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**CAP 4763 Time Series Modelling and Forecasting** 

# **Table of Contents**

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

### 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.

#### 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.

#### **3c**

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

### **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.

### **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.

### 4b

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

### **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.

### 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.

### **Appendix A**

```
clear
 1
 2
    set more off
    cd "/Users/guslipkin/Documents/Spring2020/CAP 4763 ~ Time Series/Problem Sets/Problem
 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 fllfn fl lf
    rename flbppriv fl bp
12
13
    rename date datestring
14
15
    *2c Turn on a log file
    log using "Problem Set 1", replace
16
17
18
    *2d Generate a monthly date variable (make its display format monthly time, %tm)
19
    gen datec=date(datestring, "YMD")
    gen date=mofd(datec)
20
21
    format date %tm
    *2e tsset your data
23
    tsset date
2.4
2.5
2.6
    *2f
27
    gen ln us epr=log(us epr)
    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.
    regress ln_fl_nonfarm ln_fl_lf ln_us_epr ln_fl_bp
33
34
35
    *3c Estimate the static model with month indicators and a time trend.
    gen month=month(datec)
36
    reg ln_fl_nonfarm ln_fl_lf ln_us_epr ln_fl_bp i.month date
37
38
    *4a Estimate the distributed lag model relating monthly nonfarm employment to lags 0
39
    to 12 of the three predictor variables without month indicators and a time trend.
40
    regress ln_fl_nonfarm 1(0/12).ln_fl_lf 1(0/12).ln_us_epr 1(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 log close
```

