Econometrics: Multiple Regression and Applications
ECON4004: LAB 5

Duong Trinh

University of Glasgow

March 6, 2024

Intro

◇ Duong Trinh
  ◇ PhD Student in Economics (Bayesian Microeconometrics)
  ◇ Email: Duong.Trinh@glasgow.ac.uk

◇ ECON4004-LB01
  ◇ Wednesday 10am -12 pm
  ◇ 5 sessions (7-Feb, 14-Feb, 21-Feb, 28-Feb, 6-March)
  ◇ ST ANDREWS:357
◇ ECON4004-LB02
  ◇ Wednesday 12-2 pm
  ◇ 5 sessions (7-Feb, 14-Feb, 21-Feb, 28-Feb, 6-March)
  ◇ ST ANDREWS:357

Your Attendance & Lab Feedback

Plan for LAB 5

◇ Exercise: based on Stock & Watson, E15.1

◇ We will focus on *"Time Series Regression"*
   ◇ Time series data
   ◇ Autocorrelation
   ◇ Autoregressions
   ◇ Forecasting near future values
   ◇ Unit root test

BRIEF REVIEW

Time Series Data - What it looks like...

Time series data are data collected on the same observational unit at multiple time periods (t).

$$\{y_t\},$$
$$t = 1, \ldots, T$$

Can be of any time frequency - daily, monthly, quarterly, annual, etc.[1]

[SN] Working with dates and times in STATA

Date types in Stata[2]

Date type	Format	Unit
Datetime	%tc	Milliseconds since 01jan1960 00:00:00.000
Daily date	%td	Days since 01jan1960
Weekly date	%tw	Weeks since 1960w1
Monthly date	%tm	Months since 1960m1
Quarterly date	%tq	Quarters since 1960q1

[SN] Our Example

```
. * Import Quarterly Data from Excel file
. * first row considered as variable names
. import excel "us_macro_quarterly.xlsx", sheet("Data") firstrow clear
(5 vars, 252 obs)

. describe

Contains data
 Observations:            252
    Variables:              5
```

Variable name	Storage type	Display format	Value label	Variable label
freq	int	%td..		freq
GDPC1	double	%10.0g		GDPC1
JAPAN_IP	double	%10.0g		JAPAN_IP
PCECTPI	double	%10.0g		PCECTPI
CPIAUCSL	double	%10.0g		CPIAUCSL

[SN] Creating dates and times in STATA

(I) Option 1: Building dates and times from components.[3]

Date type	Format	Pseudofunction	Function
Daily date	`%td`	td(day-month-year)	mdy(M, D, Y)
Weekly date	`%tw`	tw(year-week)	yw(Y, W)
Monthly date	`%tm`	tm(year-month)	ym(Y, M)
Quarterly date	`%tq`	tq(year-quarter)	yq(Y, Q)

---

[3]See guideline at: https://www.stata.com/bookstore/dtguide.pdf

[SN] Our Example

```
. * Create a desired quarterly date, e.g. 1955q1
. display %tq tq(1955q1) //using pseudofunction tq(.)
1955q1

. display %tq yq(1955,1) //using function yq(.)
1955q1


.
. * Generate quarterly date variables, recursively starting from 1955q1
. * By default, tq(1960q1) is defined to be 0 in Stata.
. gen date1 = tq(1955q1) + _n-1

. gen date2 = yq(1955,1) + _n-1

. format %tq date1 date2 // express them in quarterly format, see Data Editor

. list if date1 != date2 // check if both variables are identical
```

[SN] Creating dates and times in STATA

(II) Option 2: Converting dates and times from existing variables.[4]

| | To | | | |
From	Daily date	Weekly date	Monthly date	Quarterly date
Daily date		`wofd()`	`mofd()`	`qofd()`
Weekly date	`dofw()`		`mofd(dofw())`	`qofd(dofw())`
Monthly date	`dofm()`	`wofd(dofm())`		`qofd(dofm())`
Quarterly date	`dofq()`	`wofd(dofq())`	`mofd(dofq())`	

[SN] Our Example

```
. * Generate quarterly date variable from existing "freq" var in dataset
. describe freq // note that "freq" is of daily date type (%td)

Variable        Storage   Display   Value
    name          type    format    label      Variable label

freq              int      %td..                freq

. gen date3 = qofd(freq) // convert "freq" to quarterly date type

. format %tq date3 // express it in quarterly format

. br freq date1 date2 date3 // check results, new vars are identical
```

