

*Note: I did not update my dataset from last year, so your numbers will differ. But, the difference should not be pronounced and the reasoning will be similar.

2) Prepare to analyze the data:

See the do file, Appendix A

3) Static Model

- a) Explain why the size of Florida's labor force, the prime age employment to population ratio, and Florida building permits, might be closely related to the number of nonfarm jobs in Florida in a static long run sense.

We can think of the number employed as the product of the portion of those in the labor market that are employed and the number that want work and so are in the market. Then the log of total employment is the sum of the logs of those two pieces. From there:

- The number that want to work should closely track labor force in Florida.
- The fraction of those that want to be employed that are employed tracks the strength of the Florida economy, which closely tracks the strength of the national economy, for which the employment to population ratio is a good proxy.
- Construction is a large part of Florida's economic base, due to constant in-migration. So, variations in the strength of the economy may be reflected somewhat in building permits.

- b) Estimate the static model relating monthly nonfarm employment in Florida to the other three variables (all in logs) without controlling for seasonal impacts or a time trend.

Results in the table on the next page.

- c) Estimate the static model with month indicators and a time trend.

See the do file for the code. Results in the table on the next page.

- d) Compare your results from b and c and interpret any differences. What do the seasonal and time trend variables contribute?

All three coefficients change slightly. The time trend controls for growth at a constant rate over time, while the month indicators control for seasonality. For example, construction employment varies with the weather, employment always varies with holidays, and in Florida employment also varies with tourist season. Presumably, controlling for these effects allows the model to better reveal the underlying relationships between the other variables. (The caveat is we have not checked this data for stationarity or weak dependence, which comes later.)

- e) Why should you be cautious using the results of these models for testing any hypotheses about the underlying relationships?

The sampling independence required for the standard error calculations is obviously violated in time series data, so it is likely the standard errors are incorrect.

Models for question 3

Question	3A	3B
lnfllf	1.116*** (0.00921)	0.921*** (0.0353)
lnusepr	0.784*** (0.0587)	1.230*** (0.0476)
lnflbp	0.0442*** (0.00317)	0.0351*** (0.00191)
2.month		0.00314 (0.00312)
3.month		-0.00324 (0.00312)
4.month		-0.00936** (0.00314)
5.month		-0.0212*** (0.00315)
6.month		-0.0436*** (0.00318)
7.month		-0.0611*** (0.00321)
8.month		-0.0443*** (0.00317)
9.month		-0.0315*** (0.00316)
10.month		-0.0277*** (0.00318)
11.month		-0.00891** (0.00321)
12.month		0.000140 (0.00317)
date		0.000349*** (0.0000550)
_cons	-12.56*** (0.328)	-11.38*** (0.433)
<i>N</i>	384	384
<i>R</i> ²	0.979	0.994

4) Finite Distributed Lag Model

- a) Estimate the distributed lag model relating monthly nonfarm employment to lags 0 to 12 of the three predictor variables without month indicators and a time trend.

See do file and the table below.

- b) Estimate the model in (a) but add month indicators and a time trend.

See the do file and the results table below.

- c) Compare your results from a and b and interpret any differences. What do the seasonal and time trend variables contribute?

This is largely the same as it was for question 3. The difference is that since we are controlling for one year ago, the lags themselves may capture some of the seasonal difference in the first model, and that adding seasonal effects purges that, changing the results potentially at all lags. This, though, it just more of the same basic thing.

- d) Estimate two alternative models that contain month indicators and a time trend but that impose a more parsimonious lag structure for the predictor variables. Explain your choices.

Results are below. The most important lags would seem to be the most recent month, and the same month a year ago. So, in one version I include only the first lag, in the other I include lags 1 and 12. You may have chosen something else. As long as you can defend it, that is fine.

5) Provide a neat report writing up your answers to 3 and 4. Do not simply post screenshots of the Stata results window. Rather, provide neat professional looking tables of the results you obtain. Estout and esttab are probably the easiest tools for this. Make sure any results you refer to in your answers appear near enough to the answers so that your overall submission is easy to make sense of. One exception to that might be when you need exceptionally long tables.

Your report should not look like this solution. This solution just describes what should be in your report. The report itself needs to look more like a professional work product—though we will evolve toward that over time.

