

FRED Investigation into Nonfarm jobs in Florida Pt.2

Time Series Modeling and Forecasting

Angel Sarmiento

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.

A new set of challenges arise in this analysis. Autocorrelation and Weak dependence now needed to be accounted for. Developing a dynamically complete model to represent the data is also valid, as this is the best case to produce a model that accounts for both deterministic and Autoregressive components of the data. The Breusch-Godfrey test comes in to play here for the testing of how dynamic this model is.

Part A

1) Here is a model:

$$y_t = \alpha + \delta t + \rho y_{t-1} + \beta x_{t-1} + r_t$$

$$y_t - y_{t-1} = (\alpha + \delta t + \rho y_{t-1} + \beta x_{t-1} + r_t) - (\alpha + \delta(t-1) + \rho y_{t-2} + \beta x_{t-2} + r_{t-1})$$

After Differencing:

$$\Delta y_t = \delta + \rho(y_{t-1} - y_{t-2}) + \beta(x_{t-1} - x_{t-2}) + (r_t - r_{t-1})$$

$$\Delta y_t = \delta + \rho \Delta y_{t-1} + \beta \Delta x_{t-1} + \Delta r_t$$

2) The first difference of a new model is:

$$\Delta y_t = \delta - \phi + 2\phi t + \rho \Delta y_{t-1} + \beta \Delta x_{t-1} + \Delta r_t$$

The original Model of this difference is:

$$y_t = \delta t - \phi t + \phi(t^2 + 1) + \rho(y_{t-1}) + \beta(x_{t-1}) + r_t$$

This model exhibits an accelerating time trend. This would mean that differencing and accounting for lags would not entirely get rid of a time trend. A time trend would still be required for the model to become stationary.

- 3) A new model has residuals that follow an AR(1) process. This model needs to be differenced. The original model is

$$y_t = \alpha + \delta t + \rho y_{t-1} + \beta x_{t-1} + r_t$$

Where $r_t = \gamma r_{t-1} + \varepsilon_t$ and ε_t is *ideally* white noise. Writing this dynamical model:

$$y_t = \alpha + \delta t + \rho y_{t-1} + \beta x_{t-1} + \gamma r_{t-1} + \varepsilon_t$$

This model in first differences:

$$\Delta y_t = \rho \Delta y_{t-1} + \beta \Delta x_{t-1} + \gamma (\Delta y_{t-1} + \rho \Delta y_{t-2} + \beta \Delta x_{t-1}) + \Delta \varepsilon_t$$

Autocorrelograms and Partial Autocorrelograms

The entire list of variables involve nonfarm employment, the number of approved building permits, the labor force, and the prime employment rate (ages 25-54). These predictors could each have their own respective autocorrelations. This will try to be deduced with Autocorrelograms (ACs) and Partial Autocorrelograms (PACs).

