

## Problem Set 1

Gus Lipkin

### CAP 4763 Time Series Modelling and Forecasting

Corrections are underlined

All uncited quotes are from the Problem Set 1 official solution

# Table of Contents

---

Section
<a href="#"><u>3 Static Model</u></a>
<a href="#"><u>3a</u></a>
<a href="#"><u>3b</u></a>
<a href="#"><u>3c</u></a>
<a href="#"><u>3d</u></a>
<a href="#"><u>3e</u></a>
<a href="#"><u>4 Finite Distributed Lag Model</u></a>
<a href="#"><u>4a</u></a>
<a href="#"><u>4b</u></a>
<a href="#"><u>4d</u></a>
<a href="#"><u>4e</u></a>
<a href="#"><u>Appendix A</u></a>
<a href="#"><u>Appendix B</u></a>

## 3 Static Model

---

### 3a

---

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. You might want to make some time series plots to give your data context. (Perhaps where one variable is employment and the other, on the other axis, is one of the other variables.)

The size of Florida's labor force can only increase for a few reasons. People either grow up and get a job or people move into the state for one reason or another. These would increase the prime age employment to population ratio but those people need places to work. They could either work in construction or any affiliated field which handles building permits or they could work in a building being constructed by the people handling those permits. In the meantime, as farming becomes more efficient and reliant on technology, not as many people are needed to farm the same parcels of land. This leads to more people employed in non-farm jobs.

"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."

### 3b

---

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.

Source	SS	df	MS Number of obs =	396
	F(3, 392) =	5972.65		
Model	10.5356085	3	3.51186951 Prob > F =	0.0000
Residual	.230492978	392	.000587992 R-squared =	0.9786
	Adj R-squared =	0.9784		
Total	10.7661015	395	.027255953 Root MSE =	.02425
ln_fl_nonf~m	Coef.	Std. Err.	t P>t [95% Conf.	Interval]
ln_fl_lf	1.110504	.0092305	120.31 0.000 1.092356	1.128651
ln_us_epr	.6006702	.047797	12.57 0.000 .5066997	.6946407
ln_fl_bp	.0516831	.0028713	18.00 0.000 .0460379	.0573282
_cons	-11.78364	.2925244	-40.28 0.000 -12.35875	-11.20852

### 3c

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

Source	SS	df	MS Number of obs =	396
	F(15, 380) =	2935.69		
Model	10.6739911	15	.711599408 Prob > F =	0.0000
Residual	.092110398	380	.000242396 R-squared =	0.9914
	Adj R-squared =	0.9911		
Total	10.7661015	395	.027255953 Root MSE =	.01557
ln_fl_nonf~m	Coef.	Std. Err.	t P>t [95% Conf.	Interval]
ln_fl_lf	.9282631	.0413265	22.46 0.000 .8470059	1.00952

ln_us_epr	.9105558	.0514333	17.70 0.000 .8094263	1.011685
ln_fl_bp	.0466812	.0021579	21.63 0.000 .0424382	.0509242
month				
2	.0045623	.0038378	1.19 0.235 -.0029837	.0121084
3	-.001379	.003839	-0.36 0.720 -.0089274	.0061694
4	-.0029373	.0038393	-0.77 0.445 -.0104863	.0046116
5	-.0142748	.0038468	-3.71 0.000 -.0218384	-.0067112
6	-.0356123	.0038709	-9.20 0.000 -.0432234	-.0280012
7	-.0519102	.0038917	-13.34 0.000 -.0595622	-.0442582
8	-.0380965	.0038668	-9.85 0.000 -.0456995	-.0304936
9	-.026004	.0038581	-6.74 0.000 -.0335899	-.0184181
10	-.0215894	.0038763	-5.57 0.000 -.029211	-.0139678
11	-.0014672	.0039082	-0.38 0.708 -.0091517	.0062173
12	.0054514	.0038735	1.41 0.160 -.0021648	.0130675
date	.0003124	.0000637	4.90 0.000 .000187	.0004377
_cons	-10.26323	.498888	-20.57 0.000 -11.24416	-9.282304

### 3d

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

Adding the seasonal and time trend variables transform the data into true time series data and give context to the changes. From both you can see that there is a general increase in nonfarm employment. However, by adding the month indicators, you can see that nonfarm employment decreases ever so slightly from March to November, presumably due to prime farming season. "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.)"

## 3e

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

In time series data, the past affects the future and observations are not independent. Standard error and p-value assume that your data is independent which we just established time series data is not.

## 4 Finite Distributed Lag Model

### 4a

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.