[SN] STATA command for Setting Data as Time Series

Once having the date variable in a *date format*, we need to declare our data as time series to use the time series operators in Stata.

```
*tsset datevar
//choose suitable 'datevar' in the dataset
```

```
. * Declare 'us_macro_quarterly' dataset to be time-series data
. tsset date1

Time variable: date1, 1955q1 to 2017q4
        Delta: 1 quarter
```

[SN] STATA command for Visualizing Time Series Data

```
*[twoway] tsline varlist_of_inteterest
```

```
. * Line graph of two Price Index series
. twoway tsline PCECTPI CPIAUCSL // create a line graph using declared time-series data

. twoway line PCECTPI CPIAUCSL date1, yline(0) // equivalent graph when using standard command with datevar
```
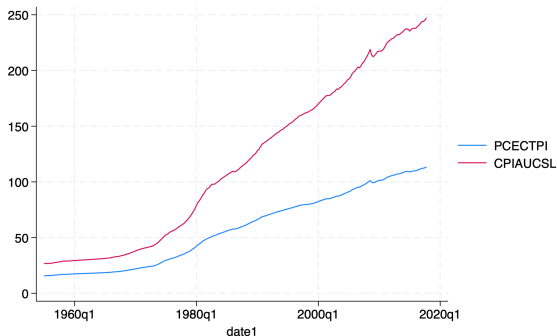
[SN] Subsetting tin/twithin in STATA

◇ `tin` ("times in", from a to b)

◇ `twithin` ("times within", between a and b, it excludes a and b).

[SN] Time-series operators in STATA

Transforming a time-series y

Stata

L operator	first *lag* y_{t-1}	L1.y
	2-period *lag* y_{t-2}	L2.y
	3-period *lag* y_{t-3}	L3.y
D operator	first *difference* $\Delta y_t = y_t - y_{t-1}$	D1.y
	double *difference* $\Delta y_t - \Delta y_{t-1}$	D2.y
	triple *difference* $(\Delta y_t - \Delta y_{t-1}) - (\Delta y_{t-1} - \Delta y_{t-2})$	D3.y

The first difference of the logarithm of y_t is $\Delta \ln(y_t) = \ln(y_t) - \ln(y_{t-1})$

$$\Delta \ln(y_t) \approx \frac{\text{percentage change of time-series y between } t \text{ and } t-1}{100}$$

(!) approximation is most accurate when the percentage change is small.

Autocorrelation and Autocovariance

The covariance between y_t and its jth lag y_{t-j} is called the jth *autocovariance* of the series y_t

$$j^{\text{th}}\text{autocovariance} \equiv Cov(y_t, y_{t-j})$$

The correlation between y_t and its jth lag y_{t-j} is called the jth *autocorrelation coefficient*, aka *serial correlation coefficient*

$$j^{\text{th}}\text{autocorrelation} \equiv \rho_j = \rho_{y_t, y_{t-j}} = \frac{Cov(y_t, y_{t-j})}{\sqrt{Var(y_t)\,Var(y_{t-j})}} \in [-1, 1]$$

$\rightarrow$ Measure how dependent y_t is on its past value y_{t-j}.

Autocorrelations of y as a function of its lags j is known as the *autocorrelation function*.

[SN] Tabulate and Graph Autocorrelations in STATA

Produce a table of the autocorrelations for a time series

```
*corrgram yvar [, lags(p)]
// limit the number of computed autocorrelations to p
```

Plot the autocorrelation function for a time series (correlogram) with pointwise confidence intervals

```
*ac yvar [, lags(p)]
// limit the number of computed autocorrelations to p
```

[SN] STATA command for Autoregression Model

The autoregressive model of order p - $AR(p)$

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \ldots + \beta_p y_{t-p} + \epsilon_t$$

To regress y_t against its own lagged values, run one of the followings

```
*regress yvar L1.yvar L2.yvar Lp.yvar [, robust]
```

```
*regress yvar L(1/p).yvar [, robust]
//'p' is the number of lags
```

[SN] Forecasting in STATA

Step1. Expanding the Dataset Before Forecasting

Given a set of time-series observations, STATA typically records the dates as running from the first until the last observation.

