Time Series Modeling and Forecasting

Spring 2019 Midterm

The questions and Stata output below relate to three monthly non-seasonally adjusted time series from January 1990 through December 2017. Variable definitions are:

- fl_unemprate_m: Florida unemployment fate.
- us_unemprate_m: US unemployment rate.
- fl bldpmt m: Florida building permits issued, in hundreds of thousands

Part A: Time Series Basics and Static Models

- 1) The first model in the Stata output regresses the unemployment rate in Florida on the US unemployment rate. The second adds month indicators and a linear time trend.
- a) What is the purpose of adding the month indicators and the time trend?
- b) What do you make of the change in the coefficient on US unemployment and its standard error that occurred when month indicators and a time trend were added?
- 2) Nonstationarity
- 2a) What is a non-stationary process and why do we need to be wary of them?
- 2b) Interpret the partial autocorrelogram and Dickey-Fuller test results for the Florida unemployment rate that follow the second regression model.
- 3) The third regression model in the output regresses the first difference of the unemployment rate in Florida on the first difference of the US unemployment rate, including month indicators and a time trend.
- a) The time trend was much smaller and less statistically significant in the third model than in the second model. What do you make of that?
- b) Compare the coefficients on US unemployment in the second and third models. What likely explains the difference?
- c) Interpret the Breusch-Godfrey test results that follow estimation of the third model.
- d) In November 2017, the Florida unemployment rate was 3.8 and the US unemployment rate was 3.9. In December 2017, date was 695 and the US unemployment rate was 3.9. Using the third regression, what are the predicted values of the change in Florida unemployment rate and the Florida unemployment rate in December 2017? Show your work.

Part B: Model Selection

The Stata output for Part B contains four ARDL models relating the unemployment rate in Florida to the US unemployment rate and Florida building permits (in hundreds of thousands). Thoroughly make the case that Model 4 is the best of them.

Stata Results Log - Graphs Added

- . import delimited using "fl and us monthly data.csv" (11 vars, 338 obs)
- . gen date=ym(year, month)
- . tsset date

time variable: date, 360 to 697

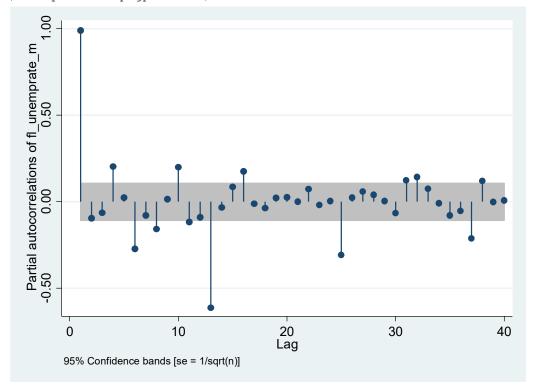
delta: 1 unit

- . format date %tm
- . replace fl_bldpmt_m=fl_bldpmt_m/100000
 variable fl_bldpmt_m was int now float
 (337 real changes made)

. **Part A: Time Series Modeling

	rate_m us_unemp	-				
Source	SS	df	MS		of obs =	336
+ Model	1373.01017	 1 13	73.01017	F(1, 3 Prob >		3624.90 0.0000
Residual	126.509734		37877166	R-squa	red =	0.9156
+				_	squared =	0.9154
Total	1499.5199	335 4.	47617882	Root M	SE =	.61544
fl_unemprate_m	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
us_unemprate_m _cons	1.280026	.0212604	60.21 -12.64	0.000	1.238205 -1.923707	1.321847 -1.4057
. reg fl_unemp Source	rate_m us_unemp	prate_m i.mo df	onth date MS		of obs =) 336 460.66
Model	1423.00571	13 10	9.461978	Prob >	F =	0.0000
Residual	76.514196		37621727	R-squa		0.9490
+					±	0.9469
Total	1499.5199	335 4.	47617882	Root M	SE =	.48746
fl_unemprate_m	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
us_unemprate_m month		.017358	76.40	0.000	1.291961	1.36026
2	1012826	.1302994	-0.78	0.438	3576282	.1550631
3	.0658376	.1304181	0.50	0.614	1907416	.3224168
4 5	.5238028 .6580757	.1310942	4.00 5.02	0.000	.2658936 .4002212	.781712 .9159302
6	.5810037	.1304729	4.45	0.000	.3243166	.8376907
7	1 .7009909	.1304723	5.37	0.000	.4443255	.9576564
8	.9560773	.1307372	7.31	0.000	.6988704	1.213284
9	1.081505	.1311109	8.25	0.000	.8235628	1.339447
10	1.032552	.1313954	7.86	0.000	.7740497	1.291054
11	.8967929	.1313044	6.83	0.000	.63847	1.155116
12	.6858793	.1312625	5.23	0.000	.4276389	.9441196
date		.0002771	-2.93	0.004	0013558	0002655
_cons	-2.103154	.1944202	-10.82	0.000	-2.485648	-1.72066

