FRED Investigation into Nonfarm jobs in Florida

Time Series Modeling and Forecasting

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Introduction

There are multiple factors that contribute to rises and declines in Nonfarm Employment in Florida. In that regard, this is an investigation on several factors and their proposed effects on the total number of nonfarm jobs in the Florida Job market. In this investigation, a list of variables from FRED (Federal Reserve Economic Database) will function as independent variables for the dependent variable of nonfarm jobs. These variables are: Civilian Labor Force in Florida (fl_lf), New Private Housing Units Authorized by Building Permits for Florida (fl_bp), US Employment Population Ratio: 25 - 54 years (us_epr25to54). All of these variables are monthly non-seasonally adjusted and require multiple modifications to build models that can actually display the significance in relationships between the variables.

Importing and Wrangling the data

Importing the data involves a number of functions that will be shown below. The *kable* library in R will be used to generate nice tables to show the regression outputs of the multiple models used in this investigation. All of the codebase will be in STATA.

```
clear
set more off
# Importing the data
cd "/Users/angelsarmiento/Documents/Graduate/First Year/Time Series/STATA/HW1"
import delimited "data.csv"
```

After importing the data a series of different date variables will be created for further use later. This involves the creation of a monthly time date.

```
rename date datestring
gen datec=date(datestring,"YMD")
gen mdate=mofd(datec)
format mdate %tm
tsset mdate
```

Converting all string values to Float ignoring NA values.

```
destring fl_lf, replace ignore("NA")
destring fl_bp, replace ignore("NA")
destring us_epr_25to54, replace ignore("NA")
```

Creating log versions of the variables

```
gen ln_fl_nonfarm = ln(fl_nonfarm)
gen ln_fl_lf = ln(fl_lf)
gen ln_fl_bp = ln(fl_bp)
gen ln_us_epr = ln(us_epr_25to54)
```

The Static Model

In the interest of hypothesizing the relationship between nonfarm jobs and the other variables, a static model is the first attempt to represent this relationship. The size of Florida's labor force is something that is most likely generally correlated with the number of nonfarm jobs. More people who can work, means more jobs that can and will be filled. The prime age employment to population ratio might be related to total nonfarm jobs in that a larger ratio means more jobs that can be filled and a higher workforce percentage of the population would be able to pursue jobs outside of the farming industries. The other variable, the amount of Florida Building permits would also be positively correlated in a long run sense. A higher amount of approved building permits would mean more more spaces for employment and more people needed to operate in the building. Inversely, a lower number of building permits implies less spaces for work and lower employment in nonfarm jobs.

Developing the static model without accounting for time trends and then following it with another model that accounts for the linear time trend and monthly seasonality. β_n is the coefficients, X_t is the variable at time t, δ_k is the coefficient of the month, \hat{Y} is the nonfarm detrending with time, and $\hat{\beta}_n$ is the coefficients for the detrended series.

$$Y_{nonfarm} = \alpha_0 + \beta_1 log X_{lf} + \beta_2 log X_{bp} + \beta_3 log X_{epr}$$

```
reg ln_fl_nonfarm ln_fl_lf ln_fl_bp ln_us_epr
eststo lnnonfarm1
```

```
\hat{Y}_{nonfarm} = \hat{\alpha}_0 + \Sigma \hat{\beta}_1 log X_{lf,t} + \Sigma \hat{\beta}_2 log X_{bp,t} + \Sigma \hat{\beta}_3 log X_{epr,t} + \delta_1 Feb_t + \delta_2 Mar_t + ... \delta_k month_t where t = 0, 1, 2, 3... and k = 1, 2, 3... 11
```

```
gen monthly = month(datec)

reg ln_fl_nonfarm ln_fl_lf ln_fl_bp ln_us_epr i.monthly datec
eststo lnnonfarm2
esttab lnnonfarm*
```

The regression output is shown below.

Table 1: Static Model Comparison

X1	ln fl nonfarm	ln fl nonfarm 1	Γ=
ln fl lf	1.116***	0.916***	
	(120.72)	(25.93)	
	(====)	(2000)	
ln_fl_bp	0.0441***	0.0351***	
	(13.92)	(18.41)	
	/	,	
ln_us_epr	0.784***	1.236***	
	(13.35)	(25.95)	
1.monthly		0	
		(.)	
2.monthly		0.00312	
		(1.00)	
3.monthly		-0.00323	
		(-1.04)	
4.monthly		-0.00939**	
		(-3.00)	
5.monthly		-0.0212***	
		(-6.77)	
6.monthly		-0.0436***	
		(-13.78)	
7.monthly		-0.0611***	
		(-19.10)	
8.monthly		-0.0443***	
		(-14.04)	
9.monthly		-0.0315***	
		(-10.01)	
10.monthly		-0.0278***	
		(-8.77)	
11.monthly	1	-0.00898**	
10 11		(-2.80)	
12.monthly	1	0.000800	
		(0.25)	
		0.0000110***	
datec		0.0000118***	
		(6.52)	
aana	19 56***	-11.32***	
cons	-12.56***		
	(-38.28)	(-26.18)	
N	202	202	
N	383	383	
t statistics in parantheses			
t statistics in parentheses	** n < 0.01	*** n <0.001"	
="* p<0.05	** p<0.01	*** p<0.001"	

The non-seasonally, non-detrended model shows that every one of the variables is a significant predictor of the number of nonfarm jobs. Viewing the R-squared value shows that 97.9% of the residuals can be explained by each of variables. The seasonally adjusted, detrended model, shows a better picture of the significance.

It looks as though the first month and months 4 through 11 are the most significant. However, the all of the log variables have a perfect (p << 0.05) of significance which is questionable.

Static Model Results

While the regression output shows a promising relationship between the predictors (civilian labor force, Building permits, and prime age employment population ratio) and the response variables (total nonfarm labor), there is no way to tell from the data alone that these are the only variables that are significant. The model shows that every single one of the predictors is significant when a linear time trend and monthly indicators (seasonality) are factored in. There might however be a spurious correlation present as other factors are present in reality which could affect the total nonfarm employee numbers. One such factor is the existence of lags over time, in which the cumulative effects occur in a series over time. This could explain why every variable seems to be a significant predictor. One event occuring over time is the general increase in population. The increase in population can be a source for spurious correlations in the data. It would seem that a more dynamic model can help in this regard.