To forecast a date out-of-sample, these dates need to be in the data set, which requires expanding the dataset to include them.

```
*tsappend, add(k)
//add 'k' dates to the end of the sample
```

Step2. Point Forecasting Out-of-Sample

To create a series of predicted values both in-sample and out-of-sample, after the regress command

```
*predict yvar_hat [if]
//use 'if' condition to restrict the predicted values
```

Unit Root Test

⬦ Testing for unit roots/stochastic trend is a crucial step in time series analysis. The presence of a unit root in a time series signifies that the series is non-stationary, which can lead to spurious regressions and other potentially serious consequences if no further transformation is made.

   ⬦ $H_0 : y_t$ has a unit root (y_t is non-stationary).
   ⬦ $H_1 : y_t$ has no unit root (y_t is stationary).

⬦ The Dickey–Fuller test involves fitting the model

$$y_t = \beta_0 + \rho y_{t-1} + \delta t + u_t$$

and test $H_0 : \rho = 1$, or, equivalently, that y_t follows a unit root process.

⬦ To control for serial correlation issue, the augmented Dickey–Fuller (ADF) test instead fits

$$\Delta y_t = \beta_0 + \delta y_{t-1} + \alpha t + \gamma_1 \Delta y_{t-1} + \ldots + \gamma_k \Delta y_{t-k} + \epsilon_t$$

and test $H_0 : \delta = 0$.

<u>Note</u>: Possible restrictions: $\beta_0 = 0$ (without drift); $\alpha = 0$ (no trend term).

[SN] ADF Test for Unit Roots in STATA

Augmented Dickey–Fuller test using `tsset` data

```
* dfuller yvar
```

```
* dfuller yvar, trend
// include trend term
```

```
* dfuller yvar, lags(k) regress
// include 'k' lagged differences and display the regression table
```

Excercise: based on Stock & Watson, E15.1

Picture the Scenario

◇ **Objective:** Construct forecasting models for the rate of inflation.

◇ **Dataset:** `us_macro_quaterly.xlsx`.
  ◇ contains quarterly data on several macroeconomic series for the US.
  ◇ use the sample period $1963 : Q1 - 2017 : Q4$.(where data before 1963 may be used, as necessary, as initial values for lags in regressions)

◇ **Key variables:** For each country in each year
  ◇ PCEPI: the price index for personal consumption expenditures from the U.S. National Income and Product Accounts.

Questions

(a)

i. Compute the inflation rate, $Infl = 400 \times [ln(PCEPI_t) - ln(PCEPI_{t-1})]$. What are the units of `Infl`?

ii. Plot the values of `Infl` from 1963:Q1 through 2017:Q4. Based on the plot, do you think that `Infl` has a stochastic trend? Explain.

(b) Autocorrelations (»review)

i. Compute the first four autocorrelations of $\Delta Infl$.

ii. Plot the value of $\Delta Infl$ from 1963:Q1 through 2017:Q4. The plot should look choppy or jagged. Explain why this behaviour is consistent with the first autocorrelation that you computed in (i.).

Questions

(c) Autoregression Model (»review)

    i. Run an OLS regression of $\Delta Infl_t$ on $\Delta Infl_{t-1}$. Does knowing the change in inflation over the current quarter help predict the change in inflation over the next quarter? Explain.

   ii. Estimate an $AR(2)$ model of $\Delta Infl_t$. Is the $AR(2)$ model better than the $AR(1)$ model? Explain.

  iii. Use the $AR(2)$ model to predict the change in inflation from 2017:Q4 to 2018:Q1 - that is, to predict the value of $\Delta Infl_{2018:Q1}$.

Questions

(d) ADF test (»review)

i. Use the ADF test for $AR(p)$ regression

$$\Delta Y_t = \beta_0 + \delta Y_{t-1} + \gamma_1 \Delta Y_{t-1} + \ldots + \gamma_p \Delta Y_{t-p+1} + u_t$$

using 2 lags of $\Delta Infl$ (so that $p = 3$ in the above equation) to test for a stochastic trend in $Infl$.

ii. Is that ADF test based on the above regression preferred to the regression including a determinstic trend

$$\Delta Y_t = \beta_0 + \alpha t + \delta Y_{t-1} + \ldots + \gamma_p \Delta Y_{t-p+1} + u_t$$

for testing for a stochastic trend in $Infl$? Explain.

iii. Based on the ADF tests carried out, does the AR model for $Infl$ contain a unit root?

