Lecture 16. Autocorrelation

In which you learn to recognise whether the residuals from your model are correlated over time, the consequences of this for OLS estimation, how to test for autocorrelation and possible solutions to the problem

Given the model

$$Y_t = b_0 + b_1X_t + u_t$$

Think of autocorrelation as signifying a systematic relationship between the residuals measured at different points in time

This could be caused by inertia in economic variables (multiplier working through), incorrect functional form or data interpolation/revision

The effect is that $Cov(u_t\ u_{t-1}) \neq 0$

A simple model of this systematic relationship would be

$$u_t = \rho u_{t-1} + e_t \qquad -1 <= \rho <= 1 \qquad (1)$$

so the current value of the residual is related to last period's value together with a current period random component e_t

This is called an AR(1) process = Auto-regressive of order 1
(a regression of the variable on itself lagged by 1 period)

If $\rho=0$ then residuals are not autocorrelated

If $\rho>0$ then residuals are positively autocorrelated
(+ve residuals tend to be followed by +ve residuals and –ve by –ve)

If $\rho<0$ then residuals are negatively autocorrelated
(+ve residuals tend to be followed by -ve residuals and –ve by +ve)

Does it matter?

We know OLS estimation gives

$$\hat{\beta} = \frac{Cov(X,y)}{Var(X)} = \beta + \frac{Cov(X,u)}{Var(X)}$$

but autocorrelation does not affect the assumption that Cov(X,u)=0 so OLS remains unbiased in the presence of autocorrelation

However, can show that variance of the estimate of b in presence of autocorrelation is

$$Var(\hat{\beta}^{OLS}_{autocorr}) = Var\left(\frac{Cov(X,y\ )}{Var(X)}\right) = Var\left(\beta + \frac{Cov(X,u)}{Var(X)}\right)$$

$$= \frac{\sigma_u^2}{N*Var(X)} + 2\frac{\sigma_u^2}{(N*Var(X))^2}\sum_{t=1}^{T-1}\sum_{j=1}^{T-t}\rho^j X_t X_{t+j} = Var(b^{OLS}{}_{noauto}) + 2f(\rho)$$

where

j and t are just different time periods within the period covered by the sample
t = 1, 2…T time periods

ρ is the coefficient on the lag of the residual in model (1)

and f(ρ) is some function that depends on the value of ρ

So If $\rho \neq 0$ then can see Var($b_{Autocorrelated}^{ols}$) $\neq$ Var(b^{ols}_{noauto})

and if $\rho > 0$
(ie positive autocorrelation, which is the most common form of autocorrelation)

then Var($b_{Autocorrelated}^{ols}$) > Var(b^{ols}_{noauto})

but Var(b^{ols}_{noauto})= σ^2_u/N*Var(X) is what the computer calculates not Var($b_{Autocorrelated}^{ols}$),

so in general OLS will ***underestimate*** the true variance
so the t values on the OLS estimates will be ***larger*** than should be
so might conclude variables are statistically significant when they are not (type I error)

Testing for Autocorrelation

Given time series data

$$Y_t = b_0 + b_1X_t + u_t \qquad\qquad t = 1, 2\ldots T \quad (1)$$

the model may be subject to autocorrelation

Accepted way of testing is to specify a functional form for the persistence (correlation) in the residuals over time and test to see whether this specification is statistically valid.

Most common specification is as used above, namely the 1st Order Autoregressive process AR(1)

$$u_t = \rho u_{t-1} + e_t \qquad\qquad -1 <= \rho <= 1 \quad (2)$$

So movement in current value of residuals is related to last period’s value and a current period random component (e_t)

Good practice to test by simply plotting the residuals over time and looking at the pattern.
+ve autocorrelation means +ve residual values are followed by +ve values
(and –ve by –ve)

-ve autocorrelation means +ve residual values are followed by -ve values (and –ve by +ve)

Good practice also to use the **standardised residuals** when do this

$$u_{standardised} = \frac{\hat{u}_t}{s}$$

ie residuals made scale invariant by dividing through by the standard error of the equation,