Finite Distributed Lag Model

For a more dynamic model, a Finite Distributed lag model can work wonders to account for changes caused by lags in time. These changes over time can be cumulative and acount for the significantly low p-values that have been shown. The first model involves lags up to h = 12. The second model adjusts the lag model to accommodate a linear time trend and monthly seasonality. All of the following models are concatenated into one table below

```
#1st Model
reg ln_fl_nonfarm 1(0/12).(ln_fl_lf ln_fl_bp ln_us_epr)
#2nd Model
reg ln_fl_nonfarm 1(0/12).(ln_fl_lf ln_fl_bp ln_us_epr) datec i.monthly
```

Adding the monthly indicator and the time trend seems to function to show that past lags are not significant. The p values of all of the lags are very high but the time trend has a very low p-value. As does the intercept. In the original lag model, some of the lags had singificant p-values. The new lag model also shows that the significance that was found with the original models in Part 3 for each of the variables (other than the building permits) were not actually signicant. The new model shows that the most significant variables are the time trend, the intercept, the month of December, and the log of the florida Building Permits (denoted as ln_fl_bp). This is vastly different than before, where every one of the variables in the analysis was significant. Perhaps a more parsimonious model is necessary.

Models with More Parsimonious Lag Structure

This model is chosen because the lags past around lag 4 seem to be more and more insignificant.

```
#3rd Model
reg ln_fl_nonfarm 1(0/3).(ln_fl_lf ln_fl_bp ln_us_epr) datec i.monthly
```

This model has much more significance in the months than previous models. The time trend is still significant, as is the intercept. The number of building permits also seems significant so that is going to be adjusted for the next model.

The next model is chosen because it may better demonstrate any real relationships between the variables. From the data below, lags past a certain point will make no difference. It may also be important to see if the significance in some vairables can be explained by the data being shortened to just the dates that all of the variables share. It may be that there is some form of bias toward the building permits data because it has a smaller number of data points than the other 3 variables.

```
#4th Model
reg ln_fl_nonfarm 1(0/4, 8).(ln_fl_lf ln_fl_bp ln_us_epr) datec i.monthly
if tin(1998m1, 2019m11)
```

Table 2: Static Model Comparison

X1	ln_fl_nonfarm	ln_fl_nonfarm_1	ln_fl_nonfarm_2	ln_fl_nonfarm_3 =
ln fl lf	0.239	0.399	0.677*	0.538*
	(0.93)	(1.47)	(2.51)	(2.04)
	(0.33)	(1.11)	(2.01)	(2.04)
L.ln_fl_lf	-0.000633	-0.0604	0.0217	-0.0132
	(-0.00)	(-0.17)	(0.06)	(-0.04)
	,	,		,
L2.ln_fl_lf	0.427	0.0361	0.0124	-0.0174
	(1.25)	(0.10)	(0.03)	(-0.05)
L3.lnfllf	0.660	0.110	0.183	0.309
	(1.93)	(0.30)	(0.67)	(0.83)
L4.ln fl lf	0.055	0.00005		0.0949
	-0.255 (-0.74)	0.00885		(0.0243 (0.08)
	(-0.74)	(0.02)		(0.08)
L5.ln_fl_lf	-0.531	0.0333		
	(-1.55)	(0.09)		
	(/	(3.00)		
L6.ln_fl_lf	-0.102	0.146		
	(-0.30)	(0.39)		
	·			
L7.ln_fl_lf	0.209	0.174		
	(0.60)	(0.47)		
7.01.0.10				
L8.lnfllf	-0.153	-0.0242		-0.132
	(-0.44)	(-0.06)		(-0.92)
L9.ln_fl_lf	0.378	0.110		
	(1.10)	(0.29)		
	(1.10)	(0.20)		
L10.ln_fl_lf	-0.000297	0.157		
	(-0.00)	(0.41)		
L11.ln_fl_lf	0.0117	-0.231		
	(0.03)	(-0.61)		
T 10.1 (1.10	0.004	0.0550		
L12.ln_fl_lf	0.264	0.0559		
	(1.02)	(0.20)		
ln fl bp	0.0200***	0.0179***	0.0220***	0.00998*
	(4.25)	(4.11)	(5.03)	(2.42)
	(1120)	(1111)	(3.33)	(2.12)
L.ln_fl_bp	0.00910	0.00856	0.00999*	0.00831
	(1.81)	(1.81)	(2.19)	(1.91)
L2.ln_fl_bp	0.0121*	0.00629	0.00508	0.00386
	(2.33)	(1.30)	(1.11)	(0.85)
T.O.1. (2.1)	0.00000	0.00070	0.00007	0.00500
L3.ln_fl_bp	0.00308	0.00673	0.00385	0.00568
	(0.57)	(1.36)	(0.86)	(1.27)
L4.ln_fl_bp	0.00156	0.00414		0.00462
op	(0.29)	(0.84)		(1.06)
	()	(3.5-)		(, , , ,
L5.ln_fl_bp	0.00631	0.00388		
	(1.16)	(0.78)		
L6.ln_fl_bp	0.00648	0.00486		
	(1.18)	(0.97)		
I 7 1 0. 1	0.00015	0.00471		
L7.ln_fl_bp	0.00215	0.00471		
	(0.40)	(0.96)		

Table 3: Static Model Comparison (Cont.)