(a-i) Compute the inflation rate `Infl`. What is its unit?

(»stata)

$$Infl = 400 \times [ln(PCEPI_t) - ln(PCEPI_{t-1})]$$

`Infl` is measured in percentage points at annual rate.

(a-ii) Plot values of `Infl` from 1963:Q1 through 2017:Q4.
Do you think that `Infl` has a stochastic trend?

U.S. Inflation Rate (%)
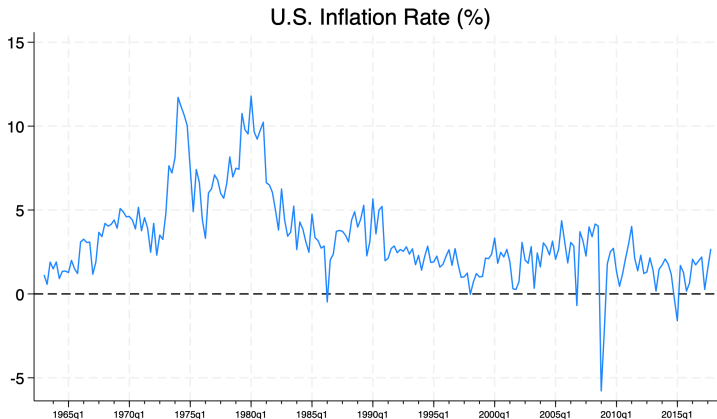
Inflation increased over the 20-year period 1960-1980, then declined for a decade and has
been reasonably stable since then. It appears to have a stochastic trend. (»stata)

(b-i) Compute the first four autocorrelations of $\Delta Infl$.

```
*corrgram yvar [, lags(p)]
// limit the number of computed autocorrelations to p
```

```
. * autocorrelation
. //autocorrelations reported in column named AC
. corrgram deltainfl if tin(1963q1,2017q4), lags(4)
```

					-1 0 1	-1 0 1
LAG	AC	PAC	Q	Prob>Q	[Autocorrelation]	[Partial autocor]
1	-0.2460	-0.2467	13.494	0.0002		
2	-0.2035	-0.2843	22.772	0.0000		
3	0.1362	0.0047	26.946	0.0000		
4	-0.0850	-0.1142	28.579	0.0000		

The first four autocorrelations are (rounded to 2 decimal places):
-0.25, -0.20, 0.14, and -0.08.

```
*ac yvar [, lags(p)]
// limit the number of computed autocorrelations to p
```

. * plot of autocorrelations with 95% confidence bands (optional)
. ac deltainfl if tin(1963q1,2017q4), lags(4)
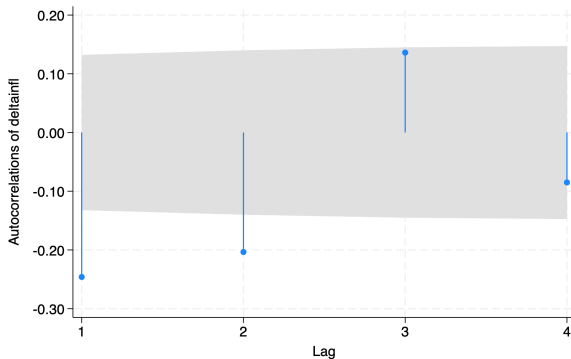
Bartlett's formula for MA(q) 95% confidence bands

(b-ii) Plot values of $\Delta Infl$ from 1963:Q1 through 2017:Q4.

Change in U.S. Inflation Rate (%)
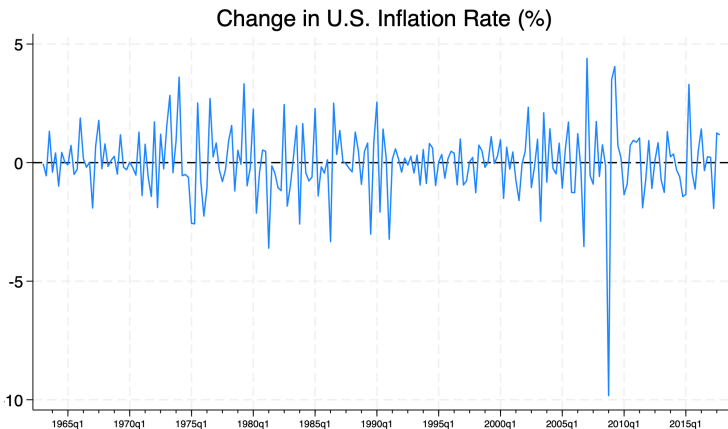
The change in inflation is slightly negatively serially correlated (the first autocorrelation is $\hat{\rho}_1 = -0.25$) so that values above the mean tend to be followed by values below the mean.
(»stata)

(c-i) Run an OLS regression of $\Delta Infl_t$ on $\Delta Infl_{t-1}$.