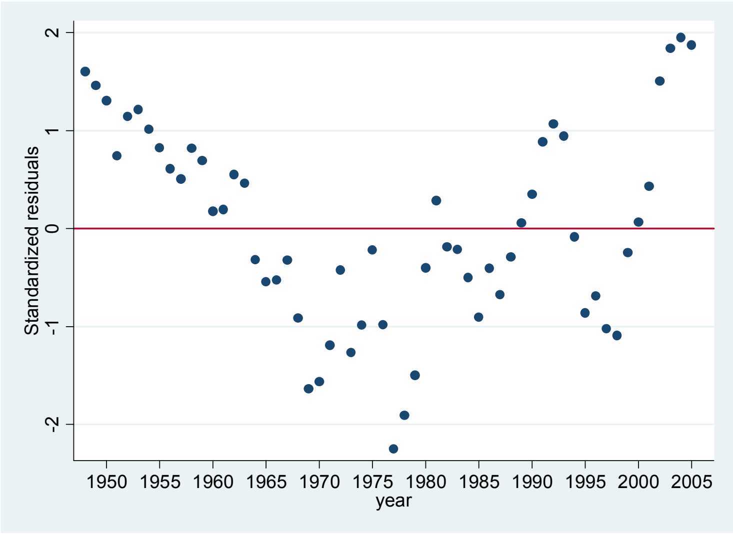
$$s = \sqrt{RSS / T - k}$$

(scale invariance means can compare across different specifications using different units of measurement)

```
. reg cons inc
      Source |       SS       df       MS              Number of obs =      58
-------------+------------------------------           F(  1,    56) =16998.53
       Model |  2.5426e+12     1  2.5426e+12           Prob > F      =  0.0000
    Residual |  8.3762e+09    56   149575459           R-squared     =  0.9967
-------------+------------------------------           Adj R-squared =  0.9967
       Total |  2.5509e+12    57  4.4753e+10           Root MSE      =   12230
------------------------------------------------------------------------------
 consumption |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      income |   .8447215    .006479   130.38   0.000     .8317425    .8577005
       _cons |  -2376.815   4398.976    -0.54   0.591    -11189.02    6435.394
------------------------------------------------------------------------------
```

Do graphical inspection using **standardised residuals** ie divide residuals by standard error of regression, s, (given by Root MSE in Stata output above)

```
. predict stanres, rstandard        /* command to get standardised residuals */
two (scatter stanres year, yline(0) xlabel(1950(5)2006) )
```



Standardised residuals confirm general (positive) autocorrelation pattern in residuals as before. Only difference is values on y axis have changed (since are now scale invariant)

However this is useful but not a formal test for the problem.

One common statistical for presence of AR(1) in the residuals is to compute **Durbin-Watson** statistic

$$DW = \frac{\sum_{t=2}^{T}(\hat{u}_t - \hat{u}_{t-1})^2}{\sum_{t=1}^{T}\hat{u}_t^2}$$

where u_t are residuals saved from from OLS estimation of (1)

Can show that DW =2(1- $\hat{\rho}$), where $\hat{\rho}$ is taken from an OLS regression of (2) using estimated residuals from (1)

Given DW = 2(1- $\hat{\rho}$)

if $\hat{\rho}$ = 0 then DW = 2 and residuals are not autocorrelated

if $\hat{\rho} \rightarrow 1$ then DW $\rightarrow$ 0 and $\exists$ +ve autocorrelation

if $\hat{\rho} \rightarrow -1$ then DW $\rightarrow$ 4 and $\exists$ -ve autocorrelation

So how close to 2 does DW have to be before we can be confident of accepting null hypothesis of no autocorrelation?

Turns out that there are 2 critical values than need to compare estimated DW against: an "upper" value and a "lower" value

Reject Null. Accept that there is +ve A/C.	Test inconclusive	Accept Null (No autocorrelation)		Test inconclusive	Reject Null Accept there is –ve A/C.
0	DW_{low}	DW_{upper}	2	$4\text{-}DW_{upper}$	$4\text{-}DW_{low}$

So

if $DW < DW_{lower}$	conclude $\exists$ +ve autocorrelation
if $DW_{upper} < DW < 4\text{-}DW_{upper}$	residuals are not autocorrelated
if $DW_{lower} < DW < DW_{upper}$	test is inconclusive