. pac fl_unemprate_m, saving(pacflunemp, replace)
(file pacflunemp.gph saved)



. dfuller fl_u Augmented Dick		st for unit	root	Numb	er of obs = Dickey-Fuller		
	Test Statistic		ical	_	tical 10		
Z(t)	-3.825	-3	.987	-	-3.427	-3.130	
MacKinnon approximate p-value for Z(t) = 0.0153							
D.fl_unemp~m	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]	
fl_unempra~m L1. LD. L2D. L3D. L5D.	.0426095 .0931672 0433071 .0097457 .0925232	.0064149 .0447195 .0447301 .0450679 .0446838	-3.82 0.95 2.08 -0.96 0.22 2.07	0.000 0.341 0.038 0.337 0.827 0.039	0371588 0453849 .005152 131987 0781785 .004644	0119138 .1306038 .1811824 .0453728 .0976699 .1804024	
L6D. L7D. L8D. L9D. L10D. L11D. L12D. _trend _cons	.021341 .0831795 .0061132 0929745 .0220614 .0518429 .6143788 .000068	.0448711 .0448882 .0449954 .0449895 .0450937 .0449283 .0451481 .0001399 .0443752	0.48 1.85 0.14 -2.07 0.49 1.15 13.61 0.49 2.92	0.635 0.065 0.892 0.040 0.625 0.249 0.000 0.627 0.004	0669518 005147 0824241 1815002 0666693 0365623 .525541 0002073 .0422007	.1096338 .1715059 .0946505 0044489 .1107922 .1402481 .7032165 .0003434 .2168345	

. reg d.fl_unemprate_m d.us_unemprate_m i.month date if tin(1990m1,2017m12)

Source		SS		df	1	MS		mber		bs	=	335 157.85
Model Residual		.4230229 60252841		13 321	2.263		Pr R-	13, 3 ob > squar	F ed	od	= =	0.0000 0.8647 0.8593
Total	34	.0255513		334	.1018	72908		ot MS	_	eu	=	.11974
D. fl_unempra~m	 -+	Coef.	Std.	Err.		t E	?> t		[95%	Conf	 	Interval]
us_unempra~m D1. month 2		9858471 2509459	.048		26. 5.	16 (0.000		.155	4911 2292		1.060203
3 4 5 6 7		4889657 6850209 5351038 4622925 5208137	.051 .059 .044 .035	7572 7468 8577	9. 11. 11. 12. 11.	46 (96 (89 (0.000 0.000 0.000 0.000		.567 .447	1959 4556 0698 7466		.5897355 .8025862 .6231378 .5328384 .6088342
8 9 10 11 12 date		5708447 4460446 .300827 2747806 1923321 .23e-06	.051 .051 .048 .043	7264 3022 8244 9874 5383	11. 8. 6. 4.	04 (69 (16 (25 (32 (0.000 0.000 0.000 0.000 0.000		.469 .345 .204 .188 .104	0791 1137		.6726102 .5469755 .3968833 .3613205 .279956
_cons		3967368	.054		-7.		0.000			0606		289413

. estat bgodfrey, lags(1,12,24) Breusch-Godfrey LM test for autocorrelation

lags (p)	 +	chi2	df	Prob > chi2
1		0.902	1	0.3422
12		25.816	12	0.0114
24		34.964	24	0.0689