- 6) As Appendix A, include the clean do file to replicate your analysis.

See appendix A below.

- 7) As Appendix B, include the log file of a run of your clean do file to your write up.

See appendix B below.

Models for question 4

Question	4A	4B	4D1	4D2
lnflf	0.248 (0.257)	0.402 (0.273)	1.006*** (0.296)	0.729* (0.294)
L.lnflf	0.0109 (0.340)	0.0216 (0.361)	-0.0917 (0.300)	-0.0327 (0.311)
L2.lnflf	0.392 (0.340)	-0.0949 (0.365)		
L3.lnflf	0.668 (0.342)	0.172 (0.369)		
L4.lnflf	-0.267 (0.343)	-0.0254 (0.374)		
L5.lnflf	-0.528 (0.342)	0.0327 (0.372)		
L6.lnflf	-0.0941 (0.343)	0.0871 (0.371)		
L7.lnflf	0.202 (0.345)	0.184 (0.372)		
L8.lnflf	-0.114 (0.347)	0.0890 (0.372)		
L9.lnflf	0.382 (0.345)	0.197 (0.375)		
L10.lnflf	-0.0175 (0.342)	0.0444 (0.378)		
L11.lnflf	-0.0136 (0.341)	-0.275 (0.381)		
L12.lnflf	0.276 (0.259)	0.0831 (0.288)		0.181 (0.0935)
lnusepr	0.766** (0.281)	0.436 (0.350)	-0.148 (0.370)	0.0469 (0.372)
L.lnusepr	-0.403 (0.394)	0.119 (0.464)	1.352*** (0.368)	0.977* (0.394)
L2.lnusepr	-0.340 (0.390)	0.0714 (0.469)		
L3.lnusepr	-0.453 (0.388)	0.0791 (0.470)		
L4.lnusepr	0.262 (0.399)	0.211 (0.475)		

L5.lnusepr	1.044** (0.400)	-0.105 (0.476)		
L6.lnusepr	0.857* (0.398)	0.402 (0.474)		
L7.lnusepr	-0.203 (0.398)	0.0309 (0.475)		
L8.lnusepr	0.466 (0.399)	-0.103 (0.475)		
L9.lnusepr	-0.185 (0.393)	-0.114 (0.477)		
L10.lnusepr	-0.282 (0.388)	0.114 (0.478)		
L11.lnusepr	0.110 (0.387)	0.497 (0.477)		
L12.lnusepr	-0.600* (0.269)	-0.405 (0.351)		0.195* (0.0856)
lnflbp	0.0202*** (0.00470)	0.0182*** (0.00438)	0.0254*** (0.00416)	0.0248*** (0.00414)
L.lnflbp	0.00939 (0.00502)	0.00924 (0.00474)	0.0125** (0.00423)	0.0140** (0.00427)
L2.lnflbp	0.0118* (0.00518)	0.00547 (0.00485)		
L3.lnflbp	0.00267 (0.00534)	0.00610 (0.00497)		
L4.lnflbp	0.00128 (0.00535)	0.00341 (0.00497)		
L5.lnflbp	0.00650 (0.00542)	0.00401 (0.00497)		
L6.lnflbp	0.00699 (0.00544)	0.00659 (0.00497)		
L7.lnflbp	0.00228 (0.00542)	0.00487 (0.00494)		
L8.lnflbp	-0.000869 (0.00544)	-0.00531 (0.00497)		
L9.lnflbp	0.00159 (0.00544)	-0.000821 (0.00493)		
L10.lnflbp	-0.00657 (0.00527)	-0.000485 (0.00480)		