Note: Unfortunately the critical values vary with sample size and number of RHS variables **excluding the constant**

```
/* Example: DETECTION OF AUTOCORRELATION */

. tsset year
        time variable:  year, 1948 to 2005

. regdw cons income

      Source |       SS       df       MS              Number of obs =      58
-------------+------------------------------           F(  1,    56) =16998.53
       Model |  2.5426e+12     1  2.5426e+12           Prob > F      =  0.0000
    Residual |  8.3762e+09    56   149575459           R-squared     =  0.9967
-------------+------------------------------           Adj R-squared =  0.9967
       Total |  2.5509e+12    57  4.4753e+10           Root MSE      =   12230
------------------------------------------------------------------------------
 consumption |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      income |   .8447215    .006479   130.38   0.000     .8317425    .8577005
       _cons |  -2376.815   4398.976    -0.54   0.591    -11189.02    6435.394
------------------------------------------------------------------------------

Durbin-Watson Statistic =  .2516256
From Tables, given T=58 and K'=1, DW_low = 1.55 and DW_high = 1.62
(k'=no. rhs variables excluding the constant)

So estimated value is less than DWlow. Hence reject null of no autocorrelation.
Accept there exists positive 1st order autocorrelation.
```

Problems with Durbin-Watson

1. The existence of an inconclusive region often reduces the usefulness of this test

2. Can show DW not valid in the presence of **lagged dependent variables or endogenous variables**

$$Y_t = b_0 + \lambda Y_{t-1} + b_1 X_t + u_t \qquad (3)$$

If there are lagged dependent variables it is possible to use Durbin's h test

$$h = \hat{\rho}\sqrt{\frac{T}{1 - TVar(\hat{\lambda})}}$$

where T = sample size (number of time periods) and var(λ) is the estimated variance of the coefficient on the lagged dependent variable from an OLS estimation of (3)

Can show that under null hypothesis of no +ve autocorrelation

$$h \sim Normal(0,1)$$

So that Pr[-1.96<= h <=1.96] = 0.95

ie 95% chance that value of h will lie between –1.96 and + 1.96

In this case if estimated h>1.96 then can reject null of no +ve autocorrelation

But: can't compute h if

$$1 - TVar(\hat{\lambda}) < 0$$

which could happen

So need alternative measure which can always be calculated.

Breusch-Godfrey Test for AR(q)

This is in fact a general test for autocorrelation of **any** order (ie residuals may be correlated over more than one period)

$$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \rho_3 u_{t-3} + \ldots \rho_q u_{t-q} + e_t$$

Eg quarterly data are often correlated with values 4 periods ago (ie 1 year)
So test for no autocorrelation of order q amounts to test

$$H0: \rho_1 = \rho_2 = \rho_3 = \ldots \rho_q = 0$$

Do this as follows:

1. Estimate original model

$$Y_t = b_0 + b_1 X_t + u_t$$

Save residuals

2. Regress estimated residuals on lagged values up to lag q **and** all the original RHS X variables

$$\hat{u}_t = \rho_1 \hat{u}_{t-1} + \rho_2 \hat{u}_{t-2} + \ldots \rho_q \hat{u}_{t-1} + \gamma_1 X_t + e_t$$

3. Either compute the F test for the joint significance of the residuals

$$\hat{u}_{t-1} \ldots \hat{u}_{t-q}$$

and if $\hat{F}$ > $F_{critical}$ **reject** null of no q order autocorrelation

or

compute $(N-q)*R^2_{auxillary} \sim \chi^2_{(q)}$

if estimated $\chi^2 > \chi^2_{critical}$ again reject null of no q order A/c.
(intuitively if lagged residuals are significant this gives a high R^2)

Useful test since

a) generalises to any order autocorrelation wish to test
b) is robust to inclusion of lagged dep. variables

But

1. Since this is a test of joint significance may not be able to distinguish which lagged residual is important
2. Test is only valid asymptotically (ie in large samples)

Example: Breusch-Godfrey Test For Autocorrelation

```
. reg cons income
      Source |       SS       df       MS              Number of obs =      61
-------------+------------------------------           F(  1,    59) =24523.30
       Model |  3.8562e+12     1  3.8562e+12           Prob > F      =  0.0000
    Residual |  9.2775e+09    59   157245264           R-squared     =  0.9976
-------------+------------------------------           Adj R-squared =  0.9976
       Total |  3.8655e+12    60  6.4424e+10           Root MSE      =   12540
------------------------------------------------------------------------------
        cons |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      income |   .8474867   .0054118   156.60   0.000     .8366576    .8583157
       _cons |  -1849.363   4109.675    -0.45   0.654     -10072.8    6374.078
------------------------------------------------------------------------------
```