**Part B: Model Selection

Model 1

Pseudo-R2

```
. crossfold reg d.fl unemprate m 1(1/24) d.fl unemprate m 1(0/24) d.us unemprate m
1(0/24) d.fl bldpmt m i.month date if tin(1992m1,2017m12) , k(10)
          RMSE
-----
       est1 | .1331984
       est2 |
              .1157289
       est3 |
              .1379295
       est4 |
              .1439543
       est5 | .1148643
       est6 | .1286004
       est7 | .1215974
       est8 | .1118732
       est9 | .1738664
      est10 | .1210292
. *Calculate the root of the MSE averaged over k folds
. \stardefine k as the number of folds
. scalar define k=10
. *calculate the sum of the k MSEs
. matrix kMSE=r(est)'*r(est)
. *Calculate the root of the MSE averaged over k folds
. scalar krmse=(el(kMSE,1,1)/k)^.5
. *List the answer
. scalar list krmse
    krmse = .1314509
. *Drop the matrix and scalar defined for the problem
. matrix drop kMSE
. scalar drop krmse
. loocv reg d.fl unemprate m 1(1/24) d.fl unemprate m ///
  1(0/24)d.us unemprate m 1(0/24)d.fl bldpmt m ///
        i.month date if tin(1992m1,2017m12)
Leave-One-Out Cross-Validation Results
______
                     | Value
-----+-----
Root Mean Squared Errors | .12998808
Mean Absolute Errors | .09923896
```

.83025246

. reg d.fl_unemprate_m 1(1/24)d.fl_unemprate_m 1(0/24)d.us_unemprate_m /// $1(0/24)d.fl_bldpmt_m$ i.month date if tin(1992m1,2017m12)

Source	SS	df	MS	Numbe F(86,	r of obs = 224) =	311 27.87
Model	29.0087693	86	.33731127	Prob		0.0000
Residual			.012101987	R-squ		0.9145
+-					-squared =	0.8817
Total	31.7196144	310	.102321337	Root 1	MSE =	.11001
D.	1					
fl_unemprate_m	Coef.	Std. Err	. t	P> t	[95% Cont	. Interval]
fl_unemprate_m						
	0235661	.0665507		0.724	1547115	.1075794
	.1451443	.0667362		0.031	.0136332	.2766555
	0211972	.0673119		0.753	1538428	.1114484
L4D.		.0680479		0.060	2625592	.0056325
L5D.		.0690339		0.457	1875075	.0845705
	0054904 .0334073	.0686087		0.936 0.629	1406915	.1297106
L7D. L8D.		.0690403		0.629	1026443 2542644	.1694388
_	0235745	.0699749		0.091	1614678	.1143188
L10D.		.0666626		0.740	1092494	.1534828
L11D.	0407309	.0666194		0.740	1720117	.0905499
L12D.		.068334		0.087	0172223	.252097
	0077621	.0686095		0.910	1429648	.1274405
L14D.		.0690218		0.143	2375531	.0344772
L15D.	1534794	.0694948		0.028	2904267	0165321
L16D.	.0659237	.0695879		0.344	0712069	.2030544
	0060275	.0694083		0.931	1428042	.1307493
L18D.	0563072	.0704327	-0.80	0.425	1951027	.0824882
L19D.	1378448	.0709156	-1.94	0.053	2775919	.0019024
L20D.	0024464	.0704269		0.972	1412303	.1363375
L21D.	.022218	.0689642		0.748	1136836	.1581196
L22D.		.0682264		0.626	1677229	.1011725
L23D.		.0677268		0.254	055996	.2109304
L24D.	.0266005	.0678182	0.39	0.695	1070427	.1602438
us_unemprate_m						
	.955707	.0467436		0.000	.8635935	1.047821
LD.		.0792622		0.876	143786	.1686038
	0717746	.0796528		0.369	2287393	.0851901
L3D. L4D.	.0483615	.079692		0.545 0.436	1086805 0955033	.2054034
L5D.		.0811932		0.436	1214865	.198514
L6D.		.080632		0.588	1151913	.2025971
L7D.		.0797639		0.368	0853078	.2290595
L8D.		.0796835		0.016	.035607	.3496572
	062427	.0804939		0.439	2210492	.0961951
L10D.		.0797193		0.295	2407847	.0734065
L11D.		.0789281		0.738	1291329	.1819403
L12D.	·	.0799503		0.048	3161792	0010772
L13D.		.0803652		0.619	1983792	.1183578
L14D.	.1479014	.0815146		0.071	0127321	.3085349
	.1761673	.0818518		0.032	.0148691	.3374654
L16D.		.0816384		0.579	2062924	.1154627
L17D.		.0810087		0.836	1763846	.1428888
L18D.		.0821026		0.137	0391876	.2843971
	.1714005	.0820161		0.038	.0097786	.3330224
L20D.	.0150449	.0809207	0.19	0.853	1444184	.1745082