Source	SS	df	MS Number of obs =	384
	F(39, 344) =	1506.36		
Model	9.45063897	39	.242324076 Prob > F =	0.0000
Residual	.055338456	344	.000160868 R-squared =	0.9942
	Adj R-squared =	0.9935		
Total	9.50597742	383	.024819784 Root MSE =	.01268
ln_fl_nonf~m	Coef.	Std. Err.	t P>t [95% Conf.	Interval]
ln_fl_lf				
-.	-.3180953	.2192272	-1.45 0.148 -.7492898	.1130992
L1.	-.4936055	.2780395	-1.78 0.077 -1.040477	.0532661
L2.	.3085466	.27846	1.11 0.269 -.239152	.8562452
L3.	1.173922	.2948363	3.98 0.000 .5940134	1.753831
L4.	-.2346487	.2905929	-0.81 0.420 -.8062113	.3369138
L5.	.2808166	.2958343	0.95 0.343 -.3010552	.8626884
L6.	-.2076341	.3372426	-0.62 0.539 -.8709511	.4556829
L7.	.428488	.3391507	1.26 0.207 -.2385821	1.095558

L8.	.4803611	.3332665	1.44 0.150 -.1751354	1.135858
L9.	.2977526	.3112925	0.96 0.339 -.3145235	.9100288
L10.	-.00028	.3217814	-0.00 0.999 -.6331867	.6326267
L11.	-.5860114	.3256137	-1.80 0.073 -1.226456	.0544331
L12.	.0176351	.2499574	0.07 0.944 -.4740021	.5092724
ln_us_epr				
-.	1.180441	.1573579	7.50 0.000 .8709364	1.489946
L1.	.2435207	.202013	1.21 0.229 -.1538155	.6408569
L2.	-.1519264	.2015081	-0.75 0.451 -.5482695	.2444166
L3.	-.719111	.2119425	-3.39 0.001 -1.135977	-.3022447
L4.	.1877102	.2014654	0.93 0.352 -.2085489	.5839692
L5.	-.1596306	.206881	-0.77 0.441 -.5665414	.2472803
L6.	.4937537	.2396216	2.06 0.040 .0224458	.9650615
L7.	-.3031484	.236988	-1.28 0.202 -.7692764	.1629796
L8.	-.2995254	.2312056	-1.30 0.196 -.7542801	.1552293
L9.	.5953076	.2915942	2.04 0.042 .0217756	1.16884
L10.	-.1656984	.352639	-0.47 0.639 -.8592984	.5279015
L11.	.5326939	.3523697	1.51 0.132 -.1603764	1.225764
L12.	-.4280274	.2543508	-1.68 0.093 -.928306	.0722511
ln_fl_bp				
-.	.0177815	.0051888	3.43 0.001 .0075758	.0279872
L1.	.0056999	.0054688	1.04 0.298 -.0050566	.0164565
L2.	.0123023	.0056879	2.16 0.031 .0011149	.0234898
L3.	-.0005041	.0058381	-0.09 0.931 -.0119871	.0109788
L4.	-.0040248	.0058282	-0.69 0.490 -.0154881	.0074385

L5.	.0053648	.0058106	0.92 0.357 -.006064	.0167937
L6.	.0122019	.0057914	2.11 0.036 .0008108	.0235929
L7.	.0146252	.0057698	2.53 0.012 .0032766	.0259737
L8.	.0114715	.0057663	1.99 0.047 .0001299	.0228131
L9.	.0100892	.0057895	1.74 0.082 -.0012981	.0214765
L10.	-.0077443	.0056515	-1.37 0.171 -.0188601	.0033715
L11.	-.0129284	.0055227	-2.34 0.020 -.0237908	-.002066
L12.	-.0156324	.0052843	-2.96 0.003 -.0260261	-.0052388
_cons	-14.00483	.220126	-63.62 0.000 -14.43779	-13.57187

## 4b

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

Source	SS	df	MS	Number of obs =	384
	F(51, 332) =	1880.48			
Model	9.47318331	51	.185748692	Prob > F =	0.0000
Residual	.03279411	332	.000098777	R-squared =	0.9966
	Adj R-squared =	0.9960			
Total	9.50597742	383	.024819784	Root MSE =	.00994
ln_fl_nonf~m	Coef.	Std. Err.	t P>t [95% Conf.	Interval]	
ln_fl_lf					
-.	.1395258	.2167149	0.64 0.520 -.2867817		.5658333
L1.	-.0728475	.2909974	-0.25 0.802 -.6452787		.4995837
L2.	-.0401378	.2914261	-0.14 0.891 -.6134123		.5331367
L3.	.4941867	.3004728	1.64 0.101 -.096884		1.085257
L4.	.0243743	.3032608	0.08 0.936 -.5721806		.6209291