L8.ln_fl_bp	-0.000387	-0.00420	X4	0.0136*** =
	(-0.07)	(-0.85)		(3.63)
L9.ln_fl_bp	0.00169	-0.000756		
	(0.31)	(-0.15)		
L10.ln_fl_bp	-0.00665	-0.000510		
	(-1.26)	(-0.11)		
T 1 1 1 0 1	0.00971	0.00500		
L11.ln_fl_bp	-0.00371 (-0.71)	-0.00598		
	(-0.71)	(-1.28)		
L12.ln_fl_bp	-0.00590	-0.00341		
	(-1.18)	(-0.77)		
	(1110)	(0.1.1)		
ln_us_epr	0.777**	0.439	0.257	0.126
	(2.76)	(1.26)	(0.76)	(0.36)
	,			
L.ln_us_epr	-0.407	0.189	0.00601	0.319
	(-1.03)	(0.41)	(0.01)	(0.68)
L2.ln_us_epr	-0.370	-0.0716	-0.0172	0.149
	(-0.94)	(-0.15)	(-0.04)	(0.31)
T.O.1	0.400	0.105	0.001**	0.110
L3.ln_us_epr	-0.428	0.185	0.961**	-0.119
	(-1.10)	(0.39)	(2.84)	(-0.25)
L4.ln_us_epr	0.244	0.157		0.185
_L4.III_us_epi	(0.61)	(0.33)		(0.47)
	(0.01)	(0.00)		(0.11)
L5.ln_us_epr	1.049**	-0.0987		
	(2.62)	(-0.21)		
	,			
L6.ln_us_epr	0.868*	0.307		
	(2.18)	(0.65)		
L7.ln_us_epr	-0.212	0.0339		
	(-0.53)	(0.07)		
T O 1	0.500	0.0449		0.201
L8.ln_us_epr	0.500	0.0443		0.321
	(1.24)	(0.09)		(1.93)
L9.ln_us_epr	-0.181	-0.0254		
La.m_us_epi	(-0.46)	(-0.05)		
	(0.10)	(0.00)		
L10.ln_us_epr	-0.290	0.0140		
	(-0.75)	(0.03)		
	` '	<u> </u>		
L11.ln_us_epr	0.0899	0.489		
	(0.23)	(1.03)		
L12.ln_us_epr	-0.598*	-0.423		
	(-2.23)	(-1.21)		

Table 4: Static Model Comparison (Cont.)

datec	X2	0.0000121***	0.0000129***	0.0000170***	=
		(7.29)	(8.05)	(11.29)	
1.monthly		0	0	0	
		(.)	(.)	(.)	
2.monthly		0.00993	0.00804	0.00782	
		(1.41)	(1.47)	(1.48)	
3.monthly		0.0118	0.0113	0.0124	
		(1.53)	(1.82)	(1.89)	
4.monthly		0.0108	0.0200***	0.00909	
		(1.27)	(3.65)	(1.25)	
F 411		0.00550	0.00056*	0.00050	
5.monthly		0.00556	0.00956*	0.00656	
		(0.91)	(2.07)	(1.29)	
6.monthly		-0.00774	-0.0102	-0.0121*	
6.monthly		(-1.05)	(-1.91)	(-2.13)	
		(-1.05)	(-1.91)	(-2.13)	
7.monthly		-0.0180*	-0.0294***	-0.0230***	
7.monthly		(-2.48)	(-5.96)	(-4.51)	
		(2.10)	(0.00)	(1.01)	
8.monthly		-0.00841	-0.0226***	-0.0130**	
		(-1.09)	(-5.84)	(-2.93)	
			,		
9.monthly		-0.00722	-0.0213***	-0.00983*	
		(-1.18)	(-5.86)	(-2.48)	
10.monthly		-0.00457	-0.0179**	-0.00346	
		(-0.55)	(-3.13)	(-0.58)	
11.monthly		0.00947	0.00305	0.00655	
		(1.24)	(0.58)	(1.16)	
12.monthly		0.0199**	0.0158***	0.0135**	
		(2.72)	(3.87)	(2.92)	
	1 4 1 1 1 1 1 1 1	11.00***	10.04***	F 150***	
cons	-14.11***	-11.38***	-10.94***	-7.172***	
	(-67.53)	(-26.72)	(-27.77)	(-13.45)	
N	271	271	200	262	
IN	371	371	380	263	
t statistics in parentheses					
="* p<0.05	** p<0.01	*** p<0.001"			
_ p<0.00	p<0.01	p<0.001			

Conclusion

Given the output of model 4, the hypothesis seems to be correct. The number of building permits is not as significant predictor of the total nonfarm jobs as was originally thought. Some of the months now show lower p-values and the civilian labor force in Florida is more significant in this model. The fourth model still shows that building permits is relatively significant but not as much as the first 3 models. This makes intuitive sense, as to this researcher, the increase in new building permits should not account for a very large amount of job increase.

There are several problems with this analysis however. First of all, some of the data imports have general formatting issues due to limitations of the software used. To be specific, certain columns are placed in tables when they should not be. Another issue is that all of the variables used in this analysis are variables that may be farcical in concluding meaningful hypotheses from the data. One might assume that any one of these variables might just accumulate naturally over time. The existence of this accumulation, even in completely

randomly generated spurious.	variables, is misleading	in analysing correlation	as any correlation	perceived may be

Appendix A: Stata Code

```
clear
set more off
* Importing the data
*cd "/Users/angelsarmiento/Documents/Graduate/First Year/Time Series/STATA/HW1"
import delimited "data.csv"
*Creating monthly time date
rename date datestring
gen datec=date(datestring, "YMD")
gen mdate=mofd(datec)
format mdate %tm
tsset mdate
*Converting all string values to Float. Ignoring NA values.
* ALL OF THESE VARIABLES WERE RENAMED IN R
destring fl_lf, replace ignore("NA")
destring fl_bp, replace ignore("NA")
destring us_epr_25to54, replace ignore("NA")
* Creating log versions of the variables
gen ln_fl_nonfarm = ln(fl_nonfarm)
gen ln_fl_lf = ln(fl_lf)
gen ln_fl_bp = ln(fl_bp)
gen ln_us_epr = ln(us_epr_25to54)
*Creating plots of each of the static models
*twoway (tsline ln_fl_bp) (tsline ln_fl_nonfarm, yaxis(2)) , name(ln_fl_bp), replace
*twoway (tsline ln_fl_lf) (tsline ln_fl_nonfarm, yaxis(2)), name(ln_fl_lf), replace
*twoway (tsline ln_fl_lf) (tsline ln_fl_nonfarm, yaxis(2)), name(ln_us_epr), replace
* this is the regression outputs for all of the variables without
* accounting for the time trends
reg ln_fl_nonfarm ln_fl_lf ln_fl_bp ln_us_epr
eststo lnnonfarm1
* this is the regression output for all of the variables using monthly
* dates and accounting for time trends
gen monthly = month(datec)
reg ln_fl_nonfarm ln_fl_lf ln_fl_bp ln_us_epr i.monthly datec
eststo lnnonfarm2
esttab lnnonfarm*
esttab lnnonfarm* using "ln_fl_nonfarm_models.csv", replace
* Finite Distributed Lag Model
reg ln_fl_nonfarm l(0/12).(ln_fl_lf ln_fl_bp ln_us_epr)
```

```
eststo nonfarm_lag
esttab nonfarm_lag

reg ln_fl_nonfarm 1(0/12).(ln_fl_lf ln_fl_bp ln_us_epr) datec i.monthly
eststo nonfarm_lag2
esttab nonfarm_lag2

*more parsimonious models

* This model is chosen because the lags past around lag 4

* seem to be more and more insignificant.
reg ln_fl_nonfarm 1(0/3).(ln_fl_lf ln_fl_bp ln_us_epr) datec i.monthly
eststo nonfarm_lag3
esttab nonfarm_lag3

reg ln_fl_nonfarm 1(0/4, 8).(ln_fl_lf ln_fl_bp ln_us_epr) datec i.monthly if tin(1998m1, 2019m11)
eststo nonfarm_lag4
esttab nonfarm_lag4
esttab nonfarm_lag4
esttab nonfarm_lag* using "ln_fl_nonfarm_lag_models.csv", replace
```