T 01 D	0458833	.0802155	-0.57	0.568	2039569	.1121902
L21D.						
L22D.	.0357954	.0798371	0.45	0.654	1215324	.1931231
L23D.	1139502	.0810678	-1.41	0.161	2737033	.0458029
L24D.	1016386	.0806861	-1.26	0.209	2606394	.0573623
fl_bldpmt_m						
_ D1.	.7579252	.5332993	1.42	0.157	2930003	1.808851
LD.	7520867	.6262269	-1.20	0.231	-1.986136	.4819629
L2D.	-1.429791	.6348991	-2.25	0.025	-2.68093	1786519
L3D.	4067094	.6384072	-0.64	0.525	-1.664762	.8513429
L4D.	-2.206063	.6404142	-3.44	0.001	-3.46807	9440557
L5D.	-1.572978	.6517656	-2.41	0.017	-2.857355	2886017
L6D.	3398947	.6485971	-0.52	0.601	-1.618027	.9382379
L7D.	.306994	.6390747	0.48	0.631	9523736	1.566361
L8D.	-1.418312	.6375356	-2.22	0.027	-2.674647	1619776
L9D.	4946929	.6449166	-0.77	0.444	-1.765573	.7761868
L10D.	598325	.6511689	-0.92	0.359	-1.881526	.6848756
L11D.	771069	.6554464	-1.18	0.241	-2.062699	.5205609
L12D.	7983019	.6646229	-1.20	0.231	-2.108015	.5114112
L13D.	2642365	.6626575	-0.40	0.690	-1.570077	1.041604
L14D.	2676502	.6639671	-0.40	0.687	-1.576071	1.040771
L15D.	-1.560773	.6624768	-2.36	0.019	-2.866257	2552892
L16D.	.4478867	.6745288	0.66	0.507	8813473	1.777121
L17D.	183118	.6792566	-0.27	0.788	-1.521668	1.155432
L18D.	6444352	.6808455	-0.95	0.345	-1.986117	.6972464
L19D.	9463943	.6871076	-1.38	0.170	-2.300416	.4076275
L20D.	-1.114874	.6918417	-1.61	0.108	-2.478225	.2484763
L21D.	-1.651977	.675783	-2.44	0.015	-2.983682	3202719
L22D.	8962605	.6761209	-1.33	0.186	-2.228632	.4361107
L23D.	-1.169693	.6612269	-1.77	0.078	-2.472714	.1333277
L24D.	4624015	.5701709	-0.81	0.418	-1.585987	.6611836
month	.4024015	.5701705	0.01	0.410	1.303307	.0011030
2	.1848949	.1292539	1.43	0.154	0698143	.439604
3		.1743256	1.43	0.060	0141441	.6729116
4	.4956766	.1947931	2.54	0.012	.1118152	.879538
5	.4608421	.1573362	2.93	0.012	.1507936	.7708905
6	.4412186	.1296285	3.40	0.004	.1857714	.6966659
7	.3068799	.1218611	2.52	0.001	.0667391	.5470206
8	.2166928	.1477249	1.47	0.012	0744155	.5078012
9	.2437908	.1680322	1.47	0.144	0873352	.5749168
			2.72	0.148		
10	.5036017	.1853133			.1384213	.868782
11	.5412636	.1652311	3.28	0.001	.2156575	.8668698
12	.2848855	.1246709	2.29	0.023	.0392076	.5305634
date	.0000449	.0000724	0.62	0.535	0000976	.0001875
_cons	3632501	.1144721	-3.17	0.002	58883	1376702

. estat ic $$\operatorname{Akaike's}$$ information criterion and Bayesian information criterion

Model	Obs 11(:	null) ll(model)	df	AIC	BIC
.	311 -86.	30552 296.1739	87	-418.3478	-92.98584

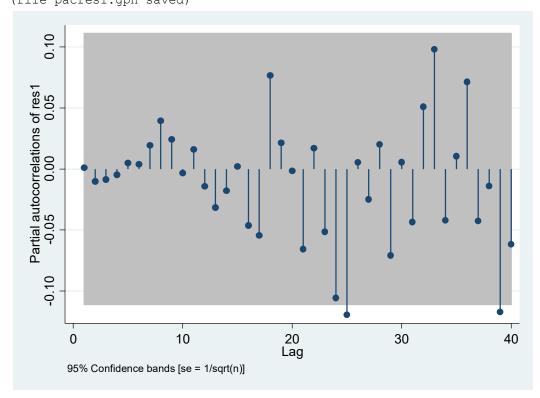
Note: N=Obs used in calculating BIC; see [R] BIC note.