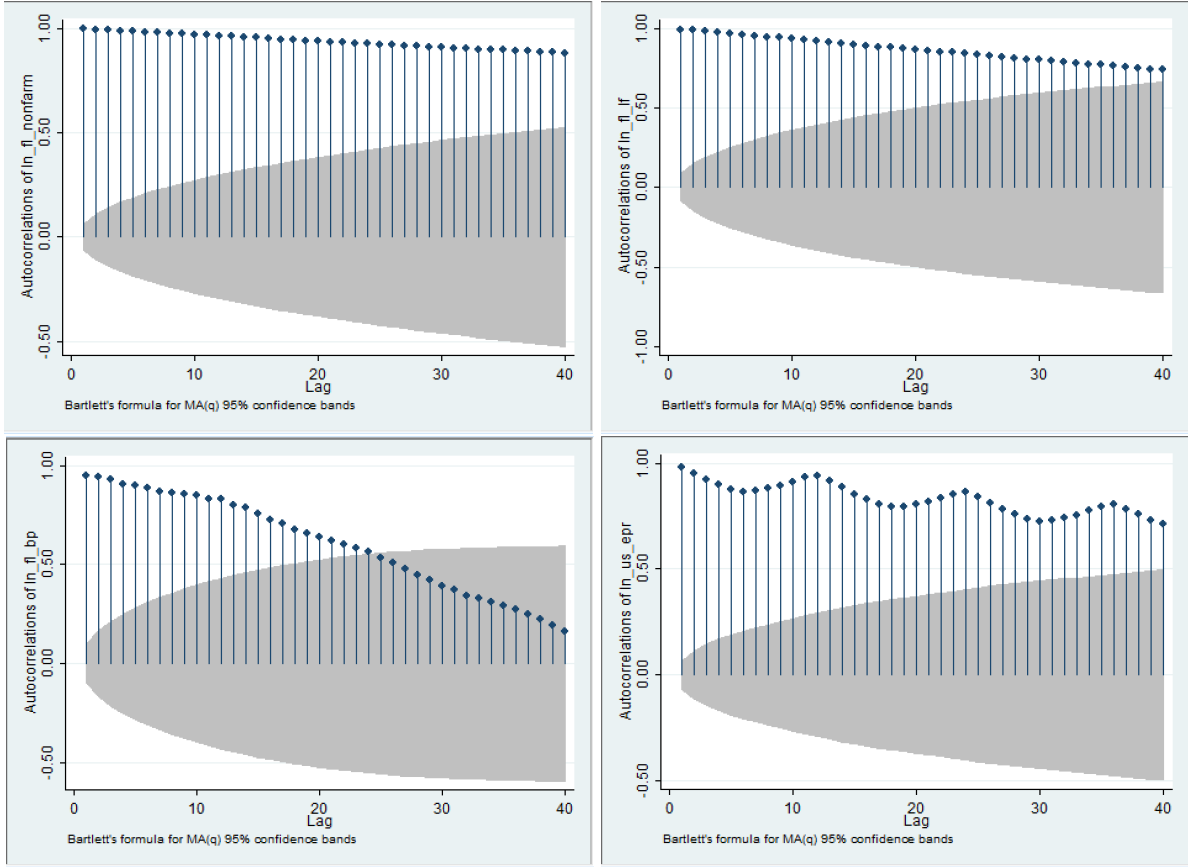


Figure 1: Autocorrelograms of the variables

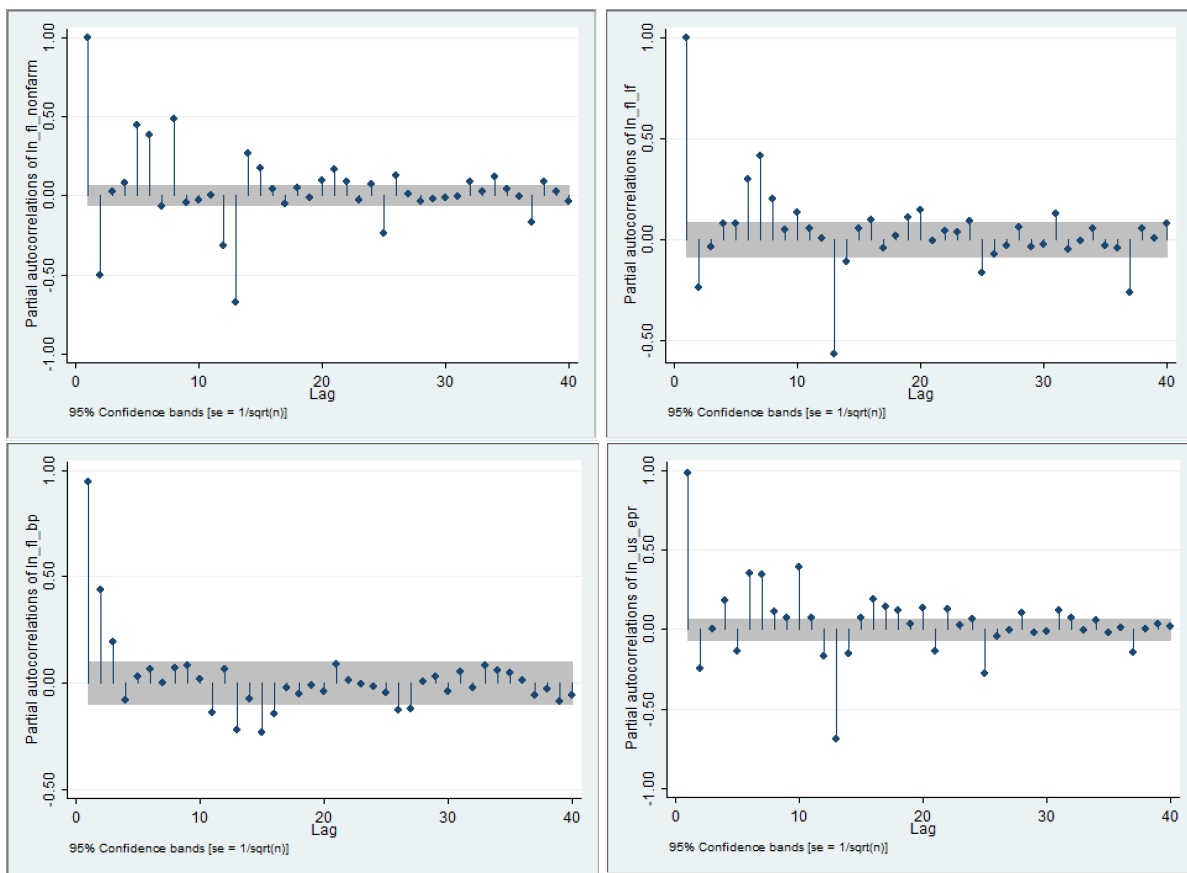


Figure 2: Partial Autocorrelograms of the variables

Looking at the Autocorrelograms and Partial Autocorrelograms, it seems reasonable to assume that all of these variables are AR(1) processes since there is no sharp dropoff in correlation after the first few lags in the ACs. For each of these variables there still seems to be some statistical significance in the effects of multiple months ago on today. This can also be seen in the PAC as the effects of past months still have significance despite the effect of last month being removed.

Dickey-Fuller tests for unit roots

Seeing that there was some evidence of autocorrelation in the correlograms, the Dickey-Fuller test for unit roots will be conducted on each variable to see which lags may be relevant for this result to exist.

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-3.447	-3.985	-3.425	-3.130

MacKinnon approximate p-value for $Z(t) = 0.0455$

D.ln_fl_no~m	Coef.	Std. Err.	t	P> t
L1.	-.0125543	.0036426	-3.45	0.001
LD.	-.0016386	.0257588	-0.06	0.949
L2D.	-.0081846	.0257419	-0.32	0.751
L3D.	.0107332	.0255801	0.42	0.675
L4D.	.0024337	.0255626	0.10	0.924
L5D.	-.0162627	.0255374	-0.64	0.525
L6D.	.0476972	.0255517	1.87	0.063
L7D.	-.0171747	.0255546	-0.67	0.502
L8D.	-.0153147	.0255342	-0.60	0.549
L9D.	-.0053613	.025545	-0.21	0.834
L10D.	-.0424083	.0255539	-1.66	0.098
L11D.	.0264836	.0256701	1.03	0.303
L12D.	.8678931	.0257733	33.67	0.000
_trend	.0000185	5.42e-06	3.40	0.001
_cons	.1076319	.0312131	3.45	0.001

Table 1. Dickey-Fuller Test for nonfarm employment

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.768	-3.985	-3.425	-3.130

MacKinnon approximate p-value for $Z(t) = 0.7197$

D.ln_fl_lf	Coef.	Std. Err.	t	P> t
L1.	-.0145241	.0082127	-1.77	0.078
LD.	-.0765454	.0440377	-1.74	0.083
L2D.	.0235824	.0440775	0.54	0.593
L3D.	-.0265862	.0440144	-0.60	0.546
L4D.	-.0107586	.0437954	-0.25	0.806
L5D.	-.0938664	.0438477	-2.14	0.033
L6D.	-.1923623	.0437026	-4.40	0.000
L7D.	-.0659403	.0437567	-1.51	0.133
L8D.	-.0039238	.0431203	-0.09	0.928
L9D.	-.0651803	.0431157	-1.51	0.131
L10D.	-.0175563	.0432789	-0.41	0.685
L11D.	.0379697	.0432671	0.88	0.381
L12D.	.5274722	.0431257	12.23	0.000
_trend	.0000183	.0000118	1.55	0.122
_cons	.2290598	.1284606	1.78	0.075

Table 2. Dickey-Fuller Test for labor force

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.624	-3.985	-3.425	-3.130

MacKinnon approximate p-value for $Z(t) = 0.7827$

D.ln_fl_bp	Coef.	Std. Err.	t	P> t
L1.	-.0256093	.0157655	-1.62	0.105
LD.	-.4892327	.0536997	-9.11	0.000
L2D.	-.1676299	.0597639	-2.80	0.005
L3D.	.0339165	.0601481	0.56	0.573
L4D.	-.04808	.0603769	-0.80	0.426
L5D.	-.0291366	.0603882	-0.48	0.630
L6D.	-.0232757	.0601083	-0.39	0.699
L7D.	-.1033175	.0599992	-1.72	0.086
L8D.	-.0443521	.0600408	-0.74	0.461
L9D.	.0357027	.059966	0.60	0.552
L10D.	.135494	.0599421	2.26	0.024
L11D.	.0551154	.0593962	0.93	0.354
L12D.	.2231371	.0522915	4.27	0.000
_trend	6.10e-06	.0000722	0.08	0.933
_cons	.2330947	.1500049	1.55	0.121

Table 3. Dickey-Fuller Test for Florida Building Permits

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.751	-3.985	-3.425	-3.130

MacKinnon approximate p-value for $Z(t) = 0.2154$

D.ln_us_epr	Coef.	Std. Err.	t	P> t
L1.	-.0191058	.0069443	-2.75	0.006
LD.	.0136959	.034809	0.39	0.694
L2D.	.0390844	.0345956	1.13	0.259
L3D.	-.1010787	.0344628	-2.93	0.004
L4D.	.0568803	.0342825	1.66	0.098
L5D.	.009185	.0343904	0.27	0.790
L6D.	-.1049015	.0342864	-3.06	0.002
L7D.	.0106907	.0340971	0.31	0.754
L8D.	.0145465	.033832	0.43	0.667
L9D.	-.0886587	.0337554	-2.63	0.009
L10D.	-.0147671	.033599	-0.44	0.661
L11D.	.0838082	.0335472	2.50	0.013
L12D.	.7299487	.0337793	21.61	0.000
_trend	-2.84e-06	1.90e-06	-1.49	0.136
_cons	.0792443	.0288557	2.75	0.006

Table 4. Dickey-Fuller Test for prime-age employment

For the null hypothesis, that there is no unit root ($\rho = 0$), all three of the predictor variables can have their null hypotheses rejected. These variables being (all log) the number of blueprint approval, the employment rate, and the size of the civilian labor force. The Dickey-Fuller test does not allow for the rejection of the null hypothesis for the nonfarm employment rate. For the former variables, this means that there is high evidence that the ρ value is very close to 1 and that the series for each of these independent variables is non-stationary. It would seem that some differencing should be done in order to create a more stationary time series.

The Autoregressive Distributed Lag Model

In order to estimate a model that might be relevant to this analysis, there must be a dynamically complete model with stationarity and little to no autocorrelation. This model will involve a full cycle of lags (12 months, 1 year) as well as the 24th lag (two years). The same will be done with the other 3 variables and monthly indicators will be added along with a time trend. All of this will be done using just the past 20 years of data, since it is hard to believe that data from before then would be helpful now. All of this will be compared to the predictand of the differenced nonfarm employment.

Choosing this particular lag structure was due in particular to the intuition that a full year before can be relatively impactful on the results of this year. From looking at graphs in the first part of this investigation, it would also seem that there is not an accelerating time trend. Looking at this model should also help to prove that as well, since the time trend will no longer be needed and its significance would be lessened. The differencing of each of the independent variables is conducive in that it helps eliminate the effects of a time trend.