Appendix B: Log File

```
. * Importing the data
. *cd "/Users/angelsarmiento/Documents/Graduate/First Year/Time Series/STATA/HW1"
. import delimited "data.csv"
file data.csv not found
r(601):
end of do-file
r(601);
. cd "Z:\Documents\Graduate\First Year\Time Series\STATA\HW1"
Z:\Documents\Graduate\First Year\Time Series\STATA\HW1
. do "C:\Users\ANGELS~1\AppData\Local\Temp\STD00000000.tmp"
. clear
. set more off
. * Importing the data
. *cd "/Users/angelsarmiento/Documents/Graduate/First Year/Time Series/STATA/HW1"
. import delimited "data.csv"
(6 vars, 971 obs)
. *Creating monthly time date
. rename date datestring
. gen datec=date(datestring,"YMD")
. gen mdate=mofd(datec)
. format mdate %tm
. tsset mdate
       time variable: mdate, 1939m1 to 2019m11
                delta: 1 month
. *Converting all string values to Float. Ignoring NA values.
. * ALL OF THESE VARIABLES WERE RENAMED IN R
. destring fl_lf, replace ignore("NA")
fl_lf: characters N A removed; replaced as long
(444 missing values generated)
. destring fl_bp, replace ignore("NA")
fl_bp: characters N A removed; replaced as int
(588 missing values generated)
```

```
. destring us_epr_25to54, replace ignore("NA")
us_epr_25to54: characters N A removed; replaced as double
(108 missing values generated)
. * Creating log versions of the variables
. gen ln_fl_nonfarm = ln(fl_nonfarm)
. gen ln_fl_lf = ln(fl_lf)
(444 missing values generated)
. gen ln_fl_bp = ln(fl_bp)
(588 missing values generated)
. gen ln_us_epr = ln(us_epr_25to54)
(108 missing values generated)
. *Creating plots of each of the static models
. *twoway (tsline ln_fl_bp) (tsline ln_fl_nonfarm, yaxis(2)) , name(ln_fl_bp), re
> place
. *twoway (tsline ln fl lf) (tsline ln fl nonfarm, yaxis(2)), name(ln fl lf), rep
. *twoway (tsline ln_fl_lf) (tsline ln_fl_nonfarm, yaxis(2)), name(ln_us_epr), re
> place
. *this is the regression outputs for all of the variables without accounting for
> the time trends
. reg ln_fl_nonfarm ln_fl_lf ln_fl_bp ln_us_epr
     Source | SS df MS
                                                    Number of obs =
                                                   F(3, 379) = 5929.08
                                                  Prob > F = 0.0000
      Model | 9.96299194 3 3.32099731
                                                    R-squared = 0.9791
   Residual | .212285612 379 .00056012
-----
                                                    Adj R-squared = 0.9790
      Total | 10.1752776 382 .026636852
                                                    Root MSE
                                                                = .02367
______
ln fl nonf~m | Coef. Std. Err. t P>|t| [95% Conf. Interval]
_______

    ln_fl_lf |
    1.116008
    .0092445
    120.72
    0.000
    1.097831
    1.134185

    ln_fl_bp |
    .0441361
    .0031709
    13.92
    0.000
    .0379013
    .050371

    ln_us_epr |
    .7841122
    .0587547
    13.35
    0.000
    .6685861
    .8996383

   _cons | -12.55897 .3281169 -38.28 0.000 -13.20413 -11.91381
```

[.] eststo lnnonfarm1

[.] * this is the regression output for all of the variables using monthly dates an

> d accounting for time trends

[.] gen monthly = month(datec)

. reg ln_fl_nonfarm ln_fl_lf ln_fl_bp ln_us_epr i.monthly dated

Source	SS 	df 	MS		Number of obs F(15, 367)	
Model	10.1187166	15 .67	4581106		Prob > F	
Residual	.056560959				R-squared	
+					Adj R-squared	
Total	10.1752776	382 .02	26636852		Root MSE	= .01241
ln_fl_nonf~m	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
ln_fl_lf	.9157156	.0353178	25.93	0.000	.846265	.9851663
ln_fl_bp	.0350855	.0019056	18.41	0.000	.0313382	.0388327
ln_us_epr	1.235839	.0476196	25.95	0.000	1.142197	1.329481
1						
monthly						
2	.003118	.0031088	1.00	0.317	0029954	.0092313
3	0032324	.0031104	-1.04	0.299	0093489	.002884
4	009392	.0031265	-3.00	0.003	0155401	0032439
5 l	0212267	.0031366	-6.77	0.000	0273947	0150587
6 I	0436098	.0031656	-13.78	0.000	0498347	0373848
7	0610826	.0031985	-19.10	0.000	0673723	0547928
8	0443029	.0031562	-14.04	0.000	0505094	0380965
9	0314803	.0031454	-10.01	0.000	0376655	0252951
10 l	02777	.0031675	-8.77	0.000	0339988	0215412
11	0089755	.0032023	-2.80	0.005	0152727	0026784
12	.0008	.00318	0.25	0.802	0054533	.0070532
1						
datec	.0000118	1.81e-06	6.52	0.000	8.24e-06	.0000154
_cons	-11.31772	.4323177	-26.18	0.000	-12.16785	-10.46759