L11.lnflbp	-0.00350 (0.00521)	-0.00568 (0.00471)		
L12.lnflbp	-0.00590 (0.00498)	-0.00338 (0.00447)		0.00388 (0.00289)
2.month		0.00921 (0.00706)	0.0229*** (0.00513)	0.0171** (0.00535)
3.month		0.0128 (0.00770)	0.0194*** (0.00511)	0.0129* (0.00531)
4.month		0.00990 (0.00853)	0.0119* (0.00595)	0.00508 (0.00623)
5.month		0.00526 (0.00612)	-0.00109 (0.00448)	-0.00688 (0.00458)
6.month		-0.00853 (0.00744)	-0.0187** (0.00577)	-0.0259*** (0.00598)
7.month		-0.0163* (0.00726)	-0.0423*** (0.00471)	-0.0474*** (0.00482)
8.month		-0.00797 (0.00774)	-0.0344*** (0.00400)	-0.0367*** (0.00405)
9.month		-0.00807 (0.00614)	-0.0213*** (0.00377)	-0.0241*** (0.00382)
10.month		-0.00658 (0.00834)	-0.00723 (0.00600)	-0.0130* (0.00626)
11.month		0.00936 (0.00768)	0.00453 (0.00492)	0.000589 (0.00510)
12.month		0.0184* (0.00730)	0.0135** (0.00424)	0.0101* (0.00434)
date		0.000358*** (0.0000504)	0.000359*** (0.0000526)	0.000416*** (0.0000571)
_cons	-14.10*** (0.209)	-11.44*** (0.428)	-11.20*** (0.416)	-10.75*** (0.480)
N	372	372	383	372
R ²	0.995	0.997	0.995	0.995

Appendix A: Do File

*Time Series - Problem Set 1 Solution
*Spring 2020

```
clear  
set more off
```

```
cd "C:\Users\jdewey\Documents\A S20 Time Series\Problem Sets\  
log using "Problem Set 2 Work", replace  
import delimited using "us and florida economic time series.txt"
```

**2 - data prep

```
rename observation_date datestring  
gen dateday=date(datestring,"YMD")  
gen date=mofd(dateday)  
format date %tm  
tsset date  
generate month=month(dateday)
```

```
rename flbppriv fl_bp  
rename fl1fn fl_lf  
rename flnan fl_nonfarm  
rename lnu02300000_20200110 us_epr
```

```
gen lnflnonfarm=ln( fl_nonfarm)  
gen lnfl1f=ln( fl_lf)  
gen lnusepr = ln(us_epr)  
gen lnflbp=ln( fl_bp)
```

```
estimates clear
```

**3 - Static Model

```
**3b  
reg lnflnonfarm lnfl1f lnusepr lnflbp  
eststo model3b
```

```
**3c  
reg lnflnonfarm lnfl1f lnusepr lnflbp i.month date  
eststo model3c
```

```
esttab model3* using models3.rtf , se r2 onecell compress replace
```

**4 Distributed Lag Model

```
**4a  
reg lnflnonfarm l(0/12).lnfl1f l(0/12).lnusepr l(0/12).lnflbp  
eststo model4a
```

```
**4b  
reg lnflnonfarm l(0/12).lnfl1f l(0/12).lnusepr l(0/12).lnflbp i.month date  
eststo model4b
```

```
**4d  
reg lnflnonfarm l(0,1).lnfl1f l(0,1).lnusepr l(0,1).lnflbp i.month date  
eststo model4e1  
reg lnflnonfarm l(0,1,12).lnfl1f l(0,1,12).lnusepr l(0,1,12).lnflbp i.month date
```

```
eststo model4e2
```

```
esttab model4* using models4.rtf , se r2 onecell compress replace
```

```
clear
```

```
log close
```


Appendix B: Log File

```
-----  
log:  C:\Users\jdewey\Documents\A S20 Time Series\Problem Sets\Problem Set 2 Work.smcl  
log type:  smcl  
opened on:   3 Feb 2020, 17:19:56
```

```
. import delimited using "us and florida economic time series.txt"  
(5 vars, 972 obs)
```

```
.  
.   
. **2 - data prep  
.   
. rename observation_date datestring  
  
. gen dateday=date(datestring,"YMD")  
  
. gen date=mofd(dateday)  
  
. format date %tm  
  
. tsset date  
    time variable:  date, 1939m1 to 2019m12  
        delta:  1 month
```

```
. generate month=month(dateday)  
  
.   
. rename flbppriv fl_bp  
  
. rename flllfn fl_lf  
  
. rename flnan fl_nonfarm  
  
. rename lnu02300000_20200110 us_epr
```

```
.   
. gen lnflnonfarm=ln( fl_nonfarm)
```

```
. gen lnflllf=ln( fl_lf)  
(444 missing values generated)
```

```
. gen lnusepr = ln(us_epr)  
(108 missing values generated)
```

```
. gen lnflbp=ln( fl_bp)  
(588 missing values generated)
```

```
.   
. estimates clear
```

```
.   
. **3 - Static Model
```

```
.   
. **3b  
. reg lnflnonfarm lnflllf lnusepr lnflbp
```