Table 9: Table 5. Autoregressive Distributed Lag Model

X1	D.ln_fl_nonfarm
LD.ln_fl_nonfarm	-0.0926*
	(-2.04)
L12D.ln_fl_nonfarm	0.444***
	(6.45)
L24D.ln_fl_nonfarm	0.292***
	(4.57)
LD.ln_fl_lf	-0.0557
	(-0.48)
L2D.ln_fl_lf	-0.0576
	(-0.49)
L3D.ln_fl_lf	0.135
	(1.15)
L4D.ln_fl_lf	-0.0342
	(-0.29)
L5D.ln_fl_lf	-0.234
	(-1.97)

L6D.ln_fl_lf	-0.0588
	(-0.51)
L7D.ln_fl_lf	0.229*
	(2.00)
L8D.ln_fl_lf	-0.107
	(-0.91)
L9D.ln_fl_lf	0.255*
	(2.10)
L10D.ln_fl_lf	0.127
	(1.07)
L11D.ln_fl_lf	-0.131
	(-1.14)
L12D.ln_fl_lf	-0.00833
	(-0.07)
L24D.ln_fl_lf	0.0975
	(0.77)
LD.ln_fl_bp	0.00323
	(1.64)
L2D.ln_fl_bp	0.00593*
	(2.49)
L3D.ln_fl_bp	0.00365
	(1.44)
L4D.ln_fl_bp	0.00456
	(1.76)
L5D.ln_fl_bp	0.00474
	(1.80)
L6D.ln_fl_bp	0.00209
	(0.81)
L7D.ln_fl_bp	0.00500*
	(1.99)
L8D.ln_fl_bp	0.00516*
	(2.07)
L9D.ln_fl_bp	0.00572*
	(2.32)

L10D.ln_fl_bp	0.00476
	(1.91)
L11D.ln_fl_bp	0.00554*
	(2.30)
L12D.ln_fl_bp	0.00390
	(1.91)
L24D.ln_fl_bp	-0.00257
	(-1.55)
LD.ln_us_epr	-0.0128
	(-0.10)
L2D.ln_us_epr	0.0769
	(0.59)
L3D.ln_us_epr	-0.208
	(-1.55)
L4D.ln_us_epr	-0.0293
	(-0.22)
L5D.ln_us_epr	0.406**
	(2.86)
L6D.ln_us_epr	0.0825
	(0.59)
L7D.ln_us_epr	-0.320**
	(-2.61)
L8D.ln_us_epr	0.207
	(1.59)
L9D.ln_us_epr	-0.310*
	(-2.36)
L10D.ln_us_epr	-0.264*
	(-2.10)
L11D.ln_us_epr	0.145
	(1.19)
L12D.ln_us_epr	0.0455
	(0.31)
L24D.ln_us_epr	-0.221
	(-1.43)

4.month	0
	(.)
5.month	-0.00275
	(-1.84)
6.month	-0.00170
	(-0.81)
7.month	-0.00373
	(-1.31)
8.month	-0.00517
	(-1.36)
9.month	-0.00554
	(-1.23)
10.month	-0.00606
	(-1.15)
11.month	-0.00801
	(-1.30)
12.month	-0.00877
	(-1.27)
mdate	0.0000352
	(1.23)
_cons	-0.0161
	(-1.19)
N	263
t statistics in parentheses	
* p<0.05	** p<0.01
*** p<0.001"	

As mentioned above, it looks like the time trend is no longer significant. This is mostly due to the fact that the differences done to the ARDL model account for the time trend and thus incorporate its significance. The model also shows that the months after may all have a small negative effect on the nonfarm employment in florida. One might assume that the significance of this time period is due to the tourist season starting for the summer, causing nonfarm employment to take a small dip toward the negative once the season is in full swing. The nonfarm employment of a full year ago and 2 full years ago are very significant in todays nonfarm employment. This could be because employment statistics are done every year and there is typically a drive to hire more to raise the employment rate. A PAC should help with further analysis.

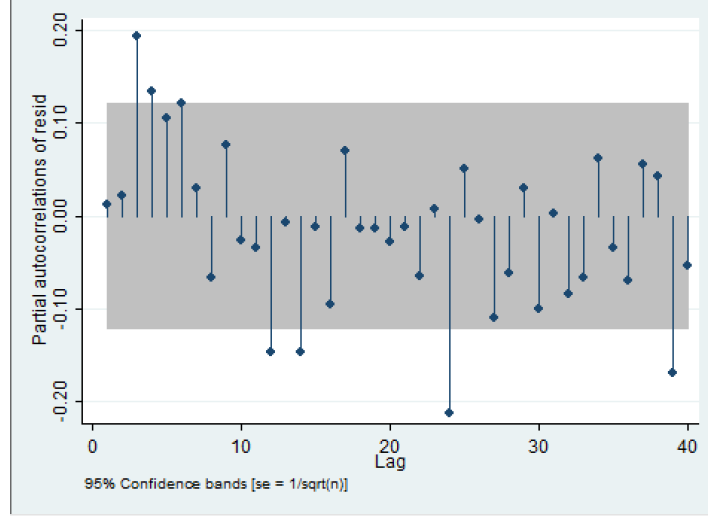


Figure 3: PAC of the residuals of the ARDL model

The PAC of the residuals shows a slight pattern that persists through lags of the data. There is a high significance in the 24th lag, meaning that the results of two years ago might highly affect today. Just as seen when looking at the ARDL model. There might be serial correlation but there is not enough evidence to assume. To obtain the evidence, a Breusch Godfrey LM test for autocorrelation will be done.

The Breusch-Godfrey LM Test for Autocorrelation

At this stage in this analytical development, a Breusch-Godfrey test is employed with up to 24 lags (2 full years) to see if there is a cumulative effect of the past lags that persist through time. The test is normally done with the simulation of a χ^2 Distribution that is then tested for the null hypothesis of no autocorrelation. Rejecting the null here would mean that the n-lags (cumulative) of the past effect the present day in a way that is significant.

This model was chosen as it seems to be a relatively parsimonious model that contains an entire cycle for all of the independent variables as well as the 1st, 12th, and 24th lag of the nonfarm employment. They also include the monthly indicators without the time trend. The time trend does not seem to be accelerating so the differencing of the model accounts for trend in the time series. This model also includes just the last 20 years since it is believable that any longer would skew the data, as the prime employment (ages 25 to 54) would be well past prime after 20 years.

lags(p)	chi2	df	Prob > chi2
1	0.017	1	0.8960
2	0.044	2	0.9785
3	5.011	3	0.1710
4	5.994	4	0.1996
5	9.451	5	0.0924
6	11.068	6	0.0863
7	11.643	7	0.1129
8	11.664	8	0.1668
9	13.670	9	0.1346
10	13.689	10	0.1876
11	14.551	11	0.2040
12	33.743	12	0.0007
13	34.538	13	0.0010
14	39.737	14	0.0003
15	39.828	15	0.0005
16	41.420	16	0.0005
17	41.673	17	0.0007
18	42.094	18	0.0011
19	45.559	19	0.0006
20	45.559	20	0.0009
21	45.616	21	0.0014
22	47.882	22	0.0011
23	48.195	23	0.0016
24	61.111	24	0.0000

Table 6. Breusch-Godfrey Test for autocorrelation

The results of the Breusch Godfrey test are surprising. It would seem that the cumulative effect of the last 24 months are very significant on the nonfarm employment. This makes some sense, as very generally put, if the amount of building permits approved, civilian labor force, and employment rate all increased two years ago, it might be true that nonfarm employment would also increase since the infrastructure and workforce are already present and have not retired. It is also shown that the cumulative effects of the last 12 months are significant for most likely the same reason with every cumulative month measure in-between 12 and 24 also being significant. Autocorrelation persists despite additions to the model. Something else must be done.

Newey-West Standard Errors

Despite all of the model additions there still seems to be some autocorrelation that exists in the model. This could likely be due to there being some relationship in the residuals not being accounted for, or maybe that the errors themselves are correlated with past versions of themselves. If this is the case, the coefficients found for any model with these parameters will not reflect the true relationship underlying the data. The autocorrelated errors will pick up some of the effects of other variables.

Looking at the regression output from the most recent model, one can see that the standard errors for the variables seem to be eerily patterned. These errors seem to hover around the same number for successive lags. So it is very possible that there is, in fact, serially correlated standard errors. A solution to this particular problem comes in the form of robust standardized errors. Specifically here, Newey-West standard errors will be used to alleviate the effect of autocorrelation amongst the errors.

To try to illustrate the effects, a very parsimonious model will be compared with a model using Newey-West standard errors. The PACs of their respective residuals will be shown below.