. eststo lnnonfarm2

. esttab lnnonfarm*

	(1) ln_fl_nonf~m	(2) ln_fl_nonf~m
ln_fl_lf	1.116*** (120.72)	0.916*** (25.93)
ln_fl_bp	0.0441*** (13.92)	0.0351*** (18.41)
ln_us_epr	0.784*** (13.35)	1.236*** (25.95)
1.monthly		0 (.)

```
2.monthly
                                0.00312
                                 (1.00)
3.monthly
                                -0.00323
                                (-1.04)
                                -0.00939**
4.monthly
                                (-3.00)
5.monthly
                                -0.0212***
                                (-6.77)
                                -0.0436***
6.monthly
                                (-13.78)
7.monthly
                                -0.0611***
                                (-19.10)
8.monthly
                                -0.0443***
                                (-14.04)
9.monthly
                                -0.0315***
                                (-10.01)
10.monthly
                                -0.0278***
                                (-8.77)
                               -0.00898**
11.monthly
                                (-2.80)
12.monthly
                               0.000800
                                 (0.25)
                              0.0000118***
datec
                                 (6.52)
_cons
                 -12.56***
                                -11.32***
                (-38.28)
                           (-26.18)
                    383
_____
t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
. esttab lnnonfarm* using "ln_fl_nonfarm_models.csv", replace
(output written to ln_fl_nonfarm_models.csv)
. * Finite Distributed Lag Model
. reg ln_fl_nonfarm 1(0/12).(ln_fl_lf ln_fl_bp ln_us_epr)
```

Source	SS	df 	MS		Number of obs F(39, 331)	= 371 = 1816.69
Model	8.92677921	39 .22	8891775		Prob > F	= 0.0000
Residual	.041703887		0125994		R-squared	= 0.9953
+					Adj R-squared	
Total	8.9684831	370 .02	4239144		Root MSE	= .01122
 ln_fl_nonf~m	Coef.	 Std. Err.	t	 P> t	 [95% Conf.	Interval]
+						
ln_fl_lf	0200547	0570007	0.00	0.054	0000070	7445760
	. 2388547	.2570827	0.93	0.354	2668673	.7445768
L1. L2.	000633	.3402865	-0.00	0.999 0.213	6700299	.668764
L2. L3.	.4273622 .6595995	.3427384	1.25 1.93		2468579 01346	1.101582 1.332659
L3. L4.		.3421484	-0.74	0.055 0.459	9305681	.42103
L4. L5.		.343341	-0.74 -1.55	0.439	-1.20411	.1428942
L6.		.3423733	-0.30	0.122	7766423	.5723448
L7.		.3449754	0.60	0.766	4699253	.8873163
L8.	1533024	.3506231	-0.44	0.662	8430331	.5364283
L9.		.3450936	1.10	0.002	3008387	1.056868
L10.	0002975	.3424737	-0.00	0.274	6739969	.673402
L11.	.011717	.3429308	0.00	0.973	6628817	.6863157
L12.	.2640682	.2592787	1.02	0.309	2459737	.7741101
	.2040002	.2002101	1.02	0.005	.2403707	.1141101
ln_fl_bp						
	.0200186	.0047081	4.25	0.000	.010757	.0292802
L1.	.009102	.0050417	1.81	0.072	0008158	.0190197
L2.	.0121479	.0052074	2.33	0.020	.0019041	.0223916
L3.	.0030827	.0053641	0.57	0.566	0074693	.0136347
L4.	.0015596	.0053643	0.29	0.771	0089929	.0121121
L5.	.0063135	.0054296	1.16	0.246	0043675	.0169944
L6.	.00648	.0054768	1.18	0.238	0042937	.0172536
L7.	.0021471	.0054253	0.40	0.693	0085254	.0128195
L8.	0003866	.0054727	-0.07	0.944	0111522	.010379
L9.	.0016925	.0054476	0.31	0.756	0090238	.0124088
L10.	0066535	.0052764	-1.26	0.208	0170329	.003726
L11.	0037053	.0052177	-0.71	0.478	0139693	.0065587
L12.	0058999	.0049853	-1.18	0.237	0157067	.003907
ا ln_us_epr						
	.776536	. 2815287	2.76	0.006	.222725	1.330347
L1.	4071616	.3944698	-1.03	0.303	-1.183146	.3688224
L2.	3697759	.3917769	-0.94	0.346	-1.140463	.4009107
L3.	428252	.389415	-1.10	0.272	-1.194292	.3377884
L4.	. 2437774	.3993805	0.61	0.542	5418668	1.029422
L5.	1.048525	.400493	2.62	0.009	.2606926	1.836358
L6.	.867988	.3981498	2.18	0.030	.0847649	1.651211
L7.	2119943	.3981801	-0.53	0.595	995277	.5712883
L8.	.5000648	.4018268	1.24	0.214	2903915	1.290521
L9.	1814755	.3932542	-0.46	0.645	9550683	.5921172
L10.	2895834	.3885568	-0.75	0.457	-1.053935	.4747687
L11.	.0899008	.3880226	0.23	0.817	6734004	.8532021
L12.	5984199	.2689136	-2.23	0.027	-1.127415	0694247
212. 1	. 500 - 100	5 5 5 5 5 5	20		110	

_cons | -14.10868 .2089183 -67.53 0.000 -14.51966 -13.69771

. eststo nonfarm_lag

. esttab nonfarm_lag

	(1) ln_fl_nonf~m
ln_fl_lf	0.239 (0.93)
L.ln_fl_lf	-0.000633 (-0.00)
L2.ln_fl_lf	0.427 (1.25)
L3.ln_fl_lf	0.660 (1.93)
L4.ln_fl_lf	-0.255 (-0.74)
L5.ln_fl_lf	-0.531 (-1.55)
L6.ln_fl_lf	-0.102 (-0.30)
L7.ln_fl_lf	0.209 (0.60)
L8.ln_fl_lf	-0.153 (-0.44)
L9.ln_fl_lf	0.378 (1.10)
L10.ln_fl_lf	-0.000297 (-0.00)
L11.ln_fl_lf	0.0117 (0.03)
L12.ln_fl_lf	0.264 (1.02)
ln_fl_bp	0.0200*** (4.25)