Autoregressive model of order one - AR(1)

$$\Delta Infl_t = \beta_0 + \beta_1 \cdot \Delta Infl_{t-1} + \epsilon_t$$

(c-i) Run an OLS regression of $\Delta Infl_t$ on $\Delta Infl_{t-1}$.

```
*regress yvar L1.yvar [, robust]
```

```
. * AR(1) regression - OLS estimates
. * L. takes the lag
. //ldeltainfl = deltainfl[_n] - deltainfl[_n-1]
. regress deltainfl L1.deltainfl if tin(1963q1,2017q4), robust
```

```
Linear regression                               Number of obs   =        220
                                                F(1, 218)       =      13.03
                                                Prob > F        =     0.0004
                                                R-squared       =     0.0607
                                                Root MSE        =     1.4383
```

deltainfl	Coefficient	Robust std. err.	t	P>|t|	[95% conf. interval]	
deltainfl L1.	-.2466842	.0683325	-3.61	0.000	-.3813611	-.1120074
_cons	.0073719	.0969709	0.08	0.939	-.1837485	.1984923

(c-i) Run an OLS regression of $\Delta Infl_t$ on $\Delta Infl_{t-1}$. Does knowing the change in inflation over the current quarter help predict the change in inflation over the next quarter?

Autoregressive model of order one - AR(1)

$$\Delta Infl_t = \beta_0 + \beta_1 \cdot \Delta Infl_{t-1} + \epsilon_t$$

OLS estimation results (»stata)

$$\widehat{\Delta Infl_t} = \underset{(se)}{0.007} - \underset{(0.096)}{0.247} \cdot \Delta Infl_{t-1}, \qquad R^2 = 0.061$$
$$\phantom{\widehat{\Delta Infl_t} = 0.007 - } {\scriptstyle(0.068)}$$

◇ The coefficient on lagged inflation is statistically significant, so that lagged inflation helps predict current inflation.

(c-ii) Estimate an $AR(2)$ model of $\Delta Infl_t$. Is the $AR(2)$ model better than the $AR(1)$ model?

AR(2) model

$$\Delta Infl_t = \beta_0 + \beta_1 \cdot \Delta Infl_{t-1} + \beta_2 \cdot \Delta Infl_{t-2} + \epsilon_t$$

(c-ii) Estimate an $AR(2)$ model of $\Delta Infl_t$. Is the $AR(2)$ model better than the $AR(1)$ model?

AR(2) model

$$\Delta Infl_t = \beta_0 + \beta_1 \cdot \Delta Infl_{t-1} + \beta_2 \cdot \Delta Infl_{t-2} + \epsilon_t$$

OLS estimation results (»stata)

$$\underset{(se)}{\widehat{\Delta Infl_t}} = \underset{(0.093)}{0.006} - \underset{(0.064)}{0.138} \cdot \Delta Infl_{t-1} - \underset{(0.076)}{0.284} \cdot \Delta Infl_{t-2}, \qquad \text{Adj-}R^2 = 0.128$$

- ◇ The estimated coefficient on $\Delta Infl_{t-2}$ is statistically significant, so the AR(2) model is preferred to the AR(1) model.
- ◇ Note also that adjusted R-squared increases from 0.061 in the AR(1) model to 0.128 in the AR(2) model, showing better goodness-of-fit.

(c-iii) Use the $AR(2)$ model to predict change in inflation from 2017:Q4 to 2018:Q1 - that is, value of $\Delta Infl_{2018:Q1}$.

```
. * Forecasting 1 period ahead deltainflation
. * add the extra period2 (next quarter)
. tsappend, add(1)

. * estimate AR(2)
. quiet regress deltainfl L.deltainfl L2.deltainfl if tin(1963q1,2017q4), r

. * predict for next quarter
. predict deltainflhat
(option xb assumed; fitted values)
(4 missing values generated)

. list deltainflhat if tin(2017q4,2018q1)
```

	deltain~t
252.	.1589877
253.	−.7205634

```
. // the last observation is the predicted inflation change
```

(c-iii) Use the $AR(2)$ model to predict change in inflation from 2017:Q4 to 2018:Q1 - that is, value of $\Delta Infl_{2018:Q1}$.