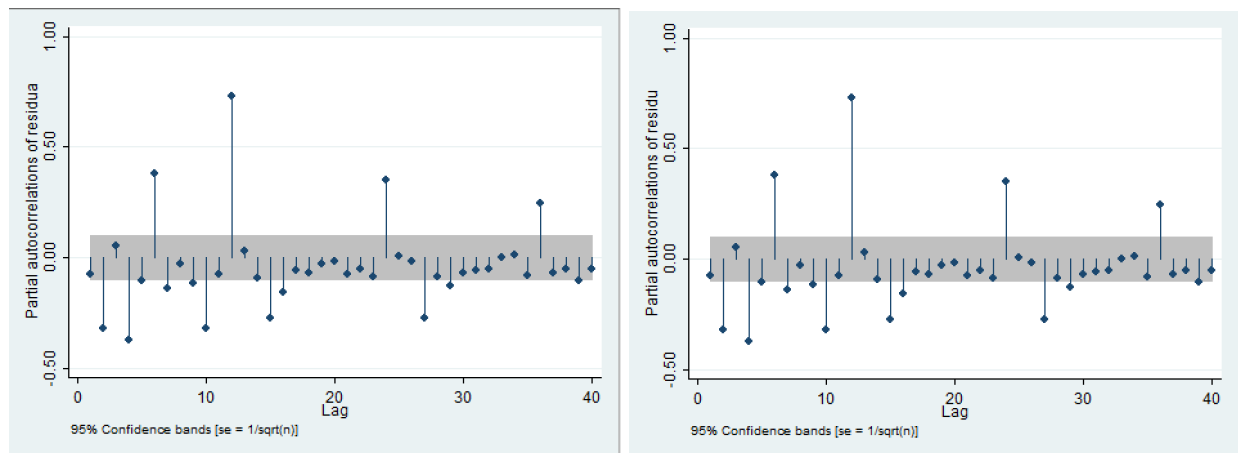


Figure 4: Left: PAC without Newey West. Right: PAC with Newey-West

Now the same graphics, but with the ARDL model from before:

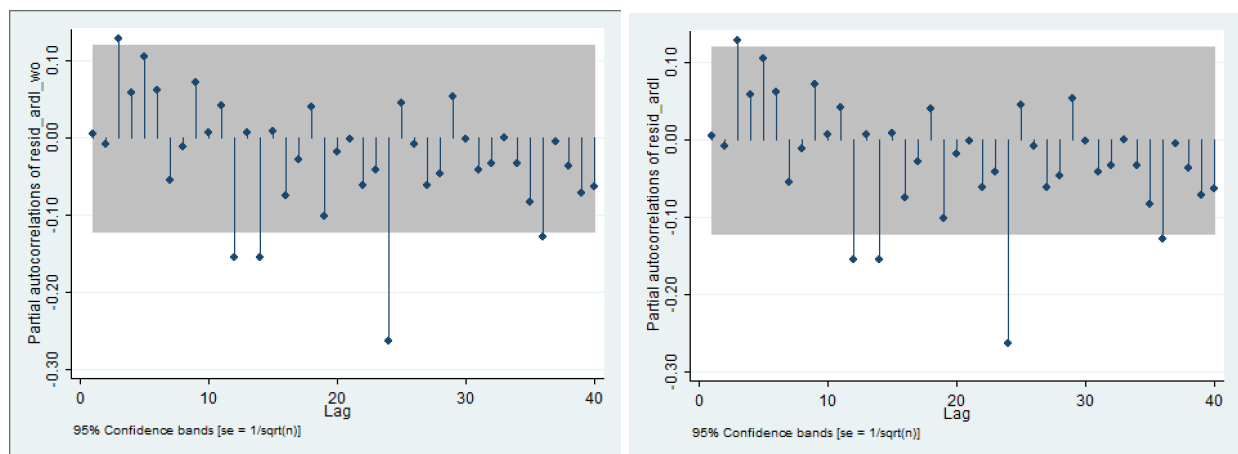


Figure 5: Left: PAC without Newey West. Right: PAC with Newey-West

Conclusions

This investigation started with the evaluation of autocorrelation and weak dependence. It was shown that the different variables were autocorrelated with ACs and PACs and was concluded that differencing the data would prove instrumental in removing autocorrelation. The Dickey-Fuller test was then ran on each of the variables to test for the unit root hypothesis. For all of the Dickey-Fuller Tests, the null hypothesis, that there is no serial correlation, was rejected at the significance level of 5% for Lags 12. The null was rejected for other lags as well and a model was created from this information.

The model was an attempt at creating a dynamically complete Autoregressive Distributed Lag Model that included lags 1 through 12 as well as lag 24 for each of the independent variables. This model also included the lagged dependent variable, a time trend, and a monthly indicator. The results of this model were interesting, as it allowed for the removal of the time trend, showed a high RMSE, and developed a better understanding of how the errors might be autocorrelated. Since there was no accelerating trend, the time detrend in the model was no longer significant. The time trend, not being significant and being accounted for in the differenced and lagged model, was removed in the model used in the Breusch-Godfrey test. The

high RMSE of this model shows decent promise, but it is most likely overfitting to the data. Model selection is needed to be done to see if the model is overfit but it seems to be likely given that the RMSE is so low. The errors also showed a relatively unique but identifiable pattern in that all of the lagged standard errors of the independent variables remained around the same range. This property seemed to be worth further investigating to see if the errors were serially correlated.

The Breusch-Godfrey test was conducted to provide more proof that autocorrelation persisted through out many lags in the model. The test showed that the cumulative effects of the past 12 to the past 24 months are all significant to the present day. This is a surprising result as it means that the autocorrelation is absolutely present and it is effecting the data as far as two years out.

Seeing that the autocorrelation problem was not disappearing, the next step was to address the option that maybe the errors were serially correlated. This would mean that past errors, ε_t have a high chance of affecting the present error, ε_t . Assuming there was serial correlation in the errors, Newey-West robust standard errors were applied to the model to hopefully identify and be rid of the serial correlation. PACs of the residuals were made comparing the models. The PAC of the residuals were the same for both models. It would seem that the errors were not serially correlated. It would seem that better model selection would need to be done in general.

Appendix A: Clean Do-file

```
clear
set more off

* Importing the data
*cd "/Users/angelsarmiento/Documents/Graduate/First Year/Time Series/STATA/HW2"

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)

*Finding the correlations of each variable with respect to a single time lag
cor ln_fl_nonfarm l1.ln_fl_nonfarm
cor ln_fl_lf l1.ln_fl_lf
cor ln_fl_bp l1.ln_fl_bp
cor ln_us_epr l1.ln_us_epr

*Looks like serial correlation to me

*Autocorrelogram and PAC for each variable
ac ln_fl_nonfarm
pac ln_fl_nonfarm

ac ln_fl_lf
pac ln_fl_lf

ac ln_fl_bp
pac ln_fl_bp

ac ln_us_epr
pac ln_us_epr

*Dickey Fuller Test for each variable.
```

```

estimates clear
dfuller ln_fl_nonfarm if tin(1988m1, 2019m12), trend lags(12) regress
eststo dfuller_1
*esttab dfuller_1 using "dfuller_nonfarm.csv", replace

dfuller ln_fl_lf if tin(1988m1, 2019m12), trend lags(12) regress
eststo dfuller_2
*esttab dfuller_2 using "dfuller_lf.csv", replace

dfuller ln_fl_bp if tin(1988m1, 2019m12), trend lags(12) regress
eststo dfuller_3
*esttab dfuller_3 using "dfuller_bp.csv", replace

dfuller ln_us_epr if tin(1988m1, 2019m12), trend lags(12) regress
eststo dfuller_4
*esttab dfuller_4 using "dfuller_epr.csv", replace

esttab dfuller_* using "all_dfuller.csv", replace

generate month = month(mdate)

reg d.ln_fl_nonfarm l(1,12, 24)d.ln_fl_nonfarm l(1/12,24)d.ln_fl_lf l(1/12,24)d.ln_fl_bp l(1/12,24)d.ln_us_epr
eststo ardl
esttab ardl using "ardl.csv", replace
*PAC of the residuals
predict resid if e(sample)==1, residual
pac resid

*Breusch Godfrey Test
reg d.ln_fl_nonfarm l(1,12,24)d.ln_fl_nonfarm l(1/12)d.ln_fl_lf l(1/12,24)d.ln_fl_bp l(1/12)d.ln_us_epr
estat bgodfrey, lag(1/24)
eststo bgodfrey_1
esttab bgodfrey_1 using "bgodfrey.csv", replace

predict resstatic, residual
pac resstatic

*model without Newey-West
reg d.ln_fl_nonfarm l(0/4)d.ln_fl_bp i.month
predict residua if e(sample)==1, residual
pac residua

*Model with Newey West
newey d.ln_fl_nonfarm l(0/4)d.ln_fl_bp i.month, lag(4)
predict residu if e(sample)==1, residual
pac residu

reg d.ln_fl_nonfarm l(1,12,24)d.ln_fl_nonfarm l(1/12)d.ln_fl_lf l(1/12,24)d.ln_fl_bp l(1/12)d.ln_us_epr

```

```

predict resid_ardl_wo if e(sample)==1, residual
pac resid_ardl_wo

newey d.ln_fl_nonfarm l(1,12,24)d.ln_fl_nonfarm l(1/12)d.ln_fl_lf l(1/12,24)d.ln_fl_bp l(1/12)d.ln_us_e
predict resid_ardl if e(sample) ==1, residual
pac resid_ardl