L.ln_fl_bp	0.00910 (1.81)
L2.ln_fl_bp	0.0121* (2.33)
L3.ln_f1_bp	0.00308 (0.57)
L4.ln_fl_bp	0.00156 (0.29)
L5.ln_f1_bp	0.00631 (1.16)
L6.ln_fl_bp	0.00648 (1.18)
L7.ln_fl_bp	0.00215 (0.40)
L8.ln_fl_bp	-0.000387 (-0.07)
L9.ln_fl_bp	0.00169 (0.31)
L10.ln_fl_bp	-0.00665 (-1.26)
L11.ln_fl_bp	-0.00371 (-0.71)
L12.ln_fl_bp	-0.00590 (-1.18)
ln_us_epr	0.777* (2.76)
L.ln_us_epr	-0.407 (-1.03)
L2.ln_us_epr	-0.370 (-0.94)
L3.ln_us_epr	-0.428 (-1.10)
L4.ln_us_epr	0.244 (0.61)
L5.ln_us_epr	1.049* (2.62)

```
L6.ln_us_epr
               0.868*
                (2.18)
               -0.212
L7.ln_us_epr
               (-0.53)
L8.ln_us_epr
                0.500
                (1.24)
               -0.181
L9.ln_us_epr
               (-0.46)
               -0.290
L10.ln_us_~r
               (-0.75)
L11.ln_us_~r
               0.0899
               (0.23)
L12.ln_us_~r
               -0.598*
               (-2.23)
               -14.11***
_cons
              (-67.53)
                  371
t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
. reg ln_fl_nonfarm 1(0/12).(ln_fl_lf ln_fl_bp ln_us_epr) datec i.monthly
                 SS
                                MS
                                             Number of obs = 371
    Source |
                         df
                                              F(51, 319) = 1857.33
     Model | 8.93838142 51 .175262381
                                             Prob > F
                                                       = 0.0000
   Residual | .030101677 319 .000094363
                                             R-squared = 0.9966
                                             Adj R-squared = 0.9961
     Total | 8.9684831 370 .024239144
                                              Root MSE
ln_fl_nonf~m | Coef. Std. Err. t P>|t| [95% Conf. Interval]
_______
   ln_fl_lf |
       --. |
                      .2718706 1.47 0.143
                                                          .9338399
              .398954
                                              -.1359319
       L1. |
                                              -.7706442
              -.060362 .3610206
                               -0.17 0.867
                                                           .6499203
       L2. |
                                              -.6887369
              .0361034
                      .3684202
                               0.10 0.922
                                                          .7609438
       L3. | .1096959
                                 0.30 0.766
                      .3681739
                                                -.61466
                                                          .8340518
                                                          .7405194
       L4. | .0088468
                      .3718929
                                 0.02 0.981
                                               -.7228259
                                              -.6949245
       L5. |
                                 0.09 0.928
            .0332763
                      .3701282
                                                           .761477
       L6. | .1460054
                                 0.39 0.693 -.5817407
                                                         .8737516
                      .3698971
       L7. | .1735757
                      .3700134 0.47 0.639 -.5543992
                                                        .9015506
       L8. | -.0241833
```

L9. | .1097723

.3755356

.3737599 -0.06 0.948 -.7595291 .7111624

0.29 0.770 -.6290671

.8486118

L10.	.1565286	.3791518	0.41	0.680	5894254	.9024825
L11.	2308017	.3789415	-0.61	0.543	976342	.5147385
L12.	.0558725	.2862178	0.20	0.845	5072406	.6189855
ln_fl_bp						
	.017885	.0043544	4.11	0.000	.0093181	.0264519
L1.	.0085614	.0047291	1.81	0.071	0007428	.0178656
L2.	.0062937	.0048413	1.30	0.195	0032312	.0158187
L3.	.0067312	.0049499	1.36	0.175	0030075	.0164698
L4.	.0041435	.0049514	0.84	0.403	005598	.013885
L5.	.0038795	.0049423	0.78	0.433	0058442	.0136031
L6.	.0048602	.005011	0.97	0.333	0049986	.0147191
L7.	.0047119	.0049165	0.96	0.339	004961	.0143849
L8.	0042013	.0049678	-0.85	0.398	0139751	.0055724
L9.	0007556	.0049059	-0.15	0.878	0104076	.0088964
L10.	0005096	.0047748	-0.11	0.915	0099036	.0088845
L11.	005979	.0046848	-1.28	0.203	0151961	.003238
L12.	0034119	.0044434	-0.77	0.443	012154	.0053301
ln_us_epr						
	.4387865	.3485176	1.26	0.209	2468968	1.12447
L1.		.4625007	0.41	0.683	7209879	1.098886
L2.	0715753	.4712786	-0.15	0.879	9987823	.8556317
L3.	.1848134	.4702766	0.39	0.695	7404222	1.110049
L4.		.4727168	0.33	0.739	772652	1.087421
L5.		.4729464	-0.21	0.835	-1.029209	.831767
L6.		.4732293	0.65	0.518	6245127	1.237577
L7.		.4718891	0.07	0.943	8944618	.9623543
L8.		.4771704	0.09	0.926	8944842	.9831131
L9.		.4757604	-0.05	0.958	9613966	.9106524
L10.		.4772669	0.03	0.977	9249793	.9529977
L11.		.4739077	1.03	0.303	4434054	1.421353
L12.	4229569	.3492525	-1.21	0.227	-1.110086	.2641724
datec	.0000121	1.65e-06	7.29	0.000	8.80e-06	.0000153
monthly		0070000	4 44	0.450	0000040	0007540
2		.0070268	1.41	0.159	0038948	.0237548
3	.0117641	.007671	1.53	0.126	003328	.0268563
4	.0108275	.0084946	1.27	0.203	0058851	.0275401
5	.0055635	.0060854	0.91	0.361	0064092	.0175361
6	0077413	.0074067	-1.05	0.297	0223134	.0068308
7	0179781	.0072575	-2.48	0.014	0322567	0036995
8	0084088	.0076984	-1.09	0.276	0235549	.0067373
9	0072233	.0061222	-1.18	0.239	0192684	.0048217
10	0045728	.0083469	-0.55	0.584	0209947	.0118492
11	.0094729	.0076324	1.24	0.215	0055433	.0244891
12	.0198697	.0072919	2.72	0.007	.0055234	.034216
		4050704	06.76	0.000	40.0400=	40 54000
_cons	-11.38017	.4259794	-26.72	0.000	-12.21825	-10.54209