Source	SS	df	MS	Number of obs	=	384
Model	10.0439101	3	3.34797004	F(3, 380)	=	5989.79
Residual	.212399492	380	.000558946	Prob > F	=	0.0000
				R-squared	=	0.9793

-----+-----				Adj R-squared	=	0.9791
Total		10.2563096	383	.026778876	Root MSE	= .02364

lnflnonfarm		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
lnfl1f		1.116328	.0092075	121.24	0.000	1.098223 1.134432
lnusepr		.7841477	.058693	13.36	0.000	.6687439 .8995515
lnflbp		.0441864	.0031657	13.96	0.000	.0379619 .0504109
_cons		-12.56463	.3275278	-38.36	0.000	-13.20863 -11.92064

```
. eststo model3b
```

```
.
. **3c
. reg lnflnonfarm lnfl1f lnusepr lnflbp i.month date
```

Source		SS	df	MS	Number of obs	=	384
-----+-----					F(15, 368)	=	4384.23
Model		10.1992366	15	.679949103	Prob > F	=	0.0000
Residual		.057073047	368	.00015509	R-squared	=	0.9944
-----+-----					Adj R-squared	=	0.9942
Total		10.2563096	383	.026778876	Root MSE	=	.01245

lnflnonfarm		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
lnfl1f		.9212237	.0352984	26.10	0.000	.8518118 .9906356
lnusepr		1.229715	.0476496	25.81	0.000	1.136015 1.323415
lnflbp		.0351044	.0019115	18.36	0.000	.0313455 .0388633
month						
2		.0031354	.0031186	1.01	0.315	-.0029971 .0092678
3		-.0032363	.0031202	-1.04	0.300	-.0093719 .0028993
4		-.0093573	.0031364	-2.98	0.003	-.0155247 -.0031898
5		-.0212137	.0031465	-6.74	0.000	-.0274011 -.0150264
6		-.0435719	.0031755	-13.72	0.000	-.0498163 -.0373275
7		-.0610547	.0032086	-19.03	0.000	-.0673642 -.0547452
8		-.0442749	.0031661	-13.98	0.000	-.0505008 -.0380491
9		-.0314627	.0031552	-9.97	0.000	-.0376673 -.0252582
10		-.0277233	.0031775	-8.72	0.000	-.0339716 -.0214751
11		-.008915	.0032122	-2.78	0.006	-.0152316 -.0025984
12		.0001403	.0031694	0.04	0.965	-.0060921 .0063727
date		.0003493	.000055	6.35	0.000	.0002411 .0004574
_cons		-11.37522	.4325196	-26.30	0.000	-12.22574 -10.5247

```
. eststo model3c
```

```
.
. esttab model3* using models3.rtf , se r2 onecell compress replace
(output written to models3.rtf)
```

```
.
.
. **4 Distributed Lag Model
.
. **4a
. reg lnflnonfarm l(0/12).lnfl1f l(0/12).lnusepr l(0/12).lnflbp
```

Source	SS	df	MS	Number of obs	=	372
Model	9.0020926	39	.230822887	F(39, 332)	=	1833.96
Residual	.041785606	332	.00012586	Prob > F	=	0.0000
				R-squared	=	0.9954
				Adj R-squared	=	0.9948
Total	9.04387821	371	.02437703	Root MSE	=	.01122