```


Appendix B: Log File

```
-----
      name: <unnamed>
      log:  Y:\Documents\Graduate\First Year\Time Series\STATA\HW2\Log_1.smcl
      log type:  smcl
      opened on: 12 Feb 2020, 01:00:29

. do "C:\Users\ANGELS~1\AppData\Local\Temp\STD01000000.tmp"

.

. clear

. set more off

.

. * Importing the data
. *cd "/Users/angelsarmiento/Documents/Graduate/First Year/Time Series/STATA/HW2"
.
. 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)

.
. *Finding the correlations of each variable with respect to a single time lag
. cor ln_fl_nonfarm l1.ln_fl_nonfarm
(obs=970)

          |               L.
          | ln_fl_~m ln_fl_~m
-----+-----
ln_fl_nonf~m |
      --. |    1.0000
      L1. |    0.9999    1.0000

. cor ln_fl_lf l1.ln_fl_lf
(obs=526)

          |               L.
          | ln_fl_lf ln_fl_lf
-----+-----
ln_fl_lf |
      --. |    1.0000
      L1. |    0.9998    1.0000

. cor ln_fl_bp l1.ln_fl_bp
(obs=382)

          |               L.
          | ln_fl_bp ln_fl_bp
-----+-----
ln_fl_bp |
      --. |    1.0000
      L1. |    0.9478    1.0000

. cor ln_us_epr l1.ln_us_epr
(obs=862)

          |               L.
          | ln_us_~r ln_us_~r
-----+-----
ln_us_epr |
      --. |    1.0000

```

```
L1. | 0.9820 1.0000
```

```
.
. *Looks like serial correlation to me
.
. *Autocorrelogram and PAC for each variable
. ac ln_fl_nonfarm

. pac ln_fl_nonfarm

.
. ac ln_fl_lf

. pac ln_fl_lf

.
. ac ln_fl_bp

. pac ln_fl_bp

.
. ac ln_us_epr

. pac ln_us_epr

.
. *Dickey Fuller Test for each variable.
. estimates clear

. dfuller ln_fl_nonfarm if tin(1988m1, 2019m12), trend lags(12) regress
```

Augmented Dickey-Fuller test for unit root Number of obs = 383

----- Interpolated Dickey-Fuller -----				
	Test	1% Critical	5% Critical	10% Critical
	Statistic	Value	Value	Value
Z(t)	-3.447	-3.985	-3.425	-3.130

MacKinnon approximate p-value for Z(t) = 0.0455

D.ln_fl_no~m	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
ln_fl_nonf~m						
L1.	-.0125543	.0036426	-3.45	0.001	-.0197173	-.0053914
LD.	-.0016386	.0257588	-0.06	0.949	-.0522914	.0490143
L2D.	-.0081846	.0257419	-0.32	0.751	-.0588042	.0424351
L3D.	.0107332	.0255801	0.42	0.675	-.0395683	.0610347
L4D.	.0024337	.0255626	0.10	0.924	-.0478334	.0527008
L5D.	-.0162627	.0255374	-0.64	0.525	-.0664801	.0339548
L6D.	.0476972	.0255517	1.87	0.063	-.0025484	.0979427
L7D.	-.0171747	.0255546	-0.67	0.502	-.0674261	.0330768

L8D.		-.0153147	.0255342	-0.60	0.549	-.0655259	.0348964
L9D.		-.0053613	.025545	-0.21	0.834	-.0555938	.0448713
L10D.		-.0424083	.0255539	-1.66	0.098	-.0926583	.0078418
L11D.		.0264836	.0256701	1.03	0.303	-.023995	.0769621
L12D.		.8678931	.0257733	33.67	0.000	.8172116	.9185747
_trend		.0000185	5.42e-06	3.40	0.001	7.79e-06	.0000291
_cons		.1076319	.0312131	3.45	0.001	.0462536	.1690103

```
. eststo dfuller_1
```

```
. *esttab dfuller_1 using "dfuller_nonfarm.csv", replace
```

```
. dfuller ln_fl_lf if tin(1988m1, 2019m12), trend lags(12) regress
```

Augmented Dickey-Fuller test for unit root Number of obs = 383

	Test Statistic	----- 1% Critical Value	Interpolated Dickey-Fuller 5% Critical Value	----- 10% Critical Value
Z(t)	-1.768	-3.985	-3.425	-3.130

MacKinnon approximate p-value for Z(t) = 0.7197

D.ln_fl_lf		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]

ln_fl_lf						
L1.		-.0145241	.0082127	-1.77	0.078	-.0306738 .0016256
LD.		-.0765454	.0440377	-1.74	0.083	-.1631424 .0100516
L2D.		.0235824	.0440775	0.54	0.593	-.063093 .1102578
L3D.		-.0265862	.0440144	-0.60	0.546	-.1131374 .0599651
L4D.		-.0107586	.0437954	-0.25	0.806	-.0968793 .0753621
L5D.		-.0938664	.0438477	-2.14	0.033	-.1800899 -.0076429
L6D.		-.1923623	.0437026	-4.40	0.000	-.2783005 -.1064242
L7D.		-.0659403	.0437567	-1.51	0.133	-.1519848 .0201042
L8D.		-.0039238	.0431203	-0.09	0.928	-.0887169 .0808694
L9D.		-.0651803	.0431157	-1.51	0.131	-.1499644 .0196039
L10D.		-.0175563	.0432789	-0.41	0.685	-.1026614 .0675488
L11D.		.0379697	.0432671	0.88	0.381	-.047112 .1230514
L12D.		.5274722	.0431257	12.23	0.000	.4426684 .612276
_trend		.0000183	.0000118	1.55	0.122	-4.93e-06 .0000416
_cons		.2290598	.1284606	1.78	0.075	-.0235491 .4816686

```
. eststo dfuller_2
```

```
. *esttab dfuller_2 using "dfuller_lf.csv", replace
```

```
. dfuller ln_fl_bp if tin(1988m1, 2019m12), trend lags(12) regress
```

Augmented Dickey-Fuller test for unit root Number of obs = 370

	Test Statistic	----- Interpolated Dickey-Fuller -----		
		1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.624	-3.985	-3.425	-3.130

MacKinnon approximate p-value for Z(t) = 0.7827

D.ln_fl_bp	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ln_fl_bp						
L1.	-.0256093	.0157655	-1.62	0.105	-.0566148	.0053962
LD.	-.4892327	.0536997	-9.11	0.000	-.5948422	-.3836233
L2D.	-.1676299	.0597639	-2.80	0.005	-.2851658	-.050094
L3D.	.0339165	.0601481	0.56	0.573	-.0843749	.152208
L4D.	-.04808	.0603769	-0.80	0.426	-.1668214	.0706614
L5D.	-.0291366	.0603882	-0.48	0.630	-.1479001	.089627
L6D.	-.0232757	.0601083	-0.39	0.699	-.1414889	.0949375
L7D.	-.1033175	.0599992	-1.72	0.086	-.2213162	.0146811
L8D.	-.0443521	.0600408	-0.74	0.461	-.1624323	.0737282
L9D.	.0357027	.059966	0.60	0.552	-.0822307	.153636
L10D.	.135494	.0599421	2.26	0.024	.0176078	.2533802
L11D.	.0551154	.0593962	0.93	0.354	-.0616973	.1719282
L12D.	.2231371	.0522915	4.27	0.000	.120297	.3259772
_trend	6.10e-06	.0000722	0.08	0.933	-.0001359	.0001481
_cons	.2330947	.1500049	1.55	0.121	-.0619152	.5281046

. eststo dfuller_3

. *esttab dfuller_3 using "dfuller_bp.csv", replace

. dfuller ln_us_epr if tin(1988m1, 2019m12), trend lags(12) regress

Augmented Dickey-Fuller test for unit root Number of obs = 383

	Test Statistic	----- Interpolated Dickey-Fuller -----		
		1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.751	-3.985	-3.425	-3.130

MacKinnon approximate p-value for Z(t) = 0.2154

D.ln_us_epr	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ln_us_epr						
L1.	-.0191058	.0069443	-2.75	0.006	-.0327613	-.0054503
LD.	.0136959	.034809	0.39	0.694	-.0547537	.0821454
L2D.	.0390844	.0345956	1.13	0.259	-.0289454	.1071142
L3D.	-.1010787	.0344628	-2.93	0.004	-.1688474	-.03331
L4D.	.0568803	.0342825	1.66	0.098	-.010534	.1242945