L5.	-.0515457	.3007867	-0.17 0.864 -.6432337	.5401424
L6.	.2645611	.3042172	0.87 0.385 -.3338753	.8629975
L7.	.3032209	.3064496	0.99 0.323 -.2996069	.9060486
L8.	.0945934	.3058001	0.31 0.757 -.5069567	.6961435
L9.	-.1097755	.3559336	-0.31 0.758 -.8099451	.590394
L10.	.1539543	.375505	0.41 0.682 -.5847148	.8926234
L11.	-.2776778	.3787638	-0.73 0.464 -1.022757	.4674017
L12.	-.0112724	.279864	-0.04 0.968 -.5618026	.5392579
ln_us_epr				
-,	.8902343	.1499136	5.94 0.000 .595334	1.185135
L1.	.0725186	.1976025	0.37 0.714 -.3161923	.4612294
L2.	.0146862	.1973291	0.07 0.941 -.3734868	.4028593
L3.	-.3099001	.2109421	-1.47 0.143 -.7248517	.1050514
L4.	.137028	.215249	0.64 0.525 -.2863958	.5604519
L5.	-.0073661	.2142714	-0.03 0.973 -.4288668	.4141346
L6.	.0293898	.2200462	0.13 0.894 -.4034709	.4622504
L7.	-.1397223	.2227059	-0.63 0.531 -.5778149	.2983702
L8.	-.0598893	.2228997	-0.27 0.788 -.4983631	.3785844
L9.	.4823653	.4060878	1.19 0.236 -.3164642	1.281195
L10.	.0335197	.4684115	0.07 0.943 -.887909	.9549485
L11.	.4443457	.4733678	0.94 0.349 -.4868327	1.375524
L12.	-.3652099	.3457533	-1.06 0.292 -1.045353	.3149335
ln_fl_bp				
-,	.0174185	.0043812	3.98 0.000 .0088	.0260369
L1.	.0097915	.0047176	2.08 0.039 .0005113	.0190717



L2.	.005989	.0048174	1.24 0.215 -.0034873	.0154654
L3.	.0067099	.0049382	1.36 0.175 -.0030042	.016424
L4.	.0015463	.0049663	0.31 0.756 -.0082232	.0113157
L5.	.0025978	.0049914	0.52 0.603 -.007221	.0124166
L6.	.006001	.0049798	1.21 0.229 -.0037949	.0157968
L7.	.0066017	.0049157	1.34 0.180 -.003068	.0162715
L8.	-.0015491	.0049371	-0.31 0.754 -.011261	.0081628
L9.	.0010036	.0048898	0.21 0.838 -.0086153	.0106225
L10.	-.0004773	.0047767	-0.10 0.920 -.0098737	.008919
L11.	-.0083937	.0046846	-1.79 0.074 -.017609	.0008216
L12.	-.0041455	.0044702	-0.93 0.354 -.0129391	.004648
month				
2	.0077995	.0048077	1.62 0.106 -.001658	.017257
3	.0052085	.0041637	1.25 0.212 -.0029821	.0133991
4	-.0010198	.0053356	-0.19 0.849 -.0115156	.009476
5	-.0012298	.0047478	-0.26 0.796 -.0105694	.0081098
6	-.0122415	.0055844	-2.19 0.029 -.0232267	-.0012563
7	-.0240128	.0047031	-5.11 0.000 -.0332644	-.0147612
8	-.0152756	.0052483	-2.91 0.004 -.0255997	-.0049514
9	-.0111308	.0045365	-2.45 0.015 -.0200548	-.0022068
10	-.0046899	.006722	-0.70 0.486 -.0179129	.0085332
11	.0076979	.0057763	1.33 0.184 -.0036649	.0190607
12	.0151789	.0059337	2.56 0.011 .0035065	.0268514
date	.0003695	.000047	7.86 0.000 .000277	.0004619
_cons	-11.28083	.391293	-28.83 0.000 -12.05055	-10.5111

## 4d

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

The model in 4a is accurate to the data it was given but does not make sense and has no practical application because the data is not organized in any way and does not account for the data being time series data. "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."

## 4e

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.

### 4e Sampling each quarter

Source	SS	df	MS	Number of obs =	384
	F(24, 359) =	3636.67			
Model	9.46703767	24	.394459903	Prob > F =	0.0000
Residual	.038939751	359	.000108467	R-squared =	0.9959
	Adj R-squared =	0.9956			
Total	9.50597742	383	.024819784	Root MSE =	.01041
ln_fl_nonf~m	Coef.	Std. Err.	t	P>t [95% Conf.	Interval]
ln_fl_lf					
-.	.2198644	.118892	1.85	0.065 -.0139479	.4536767
L4.	.3640379	.1628088	2.24	0.026 .0438591	.6842168
L8.	.6241057	.1697337	3.68	0.000 .2903084	.957903
L12.	-.3365352	.1300465	-2.59	0.010 -.592284	-.0807864

ln_us_epr				
-.	.8706823	.0862833	10.09 0.000 .7009981	1.040367
L4.	.0186581	.1180743	0.16 0.875 -.213546	.2508623
L8.	-.1364675	.1363531	-1.00 0.318 -.4046187	.1316838
L12.	.4492816	.1055542	4.26 0.000 .2416993	.6568639
ln_fl_bp				
-.	.0288326	.0033225	8.68 0.000 .0222986	.0353666
L4.	.014784	.0040692	3.63 0.000 .0067816	.0227864
L8.	.0053046	.0040599	1.31 0.192 -.0026795	.0132888
L12.	-.0040886	.0034865	-1.17 0.242 -.0109452	.002768
month				
2	.003724	.0027268	1.37 0.173 -.0016384	.0090864
3	.003428	.0030747	1.11 0.266 -.0026188	.0094747
4	-.0013812	.0030302	-0.46 0.649 -.0073404	.0045779
5	-.0050709	.003101	-1.64 0.103 -.0111693	.0010275
6	-.0215379	.0030889	-6.97 0.000 -.0276125	-.0154633
7	-.0356678	.0033321	-10.70 0.000 -.0422208	-.0291149
8	-.0202856	.0032905	-6.16 0.000 -.0267567	-.0138145
9	-.0118143	.0031977	-3.69 0.000 -.0181028	-.0055257
10	-.0142884	.0031129	-4.59 0.000 -.0204102	-.0081666
11	-.0033333	.0030634	-1.09 0.277 -.0093578	.0026912
12	.0070509	.0028963	2.43 0.015 .001355	.0127468
date	.0004262	.0000476	8.96 0.000 .0003326	.0005197
_cons	-10.60852	.3857432	-27.50 0.000 -11.36712	-9.849916