[.] eststo nonfarm_lag2

. esttab nonfarm_lag2

	(1) ln_fl_nonf~m
ln_fl_lf	0.399 (1.47)
L.ln_fl_lf	-0.0604 (-0.17)
L2.ln_fl_lf	0.0361 (0.10)
L3.ln_fl_lf	0.110 (0.30)
L4.ln_fl_lf	0.00885 (0.02)
L5.ln_fl_lf	0.0333 (0.09)
L6.ln_fl_lf	0.146 (0.39)
L7.ln_fl_lf	0.174 (0.47)
L8.ln_fl_lf	-0.0242 (-0.06)
L9.ln_fl_lf	0.110 (0.29)
L10.ln_fl_lf	0.157 (0.41)
L11.ln_fl_lf	-0.231 (-0.61)
L12.ln_fl_lf	0.0559 (0.20)
ln_fl_bp	0.0179*** (4.11)
L.ln_fl_bp	0.00856 (1.81)
L2.ln_fl_bp	0.00629 (1.30)

L3.ln_f1_bp	0.00673 (1.36)
L4.ln_fl_bp	0.00414 (0.84)
L5.ln_fl_bp	0.00388 (0.78)
L6.ln_fl_bp	0.00486 (0.97)
L7.ln_fl_bp	0.00471 (0.96)
L8.ln_fl_bp	-0.00420 (-0.85)
L9.ln_fl_bp	-0.000756 (-0.15)
L10.ln_fl_bp	-0.000510 (-0.11)
L11.ln_fl_bp	-0.00598 (-1.28)
L12.ln_fl_bp	-0.00341 (-0.77)
ln_us_epr	0.439 (1.26)
L.ln_us_epr	0.189 (0.41)
L2.ln_us_epr	-0.0716 (-0.15)
L3.ln_us_epr	0.185 (0.39)
L4.ln_us_epr	0.157 (0.33)
L5.ln_us_epr	-0.0987 (-0.21)
L6.ln_us_epr	0.307 (0.65)
L7.ln_us_epr	0.0339 (0.07)

L8.ln_us_epr	0.0443 (0.09)
L9.ln_us_epr	-0.0254 (-0.05)
L10.ln_us_~r	0.0140 (0.03)
L11.ln_us_~r	0.489 (1.03)
L12.ln_us_~r	-0.423 (-1.21)
datec	0.0000121** (7.29)
1.monthly	0
2.monthly	0.00993 (1.41)
3.monthly	0.0118 (1.53)
4.monthly	0.0108 (1.27)
5.monthly	0.00556 (0.91)
6.monthly	-0.00774 (-1.05)
7.monthly	-0.0180* (-2.48)
8.monthly	-0.00841 (-1.09)
9.monthly	-0.00722 (-1.18)
10.monthly	-0.00457 (-0.55)
11.monthly	0.00947 (1.24)
12.monthly	0.0199** (2.72)

t statistics in parentheses

* p<0.05, ** p<0.01, *** p<0.001

•

. *more parsimonious models

.

. *This model is chosen because the lags past around lag 4 seem to be more and mo > re insignificant.

. reg $ln_fl_nonfarm 1(0/3).(ln_fl_lf ln_fl_bp ln_us_epr)$ datec i.monthly

Source	SS	df	MS	Number of obs = 38	0
 +-				F(24, 355) = 3727.2	7
Model	9.81947902	24	.409144959	Prob > F = 0.000	0
Residual	.038968607	355	.000109771	R-squared = 0.996	0
 +-				Adj R-squared = 0.995	8
Total	9.85844762	379	.026011735	Root MSE = $.0104$	8

ln_fl_nonf~m	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
ln_fl_lf						
	.6766356	.2696997	2.51	0.013	.1462256	1.207046
L1.	.0216692	.3740476	0.06	0.954	7139585	.757297
L2.	.0124476	.3802703	0.03	0.974	7354181	.7603133
L3. 	.1834343	.2750336	0.67	0.505	3574657	.7243343
ln_fl_bp						
	.0219692	.0043693	5.03	0.000	.0133762	.0305622
L1.	.0099885	.0045519	2.19	0.029	.0010365	.0189406
L2.	.005084	.0045734	1.11	0.267	0039104	.0140784
L3.	.0038514	.004499	0.86	0.393	0049966	.0126995
ln_us_epr						
	.257017	.338193	0.76	0.448	4080967	.9221307
L1.	.0060073	.468909	0.01	0.990	9161815	.9281961
L2.	0172199	.4738445	-0.04	0.971	9491152	.9146753
L3.	.9607057	.3379591	2.84	0.005	.296052	1.625359
datec	.0000129	1.60e-06	8.05	0.000	9.74e-06	.000016
monthly						
2	.0080382	.0054825	1.47	0.143	002744	.0188204
3	.0112847	.0061912	1.82	0.069	0008914	.0234608
4	.0200366	.0054906	3.65	0.000	.0092384	.0308349
5 l	.0095576	.0046154	2.07	0.039	.0004807	.0186345
6	0102312	.0053478	-1.91	0.057	0207486	.0002862
7	0293823	.0049313	-5.96	0.000	0390805	0196841
8	0225581	.0038641	-5.84	0.000	0301576	0149587

9	-	0212664	.0036314	-5.86	0.000	0284081	0141246
10		0178821	.0057128	-3.13	0.002	0291172	006647
11		.0030458	.0052768	0.58	0.564	0073319	.0134235
12		.015797	.00408	3.87	0.000	.007773	.023821
_cons		-10.94204	.3940918	-27.77	0.000	-11.71709	-10.167

