.0460876	.1160451	-0.40	0.692	-.2760853	.1839101
L5D.	.0929756	.1156809	0.80	0.423	-.1363003	.3222514
L6D.	.2451245	.1134313	2.16	0.033	.0203074	.4699417
L7D.	.2386793	.110899	2.15	0.034	.0188812	.4584775
L8D.	.154619	.1099346	1.41	0.162	-.0632678	.3725059
L9D.	.282376	.1093647	2.58	0.011	.0656187	.4991332
L10D.	.0314288	.1116487	0.28	0.779	-.1898554	.252713
L11D.	.170758	.1010646	1.69	0.094	-.0295488	.3710647
L12D.	-.0850619	.0875797	-0.97	0.334	-.258642	.0885182

Note: Coefficients for month indicators and constant not shown to save space.

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	133	-501.1983	-440.8931	24	929.7862	999.1546

Note: N=Obs used in calculating BIC; see [R] BIC note.

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	8.966	1	0.0028
12	26.578	12	0.0089

H0: no serial correlation

. /\*Rolling window results - Baseline Model

\*Windows over 6 years not considered as there are only 12 years of data and leaving out one year of lags plus a 6 year window leaves only 60 observations to fit.

RWrmse72 = 8.86  
 RWrmse60 = 10.46  
 RWrmse48 = 11.16  
 RWrmse36 = 13.91

3. Alternative Model					
Source	SS	df	MS	Number of obs	=
Model	7610.72315	14	543.623082	F(14, 118)	= 9.17
Residual	6996.74781	118	59.294473	Prob > F	= 0.0000
				R-squared	= 0.5210
				Adj R-squared	= 0.4642
Total	14607.471	132	110.662659	Root MSE	= 7.7003

*Note: Coefficients for month indicators and constant not shown to save space.*

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	133	-501.1983	-452.2485	15	934.4969	977.8521

Note: N=Obs used in calculating BIC; see [R] BIC note.

lags (p)	chi2	df	Prob > chi2
1	2.512	1	0.1130
12	23.524	12	0.0236

H0: no serial correlation

```
. /*Rolling window results for - Alternative Model
*Windows over 6 years not considered as there are only 12 years of data and leaving
out one year of lags plus a 6 year window leaves only 60 observations to fit.
  RWrmse72 = 8.58
  RWrmse60 = 9.24
  RWrmse48 = 10.04
  RWrmse36 = 10.57
```

Regression with Newey-West standard errors	Number of obs	=	133
maximum lag: 12	F( 14, 118)	=	23.49
	Prob > F	=	0.0000

*Note: Coefficients for month indicators and constant not shown to save space.*

## 5. Results for Forecasting March 2019

Estimated only on the last window (last 60 observations)

Source	SS	df	MS	Number of obs	=	60
				F(14, 45)	=	3.88
Model	3843.16422	14	274.51173	Prob > F	=	0.0003
Residual	3181.89571	45	70.7087935	R-squared	=	0.5471
				Adj R-squared	=	0.4062
Total	7025.05993	59	119.068812	Root MSE	=	8.4089

D.awe_priv	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
share_lh						
LD.	-38.43324	26.61219	-1.44	0.156	-92.03294	15.16647
awe_priv						
LD.	-.6407784	.1418874	-4.52	0.000	-.9265542	-.3550025
L2D.	-.4746529	.1275719	-3.72	0.001	-.7315959	-.2177099
md2	14.53186	8.573556	1.69	0.097	-2.736166	31.79989
md3	-1.158425	5.805917	-0.20	0.843	-12.85214	10.53529
_cons	1.325165	3.898538	0.34	0.736	-6.526894	9.177224

Note: Coefficients for month indicators 4-12 not shown to save space.

Summary Statistics	
Rolling Window Residuals for w=60	
Obs	84
Mean	2.22
Median	0.79
5 <sup>th</sup> Percentile	-9.06
95 <sup>th</sup> Percentile	19.54

Last 3 months of data		
Date	awe_priv	share_lh
Dec 2018	878.60	13.79
Jan 2019	874.45	13.40
Feb 2019	878.58	13.94