## 4e True Quarters

Source	SS	df	MS Number of obs =	392
	F(27, 364) =	2505.01		
Model	10.2740552	27	.380520563 Prob > F =	0.0000
Residual	.055292923	364	.000151904 R-squared =	0.9946
	Adj R-squared =	0.9942		
Total	10.3293481	391	.02641777 Root MSE =	.01232
ln_fl_nonf~m	Coef.	Std. Err.	t P>t [95% Conf.	Interval]
ln_fl_lf				
-.	.2790757	.2536131	1.10 0.272 -.2196552	.7778065
L1.	.2956093	.3348151	0.88 0.378 -.3628055	.9540241
L2.	-.2641756	.3153608	-0.84 0.403 -.8843334	.3559822
L3.	.2832334	.3167687	0.89 0.372 -.339693	.9061598
L4.	.3220421	.2469667	1.30 0.193 -.1636186	.8077029
ln_us_epr				
-.	.869919	.1763402	4.93 0.000 .5231456	1.216693
L1.	-.1508318	.2303364	-0.65 0.513 -.6037889	.3021253
L2.	.1899043	.2170821	0.87 0.382 -.2369882	.6167968
L3.	-.2262386	.2208671	-1.02 0.306 -.6605744	.2080971
L4.	.3389032	.1751932	1.93 0.054 -.0056147	.6834212
ln_fl_bp				
-.	.0204443	.0051347	3.98 0.000 .010347	.0305417
L1.	.0107528	.0054657	1.97 0.050 4.39e-06	.0215012

L2.	.0026867	.0054899	0.49 0.625 -.0081091	.0134826
L3.	.0070439	.0054993	1.28 0.201 -.0037706	.0178583
L4.	.0071123	.0051692	1.38 0.170 -.003053	.0172777
month				
2	.0052225	.0038186	1.37 0.172 -.0022868	.0127318
3	.0086375	.0041006	2.11 0.036 .0005735	.0167014
4	.0012736	.0046541	0.27 0.785 -.0078787	.0104258
5	.0022027	.0038771	0.57 0.570 -.0054216	.0098269
6	-.0193223	.0040672	-4.75 0.000 -.0273206	-.0113241
7	-.0362039	.0038883	-9.31 0.000 -.0438502	-.0285575
8	-.0245188	.0043528	-5.63 0.000 -.0330787	-.015959
9	-.0171602	.0037189	-4.61 0.000 -.0244733	-.0098471
10	-.0193132	.0044175	-4.37 0.000 -.0280001	-.0106262
11	-.004866	.0041178	-1.18 0.238 -.0129637	.0032317
12	.0058531	.0039007	1.50 0.134 -.0018177	.0135238
dateQ	.0010375	.0001584	6.55 0.000 .0007259	.001349
_cons	-10.55687	.4171884	-25.30 0.000 -11.37727	-9.736468

## 4e Explanation

I was curious to know how sampling lag for a single month from each quarter for a year would compare to generating a new quarter date variable and using that for lag. Unfortunately, I don't think I did it right and I don't know how to get what I want. Instead, what I have for the second chart is quarterly dates but the lagged variables are now only lagged for the first four months of the year.

Based on the MSE of each model, the first one is a little bit better but I don't think either is great.

"The most important lags would seem to be the most recent month, and the same month a year ago."

# Appendix A

```
1  clear
2  set more off
3
4  cd "/Users/guslipkin/Documents/Spring2020/CAP 4763 ~ Time Series/Problem Sets/Problem
   Set 1"
5
6  *2b Load the data
7  import delimited "Assignment_1_Monthly.txt"
8
9  rename lnu02300000 us_epr
10 rename flnan fl_nonfarm
11 rename flllfn fl_lf
12 rename flbppriv fl_bp
13 rename date datestring
14
15 *2c Turn on a log file
16 log using "Problem Set 1", replace
17
18 *2d Generate a monthly date variable (make its display format monthly time, %tm)
19 gen datec=date(datestring, "YMD")
20 gen date=mofd(datec)
21 format date %tm
22
23 *2e tsset your data
24 tsset date
25
26 *2f
27 gen ln_us_epr=log(us_epr)
28 gen ln_fl_nonfarm=log(fl_nonfarm)
29 gen ln_fl_lf=log(fl_lf)
30 gen ln_fl_bp=log(fl_bp)
31
32 *3b 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.
33 regress ln_fl_nonfarm ln_fl_lf ln_us_epr ln_fl_bp
34
35 *3c Estimate the static model with month indicators and a time trend.
36 gen month=month(datec)
37 reg ln_fl_nonfarm ln_fl_lf ln_us_epr ln_fl_bp i.month date
38
39 *4a 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.
40 regress ln_fl_nonfarm l(0/12).ln_fl_lf l(0/12).ln_us_epr l(0/12).ln_fl_bp
41
42 *4b Estimate the model in (a) but add month indicators and a time trend.
```

```

43 regress ln_fl_nonfarm l(0/12).ln_fl_lf l(0/12).ln_us_epr l(0/12).ln_fl_bp i.month
    date
44
45 *4e 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.
46 regress ln_fl_nonfarm l(0,4,8,12).ln_fl_lf l(0,4,8,12).ln_us_epr l(0,4,8,12).ln_fl_bp
    i.month date
47 gen dateQ = qofd(datec)
48 format dateQ %tq
49 regress ln_fl_nonfarm l(0/4).ln_fl_lf l(0/4).ln_us_epr l(0/4).ln_fl_bp i.month dateQ
50
51 log close