. estat bgodfrey, lags(1,12,24)
Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	0.015	1	0.9023
12	7.499	12	0.8229
24	34.001	24	0.0846

HO: no serial correlation

- . predict res1, residual
- (27 missing values generated)
- . pac res1 if tin(1992m1,2017m12), saving(pacres1, replace) (file pacres1.gph saved)



*Model 2

. crossfold reg d.fl_unemprate_m 1(1/6,12) d.fl_unemprate_m 1(0/6,12) d.us_unemprate_m 1(1/6,12) d.fl_bldpmt_m i.month if tin(1992m1,2017m12) , k(10)

- . * Calculate the root of the MSE averaged over k folds
- . *define k as the number of folds
- . scalar define k=10
- . *calculate the sum of the k MSEs
- . matrix kMSE=r(est)'*r(est)
- . *Calculate the root of the MSE averaged over k folds
- . scalar krmse=(el(kMSE,1,1)/k) $^.5$
- . *List the answer
- . scalar list krmse
 krmse = .12332772
- . *Drop the matrix and scalar defined for the problem
- . matrix drop kMSE
- . scalar drop krmse
- . loocv reg d.fl_unemprate_m l(1/6,12)d.fl_unemprate_m l(0/6,12)d.us_unemprate_m l(1/6,12)d.fl bldpmt m i.month if tin(1992m1,2017m12)

Leave-One-Out Cross-Validation Results

Method		Value
Root Mean Squared Errors Mean Absolute Errors Pseudo-R2		.12024645 .08705196 .85433242

. reg d.fl_unemprate_m 1(1/6,12)d.fl_unemprate_m 1(0/6,12)d.us_unemprate_m 1(1/6,12)d.fl_bldpmt_m i.month if tin(1992m1,2017m12)