lnflnonfarm	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
lnfllf						
--.	.2484859	.256641	0.97	0.334	-.2563617	.7533334
L1.	.0109242	.339549	0.03	0.974	-.6570145	.6788629
L2.	.3924249	.3395465	1.16	0.249	-.275509	1.060359
L3.	.6684095	.3417729	1.96	0.051	-.0039039	1.340723
L4.	-.2666747	.3430333	-0.78	0.437	-.9414675	.408118
L5.	-.5278119	.3421766	-1.54	0.124	-1.200919	.1452957
L6.	-.0941471	.342526	-0.27	0.784	-.7679421	.5796479
L7.	.2018592	.3446162	0.59	0.558	-.4760475	.8797658
L8.	-.1144874	.3468577	-0.33	0.742	-.7968033	.5678284
L9.	.3824765	.3448778	1.11	0.268	-.2959448	1.060898
L10.	-.0174709	.3416669	-0.05	0.959	-.6895758	.654634
L11.	-.0135512	.3411563	-0.04	0.968	-.6846517	.6575492
L12.	.2758329	.2587045	1.07	0.287	-.2330738	.7847396
lnusepr						
--.	.7664839	.2811081	2.73	0.007	.2135064	1.319461
L1.	-.402973	.394163	-1.02	0.307	-1.178345	.3723989
L2.	-.3402653	.3895914	-0.87	0.383	-1.106644	.4261135
L3.	-.4526223	.3879255	-1.17	0.244	-1.215724	.3104796
L4.	.2622366	.3985003	0.66	0.511	-.5216672	1.04614
L5.	1.044102	.4002439	2.61	0.010	.2567681	1.831436
L6.	.8574051	.3976835	2.16	0.032	.075108	1.639702
L7.	-.2025326	.3977182	-0.51	0.611	-.9848981	.5798328
L8.	.4659802	.3992073	1.17	0.244	-.3193145	1.251275
L9.	-.1851727	.3930261	-0.47	0.638	-.9583082	.5879628
L10.	-.2823105	.3882628	-0.73	0.468	-1.046076	.4814548
L11.	.1096577	.3869829	0.28	0.777	-.6515899	.8709053
L12.	-.600008	.2687647	-2.23	0.026	-1.128704	-.0713115
lnflbp						
--.	.0202182	.0046996	4.30	0.000	.0109734	.029463
L1.	.0093884	.0050239	1.87	0.063	-.0004943	.0192712
L2.	.0117593	.0051824	2.27	0.024	.0015649	.0219537
L3.	.0026682	.0053362	0.50	0.617	-.0078287	.0131652
L4.	.0012799	.0053486	0.24	0.811	-.0092415	.0118014
L5.	.0064967	.0054228	1.20	0.232	-.0041707	.017164
L6.	.0069897	.0054356	1.29	0.199	-.0037029	.0176823
L7.	.0022828	.0054189	0.42	0.674	-.0083769	.0129424
L8.	-.0008686	.0054353	-0.16	0.873	-.0115607	.0098234
L9.	.0015926	.0054429	0.29	0.770	-.0091144	.0122995
L10.	-.0065654	.0052727	-1.25	0.214	-.0169374	.0038067
L11.	-.003495	.0052083	-0.67	0.503	-.0137405	.0067505
L12.	-.0058967	.0049827	-1.18	0.237	-.0156983	.0039049
_cons	-14.10318	.2086937	-67.58	0.000	-14.51371	-13.69265

. eststo model4a

.
. **4b

```
. reg lnflnonfarm l(0/12).lnfl1f l(0/12).lnusepr l(0/12).lnflbp i.month date
```

Source	SS	df	MS	Number of obs	=	372
Model	9.01333924	51	.176732142	F(51, 320)	=	1851.87
Residual	.030538967	320	.000095434	Prob > F	=	0.0000
				R-squared	=	0.9966
				Adj R-squared	=	0.9961
Total	9.04387821	371	.02437703	Root MSE	=	.00977