```

## Appendix B

```

    name: <unnamed>
    log: /Users/guslipkin/Documents/Spring2020/CAP 4763 ~ Time Series/Problem Sets/P
> roblem Set 1/Problem Set 1.smcl
    log type: smcl
    opened on: 11 Feb 2021, 19:36:36

.
. *2d Generate a monthly date variable (make its display format monthly time, %tm)
. gen datec=date(datestring, "YMD")

. gen date=mofd(datec)

. format date %tm

.
. *2e tsset your data
. tsset date
      time variable: date, 1939m1 to 2020m12
              delta: 1 month

.
. *2f
. gen ln_us_epr=log(us_epr)
(108 missing values generated)

. gen ln_fl_nonfarm=log(fl_nonfarm)

. gen ln_fl_lf=log(fl_lf)
(444 missing values generated)

. gen ln_fl_bp=log(fl_bp)
(588 missing values generated)

.
. *3b Estimate the static model relating monthly nonfarm employment in Florida to the ot
> her three variables (all in logs) without controlling for seasonal impacts or a time t
> rend.

```

```
. regress ln_fl_nonfarm ln_fl_lf ln_us_epr ln_fl_bp
```

Source	SS	df	MS	Number of obs	=	396
Model	10.5356085	3	3.51186951	F(3, 392)	=	5972.65
Residual	.230492978	392	.000587992	Prob > F	=	0.0000
				R-squared	=	0.9786
				Adj R-squared	=	0.9784
Total	10.7661015	395	.027255953	Root MSE	=	.02425

ln_fl_nonf~m	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ln_fl_lf	1.110504	.0092305	120.31	0.000	1.092356	1.128651
ln_us_epr	.6006702	.047797	12.57	0.000	.5066997	.6946407
ln_fl_bp	.0516831	.0028713	18.00	0.000	.0460379	.0573282
_cons	-11.78364	.2925244	-40.28	0.000	-12.35875	-11.20852

```
.
```

```
. *3c Estimate the static model with month indicators and a time trend.
```

```
. gen month=month(datec)
```

```
. reg ln_fl_nonfarm ln_fl_lf ln_us_epr ln_fl_bp i.month date
```

Source	SS	df	MS	Number of obs	=	396
Model	10.6739911	15	.711599408	F(15, 380)	=	2935.69
Residual	.092110398	380	.000242396	Prob > F	=	0.0000
				R-squared	=	0.9914
				Adj R-squared	=	0.9911
Total	10.7661015	395	.027255953	Root MSE	=	.01557

ln_fl_nonf~m	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ln_fl_lf	.9282631	.0413265	22.46	0.000	.8470059	1.00952
ln_us_epr	.9105558	.0514333	17.70	0.000	.8094263	1.011685
ln_fl_bp	.0466812	.0021579	21.63	0.000	.0424382	.0509242
month						
2	.0045623	.0038378	1.19	0.235	-.0029837	.0121084
3	-.001379	.003839	-0.36	0.720	-.0089274	.0061694
4	-.0029373	.0038393	-0.77	0.445	-.0104863	.0046116
5	-.0142748	.0038468	-3.71	0.000	-.0218384	-.0067112
6	-.0356123	.0038709	-9.20	0.000	-.0432234	-.0280012
7	-.0519102	.0038917	-13.34	0.000	-.0595622	-.0442582
8	-.0380965	.0038668	-9.85	0.000	-.0456995	-.0304936
9	-.026004	.0038581	-6.74	0.000	-.0335899	-.0184181
10	-.0215894	.0038763	-5.57	0.000	-.029211	-.0139678
11	-.0014672	.0039082	-0.38	0.708	-.0091517	.0062173
12	.0054514	.0038735	1.41	0.160	-.0021648	.0130675
date	.0003124	.0000637	4.90	0.000	.000187	.0004377
_cons	-10.26323	.498888	-20.57	0.000	-11.24416	-9.282304

```
.
```

```
. *4a Estimate the distributed lag model relating monthly nonfarm employment to lags 0 t
```

```
*** 15 of the above model has been estimated without month indicators and a time trend
```



```
> o 12 of the three predictor variables without month indicators and a time trend.
. regress ln_fl_nonfarm l(0/12).ln_fl_lf l(0/12).ln_us_epr l(0/12).ln_fl_bp
```