. eststo nonfarm_lag3

. esttab nonfarm_lag3

	(1) ln_fl_nonf~m
ln_fl_lf	0.677* (2.51)
L.ln_fl_lf	0.0217 (0.06)
L2.ln_fl_lf	0.0124 (0.03)
L3.ln_fl_lf	0.183 (0.67)
ln_fl_bp	0.0220*** (5.03)
L.ln_fl_bp	0.00999* (2.19)
L2.ln_fl_bp	0.00508 (1.11)
L3.ln_fl_bp	0.00385 (0.86)
ln_us_epr	0.257 (0.76)
L.ln_us_epr	0.00601 (0.01)
L2.ln_us_epr	-0.0172 (-0.04)
L3.ln_us_epr	0.961** (2.84)
datec	0.0000129*** (8.05)

```
1.monthly
                      0
                    (.)
2.monthly
                0.00804
                 (1.47)
3.monthly
                0.0113
                 (1.82)
                 0.0200***
4.monthly
                 (3.65)
                0.00956*
5.monthly
                 (2.07)
6.monthly
                -0.0102
                (-1.91)
7.monthly
                -0.0294***
                (-5.96)
8.monthly
                -0.0226***
                (-5.84)
9.monthly
                -0.0213***
                (-5.86)
                -0.0179**
10.monthly
                (-3.13)
11.monthly
                0.00305
                (0.58)
12.monthly
                 0.0158***
                 (3.87)
                -10.94***
_cons
               (-27.77)
_____
t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
. reg ln_fl_nonfarm 1(0/4, 8).(ln_fl_lf ln_fl_bp ln_us_epr) datec i.monthly if ti
> n(1998m1, 2019m11)
     Source | SS
                          df MS
                                                   Number of obs =
                                                                     263
                                                   F(30, 232) = 842.21
```

Model | 1.67773399 30 .055924466

Residual | .015405278 232 .000066402

Prob > F = 0.0000

R-squared = 0.9909

Adj R-squared = 0.9897

ln_fl_nonf~m	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
ln_fl_lf						
		.2640614	2.04	0.043	.0176901	1.05822
L1.	0131634	.3620392	-0.04	0.971	7264682	.7001414
L2.	0173824	.3718019	-0.05	0.963	7499222	.7151574
L3.	.3094965	.3713038	0.83	0.405	4220618	1.041055
L4.	.0242732	.305861	0.08	0.937	578347	.6268934
L8.	1324231	.1442353	-0.92	0.360	4166015	.1517554
ا ln_fl_bp						
		.0041221	2.42	0.016	.0018607	.0181038
L1.	.0083077	.0043457	1.91	0.057	0002544	.0168699
L2.	.003858	.0045149	0.85	0.394	0050375	.0127535
L3.	.0056752	.0044789	1.27	0.206	0031493	.0144997
L4.	.004619	.004368	1.06	0.291	003987	.0132249
L8.	.0135956	.0037495	3.63	0.000	.0062082	.020983
ا ln_us_epr						
	.126399	.3483614	0.36	0.717	5599572	.8127552
L1.		.4681803	0.68	0.496	6032871	1.24157
L2.		.4809766	0.31	0.757	7986978	1.096583
L3.	118788	.4807789	-0.25	0.805	-1.066039	.8284627
L4.	.1851347	.3952589	0.47	0.640	5936211	.9638904
L8.	.3211695	.1668264	1.93	0.055	0075189	.6498579
 datec	.000017	1.50e-06	11.29	0.000	.000014	.0000199
!						
monthly						
2	.0078204	.0052919	1.48	0.141	0026059	.0182467
3		.0065538	1.89	0.060	0005117	.0253133
4	.0090886	.0072926	1.25	0.214	0052797	.0234568
5 I	.0065625	.0051037	1.29	0.200	003493	.0166181
6 I	0121185	.0056892	-2.13	0.034	0233277	0009094
7	0230236	.0051011	-4.51	0.000	0330741	0129731
8	0130314	.0044426	-2.93	0.004	0217844	0042784
9	0098293	.0039674	-2.48	0.014	0176461	0020125
10	0034589	.0059354	-0.58	0.561	0151531	.0082354
11	.0065546	.0056717	1.16	0.249	00462	.0177292
12 	.0135055	.0046267	2.92	0.004	.0043899	.0226211
_cons	-7.172393	.5334589	-13.45	0.000	-8.223437	-6.12135

[.] eststo nonfarm_lag4

. esttab nonfarm_lag4

(1)

ln_fl_nonf~m

ln_fl_lf	0.538*
L.ln_fl_lf	-0.0132 (-0.04)
L2.ln_fl_lf	-0.0174 (-0.05)
L3.ln_fl_lf	0.309 (0.83)
L4.ln_fl_lf	0.0243 (0.08)
L8.ln_fl_lf	-0.132 (-0.92)
ln_fl_bp	0.00998* (2.42)
L.ln_fl_bp	0.00831 (1.91)
L2.ln_f1_bp	0.00386 (0.85)
L3.ln_f1_bp	0.00568 (1.27)
L4.ln_fl_bp	0.00462 (1.06)
L8.ln_f1_bp	0.0136** [*] (3.63)
ln_us_epr	0.126 (0.36)
L.ln_us_epr	0.319 (0.68)
L2.ln_us_epr	0.149 (0.31)
L3.ln_us_epr	-0.119 (-0.25)
L4.ln_us_epr	0.185 (0.47)
L8.ln_us_epr	0.321 (1.93)

datec	0.0000170*** (11.29)
1.monthly	0
2.monthly	0.00782 (1.48)
3.monthly	0.0124 (1.89)
4.monthly	0.00909 (1.25)
5.monthly	0.00656 (1.29)
6.monthly	-0.0121* (-2.13)
7.monthly	-0.0230*** (-4.51)
8.monthly	-0.0130** (-2.93)
9.monthly	-0.00983* (-2.48)
10.monthly	-0.00346 (-0.58)
11.monthly	0.00655 (1.16)
12.monthly	0.0135** (2.92)
_cons	-7.172*** (-13.45)
N	263
t statistics in	narentheses

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001</pre>