lnflnonfarm	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
lnfl1f						
--.	.4022129	.2732552	1.47	0.142	-.1353907	.9398166
L1.	.0215758	.3606161	0.06	0.952	-.6879021	.7310536
L2.	-.0948631	.3652309	-0.26	0.795	-.8134202	.623694
L3.	.1723664	.3690394	0.47	0.641	-.5536835	.8984163
L4.	-.0253954	.3736455	-0.07	0.946	-.7605074	.7097167
L5.	.032669	.3722284	0.09	0.930	-.699655	.764993
L6.	.0871132	.370946	0.23	0.814	-.6426879	.8169143
L7.	.1836039	.3720899	0.49	0.622	-.5484476	.9156554
L8.	.0890093	.3721137	0.24	0.811	-.643089	.8211076
L9.	.197165	.3753167	0.53	0.600	-.541235	.9355651
L10.	.0444438	.3776373	0.12	0.906	-.6985216	.7874093
L11.	-.2746825	.3805238	-0.72	0.471	-1.023327	.473962
L12.	.0831178	.2875688	0.29	0.773	-.4826465	.6488822
lnusepr						
--.	.4356027	.3503781	1.24	0.215	-.2537329	1.124938
L1.	.1191917	.4636369	0.26	0.797	-.7929698	1.031353
L2.	.0713731	.4690234	0.15	0.879	-.8513858	.9941321
L3.	.0791026	.4702414	0.17	0.867	-.8460526	1.004258
L4.	.210954	.4747179	0.44	0.657	-.7230083	1.144916
L5.	-.1047653	.4756131	-0.22	0.826	-1.040489	.8309584
L6.	.4023734	.4737444	0.85	0.396	-.5296736	1.33442
L7.	.0308766	.4745537	0.07	0.948	-.9027628	.964516
L8.	-.1029041	.474868	-0.22	0.829	-1.037162	.8313536
L9.	-.113734	.4765677	-0.24	0.812	-1.051336	.8238676
L10.	.1141626	.477637	0.24	0.811	-.8255429	1.053868
L11.	.497261	.4765765	1.04	0.298	-.4403581	1.43488
L12.	-.4053088	.3511232	-1.15	0.249	-1.09611	.2854927
lnflbp						
--.	.0181623	.0043772	4.15	0.000	.0095506	.0267739
L1.	.0092362	.0047446	1.95	0.052	-.0000982	.0185707
L2.	.0054748	.0048536	1.13	0.260	-.0040741	.0150237
L3.	.0061002	.0049693	1.23	0.221	-.0036764	.0158768
L4.	.0034054	.0049669	0.69	0.493	-.0063666	.0131774
L5.	.0040145	.00497	0.81	0.420	-.0057635	.0137925
L6.	.0065861	.0049727	1.32	0.186	-.0031973	.0163695
L7.	.0048746	.0049436	0.99	0.325	-.0048515	.0146007
L8.	-.0053079	.0049686	-1.07	0.286	-.0150833	.0044674
L9.	-.0008209	.0049335	-0.17	0.868	-.0105271	.0088854
L10.	-.0004853	.0048019	-0.10	0.920	-.0099325	.008962
L11.	-.005678	.0047093	-1.21	0.229	-.014943	.003587
L12.	-.0033832	.0044686	-0.76	0.450	-.0121747	.0054083
month						
2	.0092051	.0070556	1.30	0.193	-.0046761	.0230863
3	.0128215	.0076985	1.67	0.097	-.0023246	.0279675
4	.0098972	.0085302	1.16	0.247	-.0068851	.0266795
5	.0052627	.0061186	0.86	0.390	-.006775	.0173004

6		-.0085299	.0074359	-1.15	0.252	-.0231594	.0060996
7		-.0163274	.0072572	-2.25	0.025	-.0306052	-.0020496
8		-.0079749	.0077393	-1.03	0.304	-.0232012	.0072514
9		-.008067	.0061448	-1.31	0.190	-.0201563	.0040224
10		-.0065847	.0083379	-0.79	0.430	-.0229888	.0098194
11		.0093559	.0076758	1.22	0.224	-.0057455	.0244573
12		.0184165	.0072988	2.52	0.012	.0040569	.0327761
date		.000358	.0000504	7.10	0.000	.0002588	.0004573
_cons		-11.43514	.4276261	-26.74	0.000	-12.27645	-10.59382

. eststo model4b

```
.
. **4d
. reg lnflnonfarm l(0,1).lnfl1f l(0,1).lnusepr l(0,1).lnflbp i.month date
```