Model 28.7732727 33 .871917355 Prob > F = 0.0000
Residual 3.61018866
Total 32.3834614 311 .104126885 Root MSE = .11396 D. fl_unemprate_m Coef. Std. Err. t P> t [95% Conf. Interval] fl_unemprate_m LD. .0112768 .0585922 0.19 0.848104064 .1266177 L2D. .162918 .0589143 2.77 0.006 .0469431 .2788928 L3D. .0023537 .0600798 0.04 0.9691159154 .1206227 L4D. 067508 .0605607 -1.11 0.2661867237 .0517078 L5D. 0600681 .0599647 -1.00 0.3171781106 .0579743 L6D. 0348368 .0601734 -0.58 0.5631532903 .0836167 L12D. .139398 .0612679 2.28 0.024 .01879 .2600059 us_unemprate_m DI. .9649217 .0421059 22.92 0.000 .8820348 1.047809 LD. 0617445 .0704599 -0.88 0.3822004471 .0769581 L2D. 0986369 .0705706 -1.40 0.1632375576 .0402838 L3D. .057523 .0711015 0.81 0.4190824427 .1974887 L4D. .0582209 .0715153 0.81 0.4190824427 .1974887 L4D. .0582209 .0715153 0.81 0.4190824427 .1974887 L5D. .0403882 .071411 0.57 0.5721001867 .1809631 L6D. .1094476 .0716997 1.53 0.1280316957 .2505908 L12D. 2129583 .0715949 -2.97 0.00335389540720212 fl_bldpmt_m LD. -1.074752 .490455 -2.19 0.029 -2.04023109275 L2D. -1.055492 .5772423 -1.83 0.069 -2.191813 .0808288
D. fl_unemprate_m Coef. Std. Err. t P> t [95% Conf. Interval] fl_unemprate_m LD. .0112768
fl_unemprate_m Coef. Std. Err. t P> t [95% Conf. Interval] fl_unemprate_m LD. .0112768 .0585922 0.19 0.848
fl_unemprate_m Coef. Std. Err. t P> t [95% Conf. Interval] fl_unemprate_m LD. .0112768 .0585922 0.19 0.848
fl_unemprate_m LD. .0112768 .0585922
LD. .0112768
LD. .0112768
L3D. .0023537
L3D. .0023537
L5D. 0600681
L6D. 0348368
L12D. .139398 .0612679
us_unemprate_m D1. .9649217
D1. .9649217
LD. 0617445
L2D. 0986369
L3D. .057523 .0711015
L4D. .0582209 .0715153
L5D. .0403882 .071411 0.57 0.5721001867 .1809631 L6D. .1094476 .0716997 1.53 0.1280316957 .2505908 L12D. 2129583 .0715949 -2.97 0.00335389540720212 fl_bldpmt_m LD. -1.074752 .490455 -2.19 0.029 -2.04023109275 L2D. -1.055492 .5772423 -1.83 0.069 -2.191813 .0808288
L6D. .1094476 .0716997 1.53 0.1280316957 .2505908
L12D. 2129583 .0715949 -2.97 0.00335389540720212 fl_bldpmt_m LD. -1.074752 .490455 -2.19 0.029 -2.04023109275 L2D. -1.055492 .5772423 -1.83 0.069 -2.191813 .0808288
fl_bldpmt_m LD. -1.074752
LD. -1.074752 .490455 -2.19 0.029 -2.04023109275
L2D. -1.055492 .5772423 -1.83 0.069 -2.191813 .0808288
L3D. 5130382 .5764118 -0.89 0.374 -1.647724 .6216481
L4D. -1.871989 .5752531 -3.25 0.001 -3.0043947395833
L5D. -1.528399 .5769154 -2.65 0.009 -2.6640773927218
L6D. 4263497 .5000329 -0.85 0.395 -1.410681 .557982
L12D. 2224729 .4291563 -0.52 0.605 -1.067282 .6223359
month
2 .1740037 .077361 2.25 0.025 .021716 .3262914
3 .2766958 .0922322 3.00 0.003 .0951336 .4582581
4 .3807327 .1120294 3.40 0.001 .160199 .6012665 5 .3056605 .0950786 3.21 0.001 .1184952 .4928259
7 .3118646 .0855015 3.65 0.000 .143552 .4801772
8 .3455286 .092639 3.73 0.000 .1631656 .5278916
9 .2197737 .0917152 2.40 0.017 .0392293 .4003182 10 .181251 .0872345 2.08 0.039 .0095269 .3529751
·
11 .1586501 .0731719 2.17 0.031 .0146087 .3026914 12 .0632388 .0628941 1.01 0.3160605705 .187048
_cons 2291838

estat ic Akaike's information criterion and Bayesian information criterion

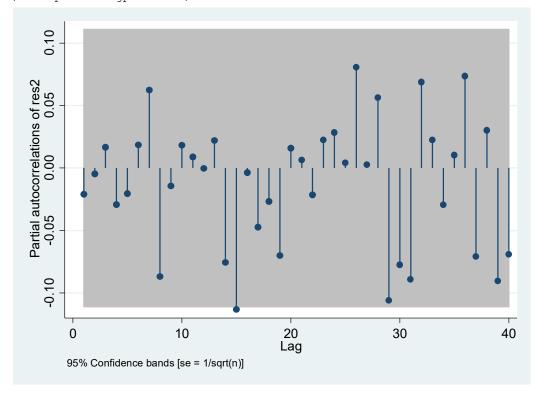
Model	0bs	ll(null)	ll(model)	df	AIC	BIC
.	312	-89.31339	252.9331	34	-437.8662	-310.6041

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

. estat bgodfrey, lags(1,12,24)
Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	2.443	1	0.1181
12	11.215	12	0.5106
24	20.408	24	0.6734

- . predict res2, residual
 (15 missing values generated)
- . pac res2 if tin(1992m1,2017m12), saving(pacres2, replace) (file pacres2.gph saved)



*Model 3

```
. crossfold reg d.fl_unemprate_m 1(1/2,12)d.fl_unemprate_m 1(0,1,12)d.us_unemprate_m 1(1/2,12)d.fl_bldpmt_m i.month if tin(1992m1,2017m12) , k(10)
```

```
est1 | .097779

est2 | .1045147

est3 | .1132839

est4 | .0780219

est5 | .1045674

est6 | .1005156

est7 | .1283471

est8 | .139189

est9 | .1798981

est10 | .1271304
```