Change in U.S. Inflation Rate (%) with 1-period-ahead Forecasts
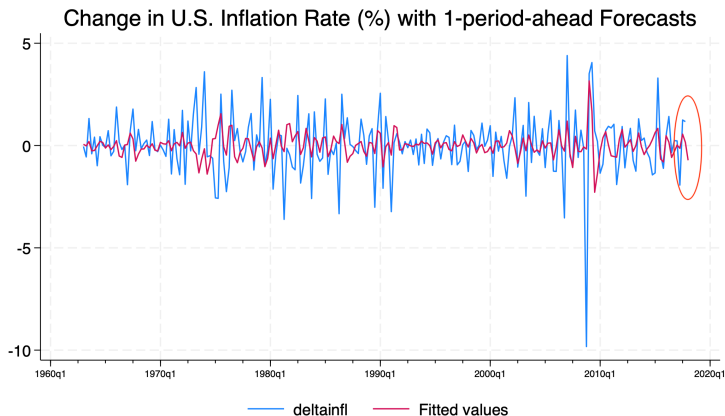
The predicted change in inflation from 2017Q4 to 2018Q1 is -0.72 (a drop).(»stata)

(d-i) Use the ADF test for $AR(p)$ regression using 2 lags of $\Delta Infl$ (so that $p = 3$ in the above equation) to test for a stochastic trend in $Infl$.

$$\Delta Y_t = \beta_0 + \delta Y_{t-1} + \gamma_1 \Delta Y_{t-1} + \ldots + \gamma_p \Delta Y_{t-p+1} + u_t$$

$$\Delta Infl_t = \beta_0 + \delta Infl_{t-1} + \gamma_1 \Delta Infl_{t-1} + \gamma_2 \Delta Infl_{t-2} + u_t$$

```
* dfuller yvar, lags(k) regress
// include 'k' lagged differences and display the regression table
```

. **dfuller infl if tin(1963q1,2017q4), lags(2) regress**

Augmented Dickey–Fuller test for unit root

Variable: **infl**   Number of obs = **220**
                                      Number of lags = **2**

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value		
		1%	5%	10%
Z(t)	**-2.740**	-3.470	-2.882	-2.572

MacKinnon approximate *p*–value for Z(t) = **0.0674**.

Regression table

D.infl	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
infl						
L1.	**-.1057272**	.0385888	-2.74	0.007	-.1817859	-.0296684
LD.	-.2543744	.0683361	-3.72	0.000	-.3890653	-.1196835
L2D.	-.2415464	.066275	-3.64	0.000	-.3721749	-.1109179
_cons	.3591525	.1582484	2.27	0.024	.0472437	.6710613

(d-i) Use the ADF test for $AR(p)$ regression using 2 lags of $\Delta Infl$ (so that $p = 3$ in the above equation) to test for a stochastic trend in $Infl$.

The ADF t-statistic is -2.74. The 10% critical vale is -2.57 and the 5% critical value of -2.88; thus the unit root null hypothesis can be rejected at the 10% but not the 5% significance level.

(d-ii) Is that ADF test based on the above regression preferred to the regression including a determinstic trend for testing for a stochastic trend in *Infl*?

$$\Delta Y_t = \beta_0 + \alpha t + \delta Y_{t-1} + \gamma_1 \Delta Y_{t-1} + \ldots + \gamma_p \Delta Y_{t-p+1} + u_t$$