Source	SS	df	MS	Number of obs	=	384
Model	9.45063897	39	.242324076	F(39, 344)	=	1506.36
Residual	.055338456	344	.000160868	Prob > F	=	0.0000
				R-squared	=	0.9942
				Adj R-squared	=	0.9935
Total	9.50597742	383	.024819784	Root MSE	=	.01268

ln_fl_nonf~m	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ln_fl_lf						
--.	-.3180953	.2192272	-1.45	0.148	-.7492898	.1130992
L1.	-.4936055	.2780395	-1.78	0.077	-1.040477	.0532661
L2.	.3085466	.27846	1.11	0.269	-.239152	.8562452
L3.	1.173922	.2948363	3.98	0.000	.5940134	1.753831
L4.	-.2346487	.2905929	-0.81	0.420	-.8062113	.3369138
L5.	.2808166	.2958343	0.95	0.343	-.3010552	.8626884
L6.	-.2076341	.3372426	-0.62	0.539	-.8709511	.4556829
L7.	.428488	.3391507	1.26	0.207	-.2385821	1.095558
L8.	.4803611	.3332665	1.44	0.150	-.1751354	1.135858
L9.	.2977526	.3112925	0.96	0.339	-.3145235	.9100288
L10.	-.00028	.3217814	-0.00	0.999	-.6331867	.6326267
L11.	-.5860114	.3256137	-1.80	0.073	-1.226456	.0544331
L12.	.0176351	.2499574	0.07	0.944	-.4740021	.5092724
ln_us_epr						
--.	1.180441	.1573579	7.50	0.000	.8709364	1.489946
L1.	.2435207	.202013	1.21	0.229	-.1538155	.6408569
L2.	-.1519264	.2015081	-0.75	0.451	-.5482695	.2444166
L3.	-.719111	.2119425	-3.39	0.001	-1.135977	-.3022447
L4.	.1877102	.2014654	0.93	0.352	-.2085489	.5839692
L5.	-.1596306	.206881	-0.77	0.441	-.5665414	.2472803
L6.	.4937537	.2396216	2.06	0.040	.0224458	.9650615
L7.	-.3031484	.236988	-1.28	0.202	-.7692764	.1629796
L8.	-.2995254	.2312056	-1.30	0.196	-.7542801	.1552293
L9.	.5953076	.2915942	2.04	0.042	.0217756	1.16884
L10.	-.1656984	.352639	-0.47	0.639	-.8592984	.5279015
L11.	.5326939	.3523697	1.51	0.132	-.1603764	1.225764
L12.	-.4280274	.2543508	-1.68	0.093	-.928306	.0722511
ln_fl_bp						
--.	.0177815	.0051888	3.43	0.001	.0075758	.0279872
L1.	.0056999	.0054688	1.04	0.298	-.0050566	.0164565
L2.	.0123023	.0056879	2.16	0.031	.0011149	.0234898
L3.	-.0005041	.0058381	-0.09	0.931	-.0119871	.0109788
L4.	-.0040248	.0058282	-0.69	0.490	-.0154881	.0074385
L5.	.0053648	.0058106	0.92	0.357	-.006064	.0167937
L6.	.0122019	.0057914	2.11	0.036	.0008108	.0235929
L7.	.0146252	.0057698	2.53	0.012	.0032766	.0259737
L8.	.0114715	.0057663	1.99	0.047	.0001299	.0228131
L9.	.0100892	.0057895	1.74	0.082	-.0012981	.0214765
L10.	-.0077443	.0056515	-1.37	0.171	-.0188601	.0033715
L11.	-.0129284	.0055227	-2.34	0.020	-.0237908	-.002066
L12.	-.0156324	.0052843	-2.96	0.003	-.0260261	-.0052388

_cons	-14.00483	.220126	-63.62	0.000	-14.43779	-13.57187
-------	-----------	---------	--------	-------	-----------	-----------

.  
. \*4b Estimate the model in (a) but add month indicators and a time trend.  
. regress ln\_fl\_nonfarm l(0/12).ln\_fl\_lf l(0/12).ln\_us\_epr l(0/12).ln\_fl\_bp i.month date