- . * Calculate the root of the MSE averaged over k folds
- . \star define k as the number of folds
- . scalar define k=10
- . *calculate the sum of the k MSEs
- . matrix kMSE=r(est)'*r(est)
- . *Calculate the root of the MSE averaged over k folds
- . scalar krmse=(el(kMSE,1,1)/k) $^.5$
- . *List the answer
- . scalar list krmse
 krmse = .12033888
- . *Drop the matrix and scalar defined for the problem
- . matrix drop kMSE
- . scalar drop krmse

. loocv reg d.fl_unemprate_m l(1/2,12)d.fl_unemprate_m l(0,1,12)d.us_unemprate_m l(1/2,12)d.fl bldpmt m i.month if tin(1992m1,2017m12)

Leave-One-Out Cross-Validation Results

Method		Value
Root Mean Squared Errors Mean Absolute Errors Pseudo-R2		.11968351 .08572123 .85543362

. reg d.fl_unemprate_m l(1,2,12)d.fl_unemprate_m l(0,1,12)d.us_unemprate_m l(1,2,12)d.fl_bldpmt_m i.month if tin(1992m1,2017m12)

Source	SS	df	MS	Numbe F(20,	r of obs	=	312 106.07
Model	28.4772607	20	1.42386304		291) > F		0.0000
Residual	3.90620062	291	.01342337	R-squ		=	0.8794
+				_	-squared		0.8711
Total	32.3834614	311	.104126885	Root	MSE	=	.11586
D. fl_unemprate_m	Coef.	Std. Err	. t	P> t	[95%	Conf.	Interval]
fl unemprate m	+ 						
LD.	•	.0567946	0.71	0.480	0716	181	.1519425
L2D.	.0977518	.0330888	2.95	0.003	.0326		.1628755
L12D.	.1620438	.0596513	2.72	0.007	.0446	412	.2794464
us unemprate m	1						
$\overline{D1}$.	.9650679	.0409797	23.55	0.000	.8844	136	1.045722
LD.	0613548	.0687722	-0.89	0.373	1967	880	.0739992
L12D.	2427502	.0700403	-3.47	0.001	3	806	1049003
fl bldpmt m	1						
LD.	-1.122741	.4749837	-2.36	0.019	-2.05	758	1879017
L2D.	7763169	.4736132	-1.64	0.102	-1.708	459	.1558248
L12D.	315547	.4179787	-0.75	0.451	-1.138	192	.5070976
month	1						
2	.1424224	.0718922	1.98	0.049	.0009	279	.283917
3	.2428755	.076358	3.18	0.002	.0925	916	.3931594
4	.4271284	.092377	4.62	0.000	.2453	167	.6089402
5	.3284653	.0743268	4.42	0.000	.1821	791	.4747515
6	.3277668	.0520739	6.29	0.000	.2252	776	.430256
7	.3250683	.0707576	4.59	0.000	.1858	068	.4643298
8	.2816609	.0837511	3.36	0.001	.1168	261	.4464956
9	.2040033	.0785062	2.60	0.010	.0494	915	.3585152
10	.1271265	.0676047	1.88	0.061	0059	297	.2601826
11	.1350026	.0582989	2.32	0.021	.0202	617	.2497434
12	.0662858	.0557649	1.19	0.236	0434	679	.1760395
_cons	2203456	.0589563	-3.74	0.000	3363	805	1043108

. estat ic Akaike's information criterion and Bayesian information criterion

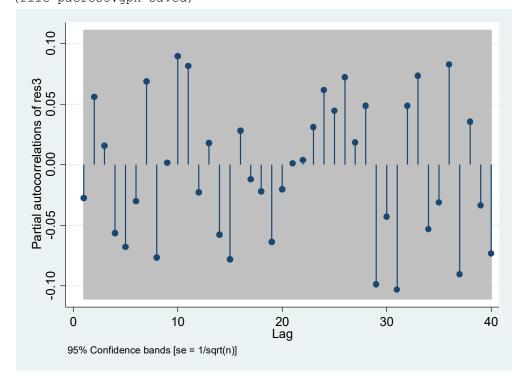
Model	Obs ll(null)	ll(model)	df	AIC	BIC
.	312 -89.31339	240.6395	21	-439.279	-360.6759