L5D.		.009185	.0343904	0.27	0.790	-.0584413	.0768113
L6D.		-.1049015	.0342864	-3.06	0.002	-.1723234	-.0374796
L7D.		.0106907	.0340971	0.31	0.754	-.0563589	.0777403
L8D.		.0145465	.033832	0.43	0.667	-.0519818	.0810748
L9D.		-.0886587	.0337554	-2.63	0.009	-.1550365	-.0222809
L10D.		-.0147671	.033599	-0.44	0.661	-.0808374	.0513031
L11D.		.0838082	.0335472	2.50	0.013	.0178399	.1497764
L12D.		.7299487	.0337793	21.61	0.000	.663524	.7963734
_trend		-2.84e-06	1.90e-06	-1.49	0.136	-6.59e-06	8.98e-07
_cons		.0792443	.0288557	2.75	0.006	.0225015	.1359871

```

. eststo dfuller_4

. *esttab dfuller_4 using "dfuller_epr.csv", replace
.
. esttab dfuller_* using "all_dfuller.csv", replace
(output written to all_dfuller.csv)

.
. generate month = month(mdate)

.
. reg d.ln_fl_nonfarm l(1,12, 24)d.ln_fl_nonfarm l(1/12,24)d.ln_fl_lf l(1/12,24)d
> .ln_fl_bp l(1/12,24)d.ln_us_epr i.month mdate if tin(1998m1, 2019m11)

```

Source	SS	df	MS	Number of obs =	263
Model	.021651496	51	.000424539	F(51, 211) =	29.76
Residual	.003009742	211	.000014264	Prob > F =	0.0000
Total	.024661238	262	.000094127	R-squared =	0.8780
				Adj R-squared =	0.8485
				Root MSE =	.00378

D.		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
ln_fl_nonfarm						
LD.		-.0926289	.0454177	-2.04	0.043	-.1821595
L12D.		.4439241	.0688348	6.45	0.000	.308232
L24D.		.291822	.0638739	4.57	0.000	.1659093
ln_fl_lf						
LD.		-.0556758	.115152	-0.48	0.629	-.2826715
L2D.		-.057551	.1169958	-0.49	0.623	-.2881813
L3D.		.1354078	.1177589	1.15	0.251	-.0967268
L4D.		-.0342497	.1179634	-0.29	0.772	-.2667874
L5D.		-.2338712	.1189406	-1.97	0.051	-.4683354
L6D.		-.0588163	.1152554	-0.51	0.610	-.2860159
L7D.		.2287214	.1142333	2.00	0.047	.0035366
L8D.		-.1067951	.1170737	-0.91	0.363	-.337579
L9D.		.2547314	.1211662	2.10	0.037	.01588
L10D.		.1270005	.118602	1.07	0.285	-.1067962
L11D.		-.1307699	.1143857	-1.14	0.254	-.3562551

L12D.		-.0083341	.1210023	-0.07	0.945	-.2468623	.2301941
L24D.		.0975144	.1260169	0.77	0.440	-.150899	.3459279
ln_fl_bp							
LD.		.0032259	.0019625	1.64	0.102	-.0006426	.0070945
L2D.		.0059268	.0023776	2.49	0.013	.0012399	.0106136
L3D.		.0036507	.0025365	1.44	0.152	-.0013493	.0086508
L4D.		.0045628	.0025887	1.76	0.079	-.0005403	.0096658
L5D.		.0047385	.0026375	1.80	0.074	-.0004608	.0099378
L6D.		.0020864	.0025827	0.81	0.420	-.0030048	.0071776
L7D.		.0050004	.002515	1.99	0.048	.0000427	.0099581
L8D.		.0051572	.0024943	2.07	0.040	.0002403	.0100741
L9D.		.0057232	.0024619	2.32	0.021	.0008701	.0105764
L10D.		.0047575	.0024956	1.91	0.058	-.000162	.009677
L11D.		.0055407	.0024112	2.30	0.023	.0007876	.0102938
L12D.		.0038981	.0020361	1.91	0.057	-.0001157	.0079119
L24D.		-.0025663	.0016539	-1.55	0.122	-.0058266	.0006939
ln_us_epr							
LD.		-.0127732	.1274416	-0.10	0.920	-.2639951	.2384488
L2D.		.076887	.1304395	0.59	0.556	-.1802445	.3340186
L3D.		-.2081819	.1346919	-1.55	0.124	-.473696	.0573322
L4D.		-.0293166	.1358049	-0.22	0.829	-.2970249	.2383916
L5D.		.4055814	.1416527	2.86	0.005	.1263455	.6848173
L6D.		.0825257	.140612	0.59	0.558	-.1946585	.35971
L7D.		-.3195117	.1225496	-2.61	0.010	-.5610903	-.0779332
L8D.		.2065095	.1296339	1.59	0.113	-.0490341	.462053
L9D.		-.309785	.1310277	-2.36	0.019	-.5680761	-.0514939
L10D.		-.2639625	.1254417	-2.10	0.037	-.511242	-.016683
L11D.		.1449821	.1213844	1.19	0.234	-.0942994	.3842636
L12D.		.0455053	.1452646	0.31	0.754	-.2408504	.3318611
L24D.		-.221349	.154407	-1.43	0.153	-.525727	.083029
month							
5		-.0027484	.0014909	-1.84	0.067	-.0056874	.0001905
6		-.0017019	.0020924	-0.81	0.417	-.0058266	.0024228
7		-.0037321	.0028513	-1.31	0.192	-.0093528	.0018886
8		-.0051651	.0037928	-1.36	0.175	-.0126417	.0023115
9		-.00554	.0045092	-1.23	0.221	-.0144288	.0033488
10		-.0060617	.0052786	-1.15	0.252	-.0164673	.0043439
11		-.0080129	.0061866	-1.30	0.197	-.0202084	.0041825
12		-.0087661	.0068832	-1.27	0.204	-.0223347	.0048026
mdate		.0000352	.0000285	1.23	0.219	-.000021	.0000913
_cons		-.0160835	.013545	-1.19	0.236	-.0427844	.0106175

```
. eststo ardl
```

```
. esttab ardl using "ardl.csv", replace
(output written to ardl.csv)
```

```
. *Pac of the residuals
. predict resid if e(sample)==1, residual
```

(708 missing values generated)

. pac resid

.

. *Breusch Godfrey Test

. reg d.ln_fl_nonfarm l(1,12,24)d.ln_fl_nonfarm l(1/12)d.ln_fl_lf l(1/12,24)d.ln_> fl_bp l(1/12)d.ln_us_epr i.month if tin(1998m1, 2019m11)

Source	SS	df	MS	Number of obs =	263
Model	.021597452	48	.000449947	F(48, 214) =	31.43
Residual	.003063786	214	.000014317	Prob > F =	0.0000
				R-squared =	0.8758
				Adj R-squared =	0.8479
Total	.024661238	262	.000094127	Root MSE =	.00378

D.						
ln_fl_nonfarm	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ln_fl_nonfarm						
LD.	-.0928733	.0453482	-2.05	0.042	-.1822596	-.003487
L12D.	.4223739	.0676589	6.24	0.000	.2890106	.5557372
L24D.	.3119833	.0629607	4.96	0.000	.1878808	.4360858
ln_fl_lf						
LD.	-.0661962	.1146952	-0.58	0.564	-.2922732	.1598809
L2D.	-.0681369	.1169093	-0.58	0.561	-.2985781	.1623044
L3D.	.1024949	.1148005	0.89	0.373	-.1237897	.3287796
L4D.	-.0421614	.1169222	-0.36	0.719	-.272628	.1883051
L5D.	-.2229006	.1166555	-1.91	0.057	-.4528416	.0070404
L6D.	-.0602908	.1146018	-0.53	0.599	-.2861836	.1656021
L7D.	.2068269	.1135664	1.82	0.070	-.017025	.4306789
L8D.	-.0870709	.1144841	-0.76	0.448	-.3127318	.13859
L9D.	.2298264	.1184066	1.94	0.054	-.0035661	.4632189
L10D.	.1097941	.1181921	0.93	0.354	-.1231758	.342764
L11D.	-.116315	.1142516	-1.02	0.310	-.3415175	.1088876
L12D.	.0590175	.1105669	0.53	0.594	-.1589222	.2769573
ln_fl_bp						
LD.	.0032351	.0019349	1.67	0.096	-.0005788	.007049
L2D.	.0053535	.0023617	2.27	0.024	.0006982	.0100087
L3D.	.0030278	.0025087	1.21	0.229	-.0019172	.0079727
L4D.	.0035367	.0025383	1.39	0.165	-.0014666	.00854
L5D.	.004315	.0026309	1.64	0.102	-.0008709	.0095008
L6D.	.0020719	.002587	0.80	0.424	-.0030274	.0071712
L7D.	.0049716	.0025189	1.97	0.050	6.56e-06	.0099366
L8D.	.0053367	.0024953	2.14	0.034	.0004182	.0102553
L9D.	.0057484	.0024563	2.34	0.020	.0009067	.0105901
L10D.	.0053161	.0024826	2.14	0.033	.0004227	.0102096
L11D.	.0054666	.0023935	2.28	0.023	.0007488	.0101845
L12D.	.004315	.0020265	2.13	0.034	.0003205	.0083094
L24D.	-.0027936	.0016258	-1.72	0.087	-.0059982	.0004111