$$\Delta Infl_t = \beta_0 + \alpha t + \delta Infl_{t-1} + \gamma_1 \Delta Infl_{t-1} + \gamma_2 \Delta Infl_{t-2} + u_t$$

```
* dfuller yvar, lags(k) trend regress
// include 'k' lagged differences and trend term
```

```
. * ADF on Infl with a deterministic trend
. dfuller infl if tin(1963q1,2017q4), lags(2) trend regress

Augmented Dickey–Fuller test for unit root

Variable: infl                          Number of obs  = 220
                                        Number of lags =   2

H0: Random walk with or without drift

                                        Dickey–Fuller
                      Test      ───────── critical value ─────────
                    statistic       1%          5%          10%
─────────────────────────────────────────────────────────────────
    Z(t)            −3.392        −4.000      −3.434      −3.134

MacKinnon approximate p-value for Z(t) = 0.0525.

Regression table

    D.infl │ Coefficient  Std. err.      t     P>|t|     [95% conf. interval]
───────────┼─────────────────────────────────────────────────────────────────
      infl │
       L1. │ −.1475798    .0435074    −3.39    0.001    −.2333354    −.0618242
       LD. │ −.2336542     .068611    −3.41    0.001    −.3688904    −.0984179
      L2D. │ −.2295046    .0660681    −3.47    0.001    −.3597287    −.0992806
           │
    _trend │ −.0033129    .0016318    −2.03    0.044    −.0065293    −.0000964
     _cons │  .8616621    .2931807     2.94    0.004     .2837856     1.439539

. // regress option to produce the regression results
. // trend option to include the linear trend in AR(p) regression
```

(d-ii) Is that ADF test based on the above regression preferred to the regression including a determinstic trend for testing for a stochastic trend in *Infl*?

⋄ Based on the t-statistic and the critical values, the results are similar to the previous regression.

⋄ The coefficient on trend is quite close to zero so the inflation rate does not exhibit a linear trend. Thus, the specification that includes an intercept, but no time trend is appropriate.

(d-iii) Based on the ADF tests carried out, does the AR model for *Infl* contain a unit root?

$$\widehat{\Delta Infl_t} = \underset{(se)}{.359} - \underset{(.158)}{.106} Infl_{t-1} - \underset{(.039)}{.254} \Delta Infl_{t-1} - \underset{(.068)}{.242} \Delta Infl_{t-2}$$

From the results in (d-i), it is clear that inflation contains a unit root, thereby being highly persistent. The null hypothesis that $\delta = 0$ or, equivalently, $\rho = 1.0$ cannot be rejected at the 5% significance level.

STATA CODES & RESULTS

Q(a-i,ii) (»back(a-i)) (»back(a-ii))

```
. * log() is the same as ln() in Stata
. gen logpce = log(PCECTPI)

. * using stata's first difference operator
. gen infl = 400*D.logpce
(1 missing value generated)

. * alternatively
. * gen infl = 400*(logpce[_n] - logpce[_n-1])




. * Plot 'infl' for defined time range
. twoway (tsline infl if tin(1963q1,2017q4), yline(0)), title(" U.S. Inflation Rate (%)") ///
>                                                       ytitle("") xtitle("") ///
>                                                       tlabel(#12, labsize(vsmall)) tmtick(##4)
```

Q(b-i,ii)

```
. * Create Delta Infl as first difference of inflation rate
. gen deltainfl = D.infl
(2 missing values generated)



. * Plot 'deltainfl' for defined time range
. twoway (tsline deltainfl if tin(1963q1,2017q4), yline(0)), title(" Change in U.S. Inflation Rate (%)") ///
>                                                            ytitle("") xtitle("") ///
>                                                            tlabel(#12, labsize(vsmall)) tmtick(##4)
```

Q(b-i)

```
*corrgram yvar [, lags(p)]
// limit the number of computed autocorrelations to p
```

```
. * autocorrelation
. //autocorrelations reported in column named AC
. corrgram deltainfl if tin(1963q1,2017q4), lags(4)
```

LAG	AC	PAC	Q	Prob>Q	-1 0 1 [Autocorrelation]	-1 0 1 [Partial autocor]
1	-0.2460	-0.2467	13.494	0.0002		
2	-0.2035	-0.2843	22.772	0.0000		
3	0.1362	0.0047	26.946	0.0000		
4	-0.0850	-0.1142	28.579	0.0000		

```
*ac yvar [, lags(p)]
// limit the number of computed autocorrelations to p
```

```
. * plot of autocorrelations with 95% confidence bands (optional)
. ac deltainfl if tin(1963q1,2017q4), lags(4)
```

Q(c-i) (»back(c-i))

```
*regress yvar L1.yvar [, robust]
```

```
. * AR(1) regression - OLS estimates
. * L. takes the lag
. //ldeltainfl = deltainfl[_n] - deltainfl[_n-1]
. regress deltainfl L1.deltainfl if tin(1963q1,2017q4), robust
```