Source		SS	df	MS	Number of obs	=	383
Model		10.0933617	18	.560742318	F(18, 364)	=	4091.26
Residual		.049889362	364	.000137059	Prob > F	=	0.0000
					R-squared	=	0.9951
					Adj R-squared	=	0.9948
Total		10.1432511	382	.026553013	Root MSE	=	.01171

lnflnonfarm		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
lnfl1f							
--.		1.005734	.2960054	3.40	0.001	.4236382	1.587829
L1.		-.0917364	.2997884	-0.31	0.760	-.6812711	.4977982
lnusepr							
--.		-.1481019	.3703225	-0.40	0.689	-.8763421	.5801383
L1.		1.351803	.3683321	3.67	0.000	.6274767	2.076129
lnflbp							
--.		.0254374	.0041611	6.11	0.000	.0172545	.0336203
L1.		.0125023	.0042286	2.96	0.003	.0041867	.0208179
month							
2		.0229252	.0051295	4.47	0.000	.0128379	.0330124
3		.0193888	.0051092	3.79	0.000	.0093415	.029436
4		.0118636	.005949	1.99	0.047	.0001649	.0235623
5		-.0010886	.0044823	-0.24	0.808	-.009903	.0077258
6		-.0186915	.0057707	-3.24	0.001	-.0300395	-.0073434
7		-.0422895	.0047089	-8.98	0.000	-.0515495	-.0330296
8		-.0343521	.0040015	-8.58	0.000	-.042221	-.0264832
9		-.0212841	.0037678	-5.65	0.000	-.0286936	-.0138747
10		-.0072332	.0060024	-1.21	0.229	-.0190369	.0045706
11		.0045345	.0049203	0.92	0.357	-.0051414	.0142103
12		.0135397	.0042449	3.19	0.002	.0051922	.0218872
date		.0003593	.0000526	6.83	0.000	.0002558	.0004628
_cons		-11.20074	.4162832	-26.91	0.000	-12.01936	-10.38212

. eststo model4d1

```
. reg lnflnonfarm l(0,1,12).lnfl1f l(0,1,12).lnusepr l(0,1,12).lnflbp i.month date
```

Source		SS	df	MS	Number of obs	=	372
--------	--	----	----	----	---------------	---	-----

-----+-----				F(21, 350)	=	3390.28
Model		8.99963587	21	.428554089	Prob > F	= 0.0000
Residual		.044242336	350	.000126407	R-squared	= 0.9951
-----+-----				Adj R-squared	=	0.9948
Total		9.04387821	371	.02437703	Root MSE	= .01124

lnflnonfarm		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----+-----						
lnfllf						
--.		.7292202	.2943467	2.48	0.014	.1503094 1.308131
L1.		-.0326746	.311443	-0.10	0.917	-.6452097 .5798605
L12.		.1809366	.0934679	1.94	0.054	-.0028928 .3647661
lnusepr						
--.		.0468984	.3719194	0.13	0.900	-.6845797 .7783765
L1.		.9767191	.3942439	2.48	0.014	.2013341 1.752104
L12.		.1954712	.0855985	2.28	0.023	.027119 .3638234
lnflbp						
--.		.0247686	.0041362	5.99	0.000	.0166337 .0329034
L1.		.0140107	.0042693	3.28	0.001	.005614 .0224074
L12.		.0038842	.0028946	1.34	0.181	-.0018088 .0095771
month						
2		.0171205	.0053484	3.20	0.001	.0066015 .0276394
3		.0129469	.0053059	2.44	0.015	.0025114 .0233824
4		.0050828	.0062317	0.82	0.415	-.0071735 .017339
5		-.0068836	.0045836	-1.50	0.134	-.0158986 .0021313
6		-.0258619	.0059779	-4.33	0.000	-.0376191 -.0141047
7		-.0474425	.0048209	-9.84	0.000	-.056924 -.0379609
8		-.0367457	.0040455	-9.08	0.000	-.0447023 -.028789
9		-.0241094	.003824	-6.30	0.000	-.0316304 -.0165884
10		-.0129705	.0062624	-2.07	0.039	-.0252873 -.0006538
11		.0005892	.0051016	0.12	0.908	-.0094444 .0106228
12		.0100853	.0043352	2.33	0.021	.0015591 .0186115
date		.0004157	.0000571	7.28	0.000	.0003034 .000528
_cons		-10.74832	.4799099	-22.40	0.000	-11.69219 -9.804451

```
. eststo model4d2
```

```
.
. esttab model4* using models4.rtf , se r2 onecell compress replace
(output written to models4.rtf)
```

```
.
. clear
```

```
. log close
name: <unnamed>
log: C:\Users\jdewey\Documents\A S20 Time Series\Problem Sets\Problem Set 2
Work.smcl
log type: smcl
closed on: 3 Feb 2020, 17:19:56
```