ln_us_epr						
LD.	-.0054782	.1273583	-0.04	0.966	-.2565156	.2455591
L2D.	.095191	.1299347	0.73	0.465	-.1609248	.3513068
L3D.	-.1588557	.1265068	-1.26	0.211	-.4082147	.0905032
L4D.	-.0286396	.1338505	-0.21	0.831	-.2924738	.2351947
L5D.	.4145147	.1405367	2.95	0.004	.1375012	.6915281
L6D.	.0994047	.1403424	0.71	0.480	-.1772257	.3760351
L7D.	-.3033355	.1223545	-2.48	0.014	-.5445099	-.0621611
L8D.	.1788148	.1279439	1.40	0.164	-.0733769	.4310065
L9D.	-.2775429	.1257502	-2.21	0.028	-.5254106	-.0296751
L10D.	-.2428093	.1247626	-1.95	0.053	-.4887304	.0031117
L11D.	.124513	.1198223	1.04	0.300	-.1116702	.3606961
L12D.	-.0987727	.1186935	-0.83	0.406	-.3327308	.1351853
month						
5	-.001582	.0011789	-1.34	0.181	-.0039057	.0007416
6	.0007852	.0010596	0.74	0.459	-.0013034	.0028737
7	-.0005038	.0011228	-0.45	0.654	-.002717	.0017093
8	-.0008509	.0015619	-0.54	0.586	-.0039295	.0022278
9	.0002907	.0010806	0.27	0.788	-.0018393	.0024208
10	.0003717	.0011274	0.33	0.742	-.0018505	.002594
11	-.0005666	.0009844	-0.58	0.566	-.002507	.0013738
12	-.0002873	.001148	-0.25	0.803	-.0025502	.0019756
_cons	.0005494	.0010264	0.54	0.593	-.0014738	.0025726

. estat bgodfrey, lag(1/24)

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	0.017	1	0.8960
2	0.044	2	0.9785
3	5.011	3	0.1710
4	5.994	4	0.1996
5	9.451	5	0.0924
6	11.068	6	0.0863
7	11.643	7	0.1129
8	11.664	8	0.1668
9	13.670	9	0.1346
10	13.689	10	0.1876
11	14.551	11	0.2040
12	33.743	12	0.0007
13	34.538	13	0.0010
14	39.737	14	0.0003
15	39.828	15	0.0005
16	41.420	16	0.0005
17	41.673	17	0.0007
18	42.094	18	0.0011
19	45.559	19	0.0006
20	45.559	20	0.0009

21		45.616	21	0.0014
22		47.882	22	0.0011
23		48.195	23	0.0016
24		61.111	24	0.0000

H0: no serial correlation

. eststo bgodfrey_1

. esttab bgodfrey_1 using "bgodfrey.csv", replace
(output written to bgodfrey.csv)

.
. predict resstatic, residual
(613 missing values generated)

. pac resstatic

.
. *model without Newey-West
. reg d.ln_fl_nonfarm l(0/4)d.ln_fl_bp i.month

Source	SS	df	MS	Number of obs =	378
Model	.002991119	16	.000186945	F(16, 361) =	1.91
Residual	.035306536	361	.000097802	Prob > F =	0.0184
				R-squared =	0.0781
				Adj R-squared =	0.0372
Total	.038297655	377	.000101585	Root MSE =	.00989

D.		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
ln_fl_nonf~m						
ln_fl_bp						
D1.		-.0066544	.0036826	-1.81	0.072	-.0138965 .0005876
LD.		-.0150368	.0042658	-3.52	0.000	-.0234257 -.0066478
L2D.		-.0022239	.0043553	-0.51	0.610	-.0107889 .0063411
L3D.		-.0047428	.0042394	-1.12	0.264	-.0130798 .0035943
L4D.		-.0051737	.0036904	-1.40	0.162	-.012431 .0020837
month						
2		.0039464	.0025891	1.52	0.128	-.0011452 .009038
3		.0034298	.0025192	1.36	0.174	-.0015245 .008384
4		.0026387	.0025444	1.04	0.300	-.002365 .0076424
5		.0010039	.0025208	0.40	0.691	-.0039535 .0059612
6		.0032243	.0025626	1.26	0.209	-.0018152 .0082638
7		-.0002813	.0025501	-0.11	0.912	-.0052962 .0047336
8		-.0039087	.0025173	-1.55	0.121	-.0088591 .0010417
9		.0030851	.0025761	1.20	0.232	-.0019809 .0081512
10		.0033142	.0025302	1.31	0.191	-.0016615 .0082899
11		.0026077	.0025458	1.02	0.306	-.0023988 .0076142
12		.0027936	.002326	1.20	0.231	-.0017807 .0073678

_cons		-.0002449	.0017829	-0.14	0.891	-.0037511	.0032612

```
. predict residua if e(sample)==1, residual
(593 missing values generated)
```

```
. pac residua
```

```
.
. *Model with Newey West
. newey d.ln_fl_nonfarm l(0/4)d.ln_fl_bp i.month, lag(4)
```

Regression with Newey-West standard errors	Number of obs	=	378
maximum lag: 4	F(16, 361)	=	2.81
	Prob > F	=	0.0003

D.						
ln_fl_nonf~m	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ln_fl_bp						
D1.	-.0066544	.0035887	-1.85	0.065	-.0137119	.000403
LD.	-.0150368	.0036394	-4.13	0.000	-.0221937	-.0078798
L2D.	-.0022239	.0043037	-0.52	0.606	-.0106873	.0062395
L3D.	-.0047428	.0048093	-0.99	0.325	-.0142005	.004715
L4D.	-.0051737	.0036142	-1.43	0.153	-.0122811	.0019338
month						
2	.0039464	.0019473	2.03	0.043	.0001168	.0077759
3	.0034298	.0019771	1.73	0.084	-.0004583	.0073179
4	.0026387	.0018841	1.40	0.162	-.0010665	.0063438
5	.0010039	.001854	0.54	0.589	-.0026421	.0046498
6	.0032243	.0018456	1.75	0.081	-.0004052	.0068538
7	-.0002813	.0021169	-0.13	0.894	-.0044442	.0038817
8	-.0039087	.0023153	-1.69	0.092	-.0084619	.0006445
9	.0030851	.0018231	1.69	0.091	-.0005	.0066703
10	.0033142	.0018847	1.76	0.080	-.0003921	.0070205
11	.0026077	.0018666	1.40	0.163	-.001063	.0062784
12	.0027936	.0017302	1.61	0.107	-.000609	.0061962
_cons	-.0002449	.0014652	-0.17	0.867	-.0031264	.0026365

```
. predict residu if e(sample)==1, residual
(593 missing values generated)
```

```
. pac residu
```