## **Appendix B**

```
name: <unnamed>
             /Users/guslipkin/Documents/Spring2020/CAP 4763 ~ Time Series/Problem Sets/P
       log:
> roblem Set 1/Problem Set 1.smcl
  log type: smcl
opened on:
            7 Feb 2021, 18:17:12
. *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, 1939ml to 2020ml2
                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
                                                   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]
<pre>ln_fl_lf ln_us_epr ln_fl_bp _cons</pre>	1.110504 .6006702 .0516831 -11.78364	.0092305 .047797 .0028713 .2925244	120.31 12.57 18.00 -40.28	0.000 0.000 0.000 0.000	1.092356 .5066997 .0460379 -12.35875	1.128651 .6946407 .0573282 -11.20852

•

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

df

MS

Number of obs =

396

. gen month=month(datec)

Source SS

. reg  $ln_fl_nonfarm\ ln_fl_lf\ ln_us_epr\ ln_fl_bp\ i.month\ date$ 

				F(15	, 380)	=	2935.69
Model	10.6739911	15	.711599408	Prob	> F	=	0.0000
Residual	.092110398	380	.000242396	R-squ	uared	=	0.9914
				- Adj F	R-squared	=	0.9911
Total	10.7661015	395	.027255953	Root	MSE	=	.01557
ln_fl_nonf~m	Coef.	Std. Err.	t	P> t	[95% Co	nf.	Interval]
ln_fl_lf	.9282631	.0413265	22.46	0.000	.847005	9	1.00952
ln_us_epr	.9105558	.0514333	17.70	0.000	.809426	3	1.011685
ln_fl_bp	.0466812	.0021579	21.63	0.000	.042438	2	.0509242
month							
2	.0045623	.0038378	1.19	0.235	002983	7	.0121084
3	001379	.003839	-0.36	0.720	008927	4	.0061694
4	0029373	.0038393	-0.77	0.445	010486	3	.0046116
5	0142748	.0038468	-3.71	0.000	021838	4	0067112
6	0356123	.0038709	-9.20	0.000	043223	4	0280012
7	0519102	.0038917	-13.34	0.000	059562	2	0442582
8	0380965	.0038668	-9.85	0.000	045699	5	0304936
9	026004	.0038581	-6.74	0.000	033589	9	0184181
10	0215894	.0038763	-5.57	0.000	02921	1	0139678
11	0014672	.0039082	-0.38	0.708	009151	7	.0062173
12	.0054514	.0038735	1.41	0.160	002164	В	.0130675
date	.0003124	.0000637	4.90	0.000	.00018	7	.0004377
_cons	-10.26323	.498888	-20.57	0.000	-11.2441	6	-9.282304

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

<sup>.</sup> 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
_					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

<sup>&</sup>gt; o 12 of the three predictor variables without month indicators and a time trend.

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
LIZi	.0170331	. 2433374	0.07	0.344	4740021	. 3032724
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.	.0122019	.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

<sup>.</sup> \*4b Estimate the model in (a) but add month indicators and a time trend.

<sup>.</sup> 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
_					F(51, 332)	=	1880.48
	Madal	0 47310331	F1 '	105740603	Duch . E	_	0 0000

Residual	.03279411	332	.100/4009	7 R-squa - Adj R-	red squared	= = d =	0.9966 0.9960
Total	9.50597742	383	.02481978	1 Root M	SE	=	.00994
ln_fl_nonf~m	Coef.	Std. Err.	t	P> t	[95% (	Conf.	Interval]
ln fl lf							

ln_fl_nonf~m	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval
ln_fl_lf						
	.1395258	.2167149	0.64	0.520	2867817	.565833
L1.	0728475	.2909974	-0.25	0.802	6452787	. 499583
L2.	0401378	.2914261	-0.14	0.891	6134123	.533136
L3.	.4941867	.3004728	1.64	0.101	096884	1.08525
L4.	.0243743	.3032608	0.08	0.936	5721806	.620929
L5.	0515457	.3007867	-0.17	0.864	6432337	.540142
L6.	.2645611	.3042172	0.87	0.385	3338753	.862997
L7.	.3032209	.3064496	0.99	0.323	2996069	.906048
L8.	.0945934	.3058001	0.31	0.757	5069567	.696143
L9.	1097755	.3559336	-0.31	0.758	8099451	.59039
L10.	.1539543	.375505	0.41	0.682	5847148	.892623
L11.	2776778	.3787638	-0.73	0.464	-1.022757	.467401
L12.	0112724	.279864	-0.04	0.968	5618026	.539257
ln_us_epr						
	.8902343	.1499136	5.94	0.000	.595334	1.18513
L1.	.0725186	.1976025	0.37	0.714	3161923	.461229
L2.	.0146862	.1973291	0.07	0.941	3734868	.402859
L3.	3099001	.2109421	-1.47	0.143	7248517	.105051
L4.	.137028	.215249	0.64	0.525	2863958	.560451
L5.	0073661	.2142714	-0.03	0.973	4288668	. 414134
L6.	.0293898	.2200462	0.13	0.894	4034709	. 462250
L7.	1397223	.2227059	-0.63	0.531	5778149	.298370
L8.	0598893	.2228997	-0.27	0.788	4983631	.378584
L9.	. 4823653	.4060878	1.19	0.236	3164642	1.28119
L10.	.0335197	.4684115	0.07	0.943	887909	.954948
L11.	. 4443457	.4733678	0.94	0.349	4868327	1.37552
L12.	3652099	.3457533	-1.06	0.292	-1.045353	.314933
ln_fl_bp						
	.0174185	.0043812	3.98	0.000	.0088	.026036
L1.	.0097915	.0047176	2.08	0.039	.0005113	.019071
L2.	.005989	.0048174	1.24	0.215	0034873	.015465
L3.	.0067099	.0049382	1.36	0.175	0030042	.01642
L4.	.0015463	.0049663	0.31	0.756	0082232	.011315
L5.	.0025978	.0049914	0.52	0.603	007221	.012416
L6.	.006001	.0049798	1.21	0.229	0037949	.015796
L7.	.0066017	.0049157	1.34	0.180	003068	.016271
L8.	0015491	.0049371	-0.31	0.754	011261	.008162
L9.	.0010036	.0048898	0.21	0.838	0086153	.010622
L10.	0004773	.0047767	-0.10	0.920	0098737	.00891
L11.	0083937	.0046846	-1.79	0.920	017609	.00031
L12.	0041455	.0044702	-0.93	0.354	0129391	.00464
month						
2	.0077995	.0048077	1.62	0.106	001658	.01725
3	.0052085	.0041637	1.25	0.212	0029821	.013399
4	0010198	.0053356	-0.19	0.849	0115156	.00947
5	_ 0010190	.0055550 0047470	_0.15	0.045 0.706	_ 010560 <i>4</i>	002100

J	0012230		-0.20	U./3U	0103034	
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
	l					

•

. 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: **7 Feb 2021, 18:17:12**