Linear regression

				Number of obs	=	220
				F(1, 218)	=	13.03
				Prob > F	=	0.0004
				R-squared	=	0.0607
				Root MSE	=	1.4383

deltainfl	Coefficient	Robust std. err.	t	P>|t|	[95% conf. interval]
deltainfl L1.	-.2466842	.0683325	-3.61	0.000	-.3813611 -.1120074
_cons	.0073719	.0969709	0.08	0.939	-.1837485 .1984923

Q(c-ii) (»back(c-ii))

```
*regress yvar L1.yvar L2.yvar [, robust]
```

```
. * AR(2) regression
. regress deltainfl L1.deltainfl L2.deltainfl if tin(1963q1,2017q4), robust

Linear regression                              Number of obs   =       220
                                               F(2, 217)       =     13.98
                                               Prob > F        =    0.0000
                                               R-squared       =    0.1361
                                               Root MSE        =    1.3826
```

deltainfl	Coefficient	Robust std. err.	t	P>|t|	[95% conf. interval]	
deltainfl						
L1.	-.3177357	.0644048	-4.93	0.000	-.4446747	-.1907966
L2.	-.2844172	.0763383	-3.73	0.000	-.4348766	-.1339578
_cons	.0060757	.0932463	0.07	0.948	-.1777087	.18986

```
. display e(r2_a) // Adjusted R-squared
.12810942
```

Q(c-iii-I)

```
. * Forecasting 1 period ahead deltainflation
. * add the extra period2 (next quarter)
. tsappend, add(1)

. * estimate AR(2)
. quiet regress deltainfl L.deltainfl L2.deltainfl if tin(1963q1,2017q4), r

. * predict for next quarter
. predict deltainflhat
(option xb assumed; fitted values)
(4 missing values generated)

. list deltainflhat if tin(2017q4,2018q1)
```

	deltain~t
252.	.1589877
253.	-.7205634

```
. // the last observation is the predicted inflation change
```

```
. * plot change in inflation vs predicted change
. twoway (tsline deltainfl) (tsline deltainflhat) if tin(1963q1,2018q1), ///
>         ytitle("") xtitle("") ///
>         tlabel(#8, labsize(vsmall)) tmtick(##4) ///
>         legend(pos(6) cols(2)) ///
>         title("Change in U.S. Inflation Rate (%) with 1-period-ahead Forecasts")
```

Q(d-i) (»back(d-i))

```
. dfuller infl if tin(1963q1,2017q4), lags(2) regress

Augmented Dickey-Fuller test for unit root

Variable: infl                          Number of obs  = 220
                                        Number of lags =   2

H0: Random walk without drift, d = 0
```

	Test statistic	Dickey–Fuller critical value		
		1%	5%	10%
Z(t)	−2.740	−3.470	−2.882	−2.572

MacKinnon approximate *p*-value for Z(t) = 0.0674.

Regression table

D.infl	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
infl						
L1.	−.1057272	.0385888	−2.74	0.007	−.1817859	−.0296684
LD.	−.2543744	.0683361	−3.72	0.000	−.3890653	−.1196835
L2D.	−.2415464	.066275	−3.64	0.000	−.3721749	−.1109179
_cons	.3591525	.1582484	2.27	0.024	.0472437	.6710613

Q(d-ii) (»back(d-ii))

```
. * ADF on Infl with a deterministic trend
. dfuller infl if tin(1963q1,2017q4), lags(2) trend regress

Augmented Dickey–Fuller test for unit root

Variable: infl                          Number of obs  = 220
                                        Number of lags =   2

H0: Random walk with or without drift

                              Dickey–Fuller
              Test     ———— critical value ————
           statistic      1%          5%          10%

   Z(t)      −3.392      −4.000      −3.434      −3.134

MacKinnon approximate p-value for Z(t) = 0.0525.

Regression table

     D.infl │ Coefficient  Std. err.      t    P>|t|     [95% conf. interval]

     infl
      L1. │  −.1475798    .0435074    −3.39   0.001    −.2333354   −.0618242
      LD. │  −.2336542    .068611     −3.41   0.001    −.3688904   −.0984179
     L2D. │  −.2295046    .0660681    −3.47   0.001    −.3597287   −.0992806

   _trend │  −.0033129    .0016318    −2.03   0.044    −.0065293   −.0000964
    _cons │   .8616621    .2931807     2.94   0.004     .2837856   1.439539

. // regress option to produce the regression results
. // trend option to include the linear trend in AR(p) regression
```