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.
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.
. reg d.ln_fl_nonfarm l(1,12,24)d.ln_fl_nonfarm l(1/12)d.ln_fl_lf l(1/12,24)d.ln_
> fl_bp l(1/12)d.ln_us_epr i.month if tin(1998m1, 2019m11)
```

Source	SS	df	MS	Number of obs =	263
Model	.021597452	48	.000449947	F(48, 214) =	31.43
Residual	.003063786	214	.000014317	Prob > F =	0.0000
				R-squared =	0.8758
				Adj R-squared =	0.8479
Total	.024661238	262	.000094127	Root MSE =	.00378

D.						
ln_fl_nonfarm	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ln_fl_nonfarm						
LD.	-.0928733	.0453482	-2.05	0.042	-.1822596	-.003487
L12D.	.4223739	.0676589	6.24	0.000	.2890106	.5557372
L24D.	.3119833	.0629607	4.96	0.000	.1878808	.4360858
ln_fl_lf						
LD.	-.0661962	.1146952	-0.58	0.564	-.2922732	.1598809
L2D.	-.0681369	.1169093	-0.58	0.561	-.2985781	.1623044
L3D.	.1024949	.1148005	0.89	0.373	-.1237897	.3287796
L4D.	-.0421614	.1169222	-0.36	0.719	-.272628	.1883051
L5D.	-.2229006	.1166555	-1.91	0.057	-.4528416	.0070404
L6D.	-.0602908	.1146018	-0.53	0.599	-.2861836	.1656021
L7D.	.2068269	.1135664	1.82	0.070	-.017025	.4306789
L8D.	-.0870709	.1144841	-0.76	0.448	-.3127318	.13859
L9D.	.2298264	.1184066	1.94	0.054	-.0035661	.4632189
L10D.	.1097941	.1181921	0.93	0.354	-.1231758	.342764
L11D.	-.116315	.1142516	-1.02	0.310	-.3415175	.1088876
L12D.	.0590175	.1105669	0.53	0.594	-.1589222	.2769573
ln_fl_bp						
LD.	.0032351	.0019349	1.67	0.096	-.0005788	.007049
L2D.	.0053535	.0023617	2.27	0.024	.0006982	.0100087
L3D.	.0030278	.0025087	1.21	0.229	-.0019172	.0079727
L4D.	.0035367	.0025383	1.39	0.165	-.0014666	.00854
L5D.	.004315	.0026309	1.64	0.102	-.0008709	.0095008
L6D.	.0020719	.002587	0.80	0.424	-.0030274	.0071712
L7D.	.0049716	.0025189	1.97	0.050	6.56e-06	.0099366
L8D.	.0053367	.0024953	2.14	0.034	.0004182	.0102553
L9D.	.0057484	.0024563	2.34	0.020	.0009067	.0105901
L10D.	.0053161	.0024826	2.14	0.033	.0004227	.0102096
L11D.	.0054666	.0023935	2.28	0.023	.0007488	.0101845
L12D.	.004315	.0020265	2.13	0.034	.0003205	.0083094
L24D.	-.0027936	.0016258	-1.72	0.087	-.0059982	.0004111
ln_us_epr						
LD.	-.0054782	.1273583	-0.04	0.966	-.2565156	.2455591
L2D.	.095191	.1299347	0.73	0.465	-.1609248	.3513068
L3D.	-.1588557	.1265068	-1.26	0.211	-.4082147	.0905032
L4D.	-.0286396	.1338505	-0.21	0.831	-.2924738	.2351947
L5D.	.4145147	.1405367	2.95	0.004	.1375012	.6915281
L6D.	.0994047	.1403424	0.71	0.480	-.1772257	.3760351
L7D.	-.3033355	.1223545	-2.48	0.014	-.5445099	-.0621611

L8D.		.1788148	.1279439	1.40	0.164	-.0733769	.4310065
L9D.		-.2775429	.1257502	-2.21	0.028	-.5254106	-.0296751
L10D.		-.2428093	.1247626	-1.95	0.053	-.4887304	.0031117
L11D.		.124513	.1198223	1.04	0.300	-.1116702	.3606961
L12D.		-.0987727	.1186935	-0.83	0.406	-.3327308	.1351853
month							
5		-.001582	.0011789	-1.34	0.181	-.0039057	.0007416
6		.0007852	.0010596	0.74	0.459	-.0013034	.0028737
7		-.0005038	.0011228	-0.45	0.654	-.002717	.0017093
8		-.0008509	.0015619	-0.54	0.586	-.0039295	.0022278
9		.0002907	.0010806	0.27	0.788	-.0018393	.0024208
10		.0003717	.0011274	0.33	0.742	-.0018505	.002594
11		-.0005666	.0009844	-0.58	0.566	-.002507	.0013738
12		-.0002873	.001148	-0.25	0.803	-.0025502	.0019756
_cons		.0005494	.0010264	0.54	0.593	-.0014738	.0025726

. predict resid_ardl_wo if e(sample)==1, residual
(708 missing values generated)

. pac resid_ardl_wo

.
. newey d.ln_fl_nonfarm l(1,12,24)d.ln_fl_nonfarm l(1/12)d.ln_fl_lf l(1/12,24)d.l
> n_fl_bp l(1/12)d.ln_us_epr i.month if tin(1998m1, 2019m11), lag(12)

Regression with Newey-West standard errors	Number of obs	=	263
maximum lag: 12	F(48, 214)	=	268.04
	Prob > F	=	0.0000

D.		Newey-West				
ln_fl_nonfarm		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]

ln_fl_nonfarm						
LD.		-.0928733	.0578079	-1.61	0.110	-.2068191 .0210725
L12D.		.4223739	.1450686	2.91	0.004	.1364277 .7083202
L24D.		.3119833	.1235832	2.52	0.012	.068387 .5555796
ln_fl_lf						
LD.		-.0661962	.0819303	-0.81	0.420	-.22769 .0952976
L2D.		-.0681369	.1112317	-0.61	0.541	-.287387 .1511133
L3D.		.1024949	.0975813	1.05	0.295	-.0898486 .2948385
L4D.		-.0421614	.0852443	-0.49	0.621	-.2101875 .1258646
L5D.		-.2229006	.1055979	-2.11	0.036	-.4310458 -.0147554
L6D.		-.0602908	.1250475	-0.48	0.630	-.3067733 .1861918
L7D.		.2068269	.1004729	2.06	0.041	.0087836 .4048703
L8D.		-.0870709	.1066424	-0.82	0.415	-.2972749 .1231331
L9D.		.2298264	.1569053	1.46	0.144	-.0794514 .5391043
L10D.		.1097941	.1092318	1.01	0.316	-.105514 .3251022
L11D.		-.116315	.1270997	-0.92	0.361	-.3668425 .1342126
L12D.		.0590175	.1021344	0.58	0.564	-.1423007 .2603358

ln_fl_bp						
LD.	.0032351	.0021398	1.51	0.132	-.0009828	.007453
L2D.	.0053535	.0023792	2.25	0.025	.0006639	.0100431
L3D.	.0030278	.0032706	0.93	0.356	-.003419	.0094745
L4D.	.0035367	.0034502	1.03	0.306	-.0032641	.0103374
L5D.	.004315	.0028928	1.49	0.137	-.001387	.0100169
L6D.	.0020719	.0028162	0.74	0.463	-.0034792	.007623
L7D.	.0049716	.003809	1.31	0.193	-.0025364	.0124795
L8D.	.0053367	.0028986	1.84	0.067	-.0003767	.0110502
L9D.	.0057484	.0027433	2.10	0.037	.0003411	.0111557
L10D.	.0053161	.0025564	2.08	0.039	.0002771	.0103552
L11D.	.0054666	.0022234	2.46	0.015	.0010841	.0098492
L12D.	.004315	.0013412	3.22	0.001	.0016713	.0069586
L24D.	-.0027936	.0019438	-1.44	0.152	-.006625	.0010379
ln_us_epr						
LD.	-.0054782	.1317183	-0.04	0.967	-.2651096	.2541531
L2D.	.095191	.1377321	0.69	0.490	-.1762942	.3666763
L3D.	-.1588557	.1078428	-1.47	0.142	-.3714259	.0537144
L4D.	-.0286396	.0958126	-0.30	0.765	-.2174968	.1602177
L5D.	.4145147	.1459318	2.84	0.005	.1268668	.7021626
L6D.	.0994047	.1547955	0.64	0.521	-.2057145	.4045238
L7D.	-.3033355	.1117579	-2.71	0.007	-.5236227	-.0830484
L8D.	.1788148	.1386088	1.29	0.198	-.0943986	.4520283
L9D.	-.2775429	.1730533	-1.60	0.110	-.6186502	.0635645
L10D.	-.2428093	.111921	-2.17	0.031	-.4634181	-.0222006
L11D.	.124513	.133401	0.93	0.352	-.1384352	.3874611
L12D.	-.0987727	.133744	-0.74	0.461	-.3623971	.1648516
month						
5	-.001582	.0011209	-1.41	0.160	-.0037914	.0006274
6	.0007852	.0009216	0.85	0.395	-.0010315	.0026018
7	-.0005038	.0010542	-0.48	0.633	-.0025818	.0015742
8	-.0008509	.0022665	-0.38	0.708	-.0053183	.0036166
9	.0002907	.0011491	0.25	0.801	-.0019743	.0025557
10	.0003717	.0009772	0.38	0.704	-.0015544	.0022979
11	-.0005666	.000742	-0.76	0.446	-.0020291	.0008959
12	-.0002873	.0007169	-0.40	0.689	-.0017004	.0011258
_cons	.0005494	.0011513	0.48	0.634	-.0017199	.0028187

```
. predict resid_ardl if e(sample) ==1, residual
(708 missing values generated)
```

```
. pac resid_ardl
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end of do-file