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

. estat bgodfrey, lags(1,12,24)
Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	2.899	1	0.0886
12	14.433	12	0.2739
24	21.004	24	0.6385

. predict res3, residual
(15 missing values generated)
. pac res3 if tin(1992m1,2017m12), saving(pacres3, replace)
(file pacres3.gph saved)



* Model 4

. crossfold reg d.fl_unemprate_m 1(2,12)d.fl_unemprate_m 1(0,12)d.us_unemprate_m 1(1,2)d.fl_bldpmt_m i.month if tin(1992m1,2017m12) , k(10)

- . *Calculate the root of the MSE averaged over k folds
- . \star define k as the number of folds
- . scalar define k=10
- . *calculate the sum of the k ${\tt MSEs}$
- . matrix kMSE=r(est)'*r(est)
- . *Calculate the root of the MSE averaged over k folds
- . $scalar krmse=(el(kMSE,1,1)/k)^.5$
- . ${}^{\star}\text{List}$ the answer
- . scalar list krmse

krmse = .12142833

- . *Drop the matrix and scalar defined for the problem
- . matrix drop kMSE
- . scalar drop krmse

. loocv reg d.fl_unemprate_m l(2,12)d.fl_unemprate_m l(0,12)d.us_unemprate_m l(1,2)d.fl bldpmt m i.month if tin(1992m1,2017m12)

Leave-One-Out Cross-Validation Results

Method		Value
	+	
Root Mean Squared Errors		.11873367
Mean Absolute Errors		.08478072
Pseudo-R2		.85768422

. reg d.fl_unemprate_m 1(2,12)d.fl_unemprate_m 1(0,12)d.us_unemprate_m 1(1,2)d.fl_bldpmt_m i.month if tin(1992m1,2017m12)

Source	SS	df	MS		r of obs	=	312
+				F(17,		=	125.42
Model				Prob :			0.0000
Residual	3.9242194	294	.013347685	R-squa			0.8788
+					-squared	=	0.8718
Total	32.3834614	311	.104126885	Root i	MSE 	= 	.11553
D.							
fl_unemprate_m	Coef.	Std. Err	t. t	P> t	[95%	Conf.	<pre>Interval]</pre>
fl unemprate m	+ 1						
L2D.		.0327543	3 2.88	0.004	.0299	419	.1588669
L12D.	.1611948	.0590992		0.007	.0448		.2775058
us unemprate m	1						
$ \overline{D1}$.	.9705587	.0403733	3 24.04	0.000	.8911	015	1.050016
L12D.	2390609	.0689852	-3.47	0.001	3748	284	1032935
fl_bldpmt_m	ı						
LD.	-1.094663	.4701631		0.021	-2.019	975	169351
L2D.	8090881	.4713098	-1.72	0.087	-1.736	657	.1184806
month	'						
2	.12734	.0620228		0.041	.005	275	.249405
3	.2568056	.0751571		0.001	.1088	914	.4047198
4	.4578534	.0879281		0.000	.2848	052	.6309016
5	.3671634	.064647		0.000	.2399		.494393
6	.3445649	.0481676		0.000	.2497		.4393619
7	.337686	.0653737		0.000	.2090		.4663457
8	.3074798	.0796466		0.000	.1507		.4642295
9	.2385065	.0720884	3.31	0.001	.0966		.3803812
10	.1530087	.0634696		0.017	.0280	963	.277921
11	.155353	.0551332	2.82	0.005	.0468	472	.2638588
12	.0752292	.0547992	1.37	0.171	0326	192	.1830776
cons	 2380817	.0562047	7 -4.24	0.000	3486	964	1274671
		.0002047	1.21		.5100		. 12 / 10 / 1

. estat ic Akaike's information criterion and Bayesian information criterion

Model	Obs ll(null)	ll(model)	df	AIC	BIC
.	312 -89.31339	239.9216	18 -4	143.8431	-376.469

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

. estat bgodfrey, lags(1,12,24)
Breusch-Godfrey LM test for autocorrelation

lags(p)	c	chi2 df	Prob > chi2
1	12	0.090 1	0.7647
12		2.312 12	0.4210
24		3.737 24	0.7658

. predict res4, residual
(15 missing values generated)
. pac res4 if tin(1992m1,2017m12), saving(pacres4, replace)
(file pacres4.gph saved)