Source	SS	df	MS	Number of obs	=	384
Model	9.47318331	51	.185748692	F(51, 332)	=	1880.48
Residual	.03279411	332	.000098777	Prob > F	=	0.0000
				R-squared	=	0.9966
				Adj R-squared	=	0.9960
Total	9.50597742	383	.024819784	Root MSE	=	.00994

ln_fl_nonf~m	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ln_fl_lf						
--.	.1395258	.2167149	0.64	0.520	-.2867817	.5658333
L1.	-.0728475	.2909974	-0.25	0.802	-.6452787	.4995837
L2.	-.0401378	.2914261	-0.14	0.891	-.6134123	.5331367
L3.	.4941867	.3004728	1.64	0.101	-.096884	1.085257
L4.	.0243743	.3032608	0.08	0.936	-.5721806	.6209291
L5.	-.0515457	.3007867	-0.17	0.864	-.6432337	.5401424
L6.	.2645611	.3042172	0.87	0.385	-.3338753	.8629975
L7.	.3032209	.3064496	0.99	0.323	-.2996069	.9060486
L8.	.0945934	.3058001	0.31	0.757	-.5069567	.6961435
L9.	-.1097755	.3559336	-0.31	0.758	-.8099451	.590394
L10.	.1539543	.375505	0.41	0.682	-.5847148	.8926234
L11.	-.2776778	.3787638	-0.73	0.464	-1.022757	.4674017
L12.	-.0112724	.279864	-0.04	0.968	-.5618026	.5392579
ln_us_epr						
--.	.8902343	.1499136	5.94	0.000	.595334	1.185135
L1.	.0725186	.1976025	0.37	0.714	-.3161923	.4612294
L2.	.0146862	.1973291	0.07	0.941	-.3734868	.4028593
L3.	-.3099001	.2109421	-1.47	0.143	-.7248517	.1050514
L4.	.137028	.215249	0.64	0.525	-.2863958	.5604519
L5.	-.0073661	.2142714	-0.03	0.973	-.4288668	.4141346
L6.	.0293898	.2200462	0.13	0.894	-.4034709	.4622504
L7.	-.1397223	.2227059	-0.63	0.531	-.5778149	.2983702
L8.	-.0598893	.2228997	-0.27	0.788	-.4983631	.3785844
L9.	.4823653	.4060878	1.19	0.236	-.3164642	1.281195
L10.	.0335197	.4684115	0.07	0.943	-.887909	.9549485
L11.	.4443457	.4733678	0.94	0.349	-.4868327	1.375524
L12.	-.3652099	.3457533	-1.06	0.292	-1.045353	.3149335
ln_fl_bp						
--.	.0174185	.0043812	3.98	0.000	.0088	.0260369
L1.	.0097915	.0047176	2.08	0.039	.0005113	.0190717
L2.	.005989	.0048174	1.24	0.215	-.0034873	.0154654
L3.	.0067099	.0049382	1.36	0.175	-.0030042	.016424
L4.	.0015463	.0049663	0.31	0.756	-.0082232	.0113157
L5.	.0025978	.0049914	0.52	0.603	-.007221	.0124166
L6.	.006001	.0049798	1.21	0.229	-.0037949	.0157968
L7.	.0066017	.0049157	1.34	0.180	-.003068	.0162715
L8.	-.0015401	.0040371	-.031	0.754	-.011261	.0081628

L0.	-.0010791	.0049371	-0.01	0.737	-.011201	.0001020
L9.	.0010036	.0048898	0.21	0.838	-.0086153	.0106225
L10.	-.0004773	.0047767	-0.10	0.920	-.0098737	.008919
L11.	-.0083937	.0046846	-1.79	0.074	-.017609	.0008216
L12.	-.0041455	.0044702	-0.93	0.354	-.0129391	.004648
month						
2	.0077995	.0048077	1.62	0.106	-.001658	.017257
3	.0052085	.0041637	1.25	0.212	-.0029821	.0133991
4	-.0010198	.0053356	-0.19	0.849	-.0115156	.009476
5	-.0012298	.0047478	-0.26	0.796	-.0105694	.0081098
6	-.0122415	.0055844	-2.19	0.029	-.0232267	-.0012563
7	-.0240128	.0047031	-5.11	0.000	-.0332644	-.0147612
8	-.0152756	.0052483	-2.91	0.004	-.0255997	-.0049514
9	-.0111308	.0045365	-2.45	0.015	-.0200548	-.0022068
10	-.0046899	.006722	-0.70	0.486	-.0179129	.0085332
11	.0076979	.0057763	1.33	0.184	-.0036649	.0190607
12	.0151789	.0059337	2.56	0.011	.0035065	.0268514
date	.0003695	.000047	7.86	0.000	.000277	.0004619
_cons	-11.28083	.391293	-28.83	0.000	-12.05055	-10.5111

```

.
. *4e 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 yo
> ur choices.
. regress ln_fl_nonfarm l(0,4,8,12).ln_fl_lf l(0,4,8,12).ln_us_epr l(0,4,8,12).ln_fl_bp
> i.month date

```

Source	SS	df	MS	Number of obs	=	384
Model	9.46703767	24	.394459903	F(24, 359)	=	3636.67
Residual	.038939751	359	.000108467	Prob > F	=	0.0000
				R-squared	=	0.9959
				Adj R-squared	=	0.9956
Total	9.50597742	383	.024819784	Root MSE	=	.01041

ln_fl_nonf~m	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ln_fl_lf						
--.	.2198644	.118892	1.85	0.065	-.0139479	.4536767
L4.	.3640379	.1628088	2.24	0.026	.0438591	.6842168
L8.	.6241057	.1697337	3.68	0.000	.2903084	.957903
L12.	-.3365352	.1300465	-2.59	0.010	-.592284	-.0807864
ln_us_epr						
--.	.8706823	.0862833	10.09	0.000	.7009981	1.040367
L4.	.0186581	.1180743	0.16	0.875	-.213546	.2508623
L8.	-.1364675	.1363531	-1.00	0.318	-.4046187	.1316838
L12.	.4492816	.1055542	4.26	0.000	.2416993	.6568639
ln_fl_bp						
--.	.0288326	.0033225	8.68	0.000	.0222986	.0353666
L4.	.014784	.0040692	3.63	0.000	.0067816	.0227864
L8.	.0053046	.0040599	1.31	0.192	-.0026795	.0132888
L12.	-.0040886	.0034865	-1.17	0.242	-.0109452	.002768

month						
2	.003724	.0027268	1.37	0.173	-.0016384	.0090864
3	.003428	.0030747	1.11	0.266	-.0026188	.0094747
4	-.0013812	.0030302	-0.46	0.649	-.0073404	.0045779
5	-.0050709	.003101	-1.64	0.103	-.0111693	.0010275
6	-.0215379	.0030889	-6.97	0.000	-.0276125	-.0154633
7	-.0356678	.0033321	-10.70	0.000	-.0422208	-.0291149
8	-.0202856	.0032905	-6.16	0.000	-.0267567	-.0138145
9	-.0118143	.0031977	-3.69	0.000	-.0181028	-.0055257
10	-.0142884	.0031129	-4.59	0.000	-.0204102	-.0081666
11	-.0033333	.0030634	-1.09	0.277	-.0093578	.0026912
12	.0070509	.0028963	2.43	0.015	.001355	.0127468
date	.0004262	.0000476	8.96	0.000	.0003326	.0005197
_cons	-10.60852	.3857432	-27.50	0.000	-11.36712	-9.849916

```
. gen dateQ = qofd(datec)
```

```
. format dateQ %tq
```

```
. regress ln_fl_nonfarm l(0/4).ln_fl_lf l(0/4).ln_us_epr l(0/4).ln_fl_bp i.month dateQ
```

Source	SS	df	MS	Number of obs	=	392
				F(27, 364)	=	2505.01
Model	10.2740552	27	.380520563	Prob > F	=	0.0000
Residual	.055292923	364	.000151904	R-squared	=	0.9946
				Adj R-squared	=	0.9942
Total	10.3293481	391	.02641777	Root MSE	=	.01232

ln_fl_nonf~m	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ln_fl_lf						
--.	.2790757	.2536131	1.10	0.272	-.2196552	.7778065
L1.	.2956093	.3348151	0.88	0.378	-.3628055	.9540241
L2.	-.2641756	.3153608	-0.84	0.403	-.8843334	.3559822
L3.	.2832334	.3167687	0.89	0.372	-.339693	.9061598
L4.	.3220421	.2469667	1.30	0.193	-.1636186	.8077029
ln_us_epr						
--.	.869919	.1763402	4.93	0.000	.5231456	1.216693
L1.	-.1508318	.2303364	-0.65	0.513	-.6037889	.3021253
L2.	.1899043	.2170821	0.87	0.382	-.2369882	.6167968
L3.	-.2262386	.2208671	-1.02	0.306	-.6605744	.2080971
L4.	.3389032	.1751932	1.93	0.054	-.0056147	.6834212
ln_fl_bp						
--.	.0204443	.0051347	3.98	0.000	.010347	.0305417
L1.	.0107528	.0054657	1.97	0.050	4.39e-06	.0215012
L2.	.0026867	.0054899	0.49	0.625	-.0081091	.0134826
L3.	.0070439	.0054993	1.28	0.201	-.0037706	.0178583
L4.	.0071123	.0051692	1.38	0.170	-.003053	.0172777
month						
2	.0052225	.0038186	1.37	0.172	-.0022868	.0127318
3	.0086375	.0041006	2.11	0.036	.0005735	.0167014

4	.0012736	.0046541	0.27	0.785	-.0078787	.0104258
5	.0022027	.0038771	0.57	0.570	-.0054216	.0098269
6	-.0193223	.0040672	-4.75	0.000	-.0273206	-.0113241
7	-.0362039	.0038883	-9.31	0.000	-.0438502	-.0285575
8	-.0245188	.0043528	-5.63	0.000	-.0330787	-.015959
9	-.0171602	.0037189	-4.61	0.000	-.0244733	-.0098471
10	-.0193132	.0044175	-4.37	0.000	-.0280001	-.0106262
11	-.004866	.0041178	-1.18	0.238	-.0129637	.0032317
12	.0058531	.0039007	1.50	0.134	-.0018177	.0135238
dateQ	.0010375	.0001584	6.55	0.000	.0007259	.001349
_cons	-10.55687	.4171884	-25.30	0.000	-11.37727	-9.736468

---

```

.
.
. log close
  name: <unnamed>
  log: /Users/guslipkin/Documents/Spring2020/CAP 4763 ~ Time Series/Problem Sets/P
> roblem Set 1/Problem Set 1.smcl
  log type: smcl
closed on: 11 Feb 2021, 19:36:37

```

---