Now save residuals and lag them

```
. predict res, resid

. sort year
g res1=l.res                  /* creates u(t-1) residual lagged 1 periods  */
(1 missing value generated)
. g res2=l2.res
(2 missing values generated)
. g res3=l3.res
(3 missing values generated)
. g res4=l4.res
(4 missing values generated)
. g res4=res[_n-4]            /* creates u(t-4) residual lagged 4 periods  */
(4 missing values generated)

/* note number of missing values, since u(t-1) does not exist for 1st observation
in data set (no information before 1955)... u(t-4) does not exist for first 4
observations in data set */
```

```
/* Now do Breusch-Godfrey test for residuals of AR(1) manually */
. reg res res1

      Source |       SS       df       MS              Number of obs =      60
-------------+------------------------------           F(  1,    58) =  153.91
       Model |  6.4416e+09     1  6.4416e+09           Prob > F      =  0.0000
    Residual |  2.4275e+09    58  41853993.6           R-squared     =  0.7263
-------------+------------------------------           Adj R-squared =  0.7216
       Total |  8.8691e+09    59   150324349           Root MSE      =  6469.5

------------------------------------------------------------------------------
         res |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        res1 |   .8392392   .0676483    12.41   0.000     .7038264    .9746521
       _cons |  -174.8461    835.303    -0.21   0.835    -1846.887    1497.195
------------------------------------------------------------------------------
```

Regress residuals from original regression on residual lagged one period and original rhs variables (doesn't matter if include constant or not – results the same asymptotically)

Given the output from this auxiliary regression compute $(N\text{-}q)^*R^2_{aux}$ = (60)*.7263= 42.9

(Note N-q = number of observations in auxiliary regression)

This statistic has a chi-squared distribution with 1 degree of freedom (equal to the number of lags tested)

From tables $\chi^2_{critical}$ at 5% level = 3.84

So estimated $\chi^2 > \chi^2_{critical}$, so **reject** null that residuals are **uncorrelated** over one year to the next.

```
For test of AR(4)

. reg res res1 res2 res3 res4
      Source |       SS       df       MS              Number of obs =      57
-------------+------------------------------           F(  4,    52) =   37.67
       Model |  6.0494e+09     4  1.5123e+09           Prob > F      =  0.0000
    Residual |  2.0878e+09    52    40150026           R-squared     =  0.7434
-------------+------------------------------           Adj R-squared =  0.7237
       Total |  8.1372e+09    56   145307141           Root MSE      =  6336.4
------------------------------------------------------------------------------
         res |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        res1 |   1.169038   .1404633     8.32   0.000     .8871782    1.450899
        res2 |  -.5828606   .2130979    -2.74   0.009    -1.010473   -.1552484
        res3 |   .3841644    .215656     1.78   0.081    -.0485811    .8169099
        res4 |  -.1542909   .1443235    -1.07   0.290    -.4438971    .1353153
       _cons |  -132.8521   843.6854    -0.16   0.875    -1825.831    1560.127
------------------------------------------------------------------------------
```

and $(N\text{-}q)^*R^2_{aux}$ = 57*.7473 = 42.6

This statistic has a chi-squared distribution with 4 degree of freedom (equal to the number of lags tested)

From tables $\chi^2_{critical\ (4)}$ at 5% level = 9.5

So estimated $\chi^2 > \chi^2_{critical}$, so again **reject** null that residuals are **not correlated** over 4 year periods (even though last two residuals are not individually significant). Hence a joint test can obscure individual significance.

```
/* Stata will do this automatically */
bgtest
Breusch-Godfrey LM statistic:  43.83968  Chi-sq( 1)  P-value =  3.6e-11

. bgtest, lag(4)
Breusch-Godfrey LM statistic:  42.56371  Chi-sq( 4)  P-value =  1.3e-08
```

Remember the test is a test of the **joint** significance of the residuals, so it may not be able to pinpoint the exact lag structure. In the example above, inspection of the t statistics on each lagged residual in the auxiliary regression suggests that the 1^{st} and 2^{nd} order residuals are doing all the work, so that a test for AR(2) would seem more appropriate.

With monthly data may wish to test up to AR(12) – observations one year ago may influence current value, particularly if there is a seasonal pattern to the data, (try using the data set bop.dta to test this)

Similarly with quarterly data may wish to test for AR(4)

What to do about autocorrelation?

1. If tests show it exists then try a different functional form, add/delete variables, increase the interval between observations (eg monthly to quarterly)

Example: Model Misspecification

Sometimes autocorrelation in residuals can be caused by incorrect functional form in your model or (effectively the same thing) the omission of relevant variables

The data set *gdp.dta* contains quarterly time series data on US GDP growth and inflation over the period 1956:q1 to 2002:q4

A simple regression of inflation rate on 1-period lagged growth rate of GDP gives
(using lagged growth to try and deal with possible endogeneity concerns)

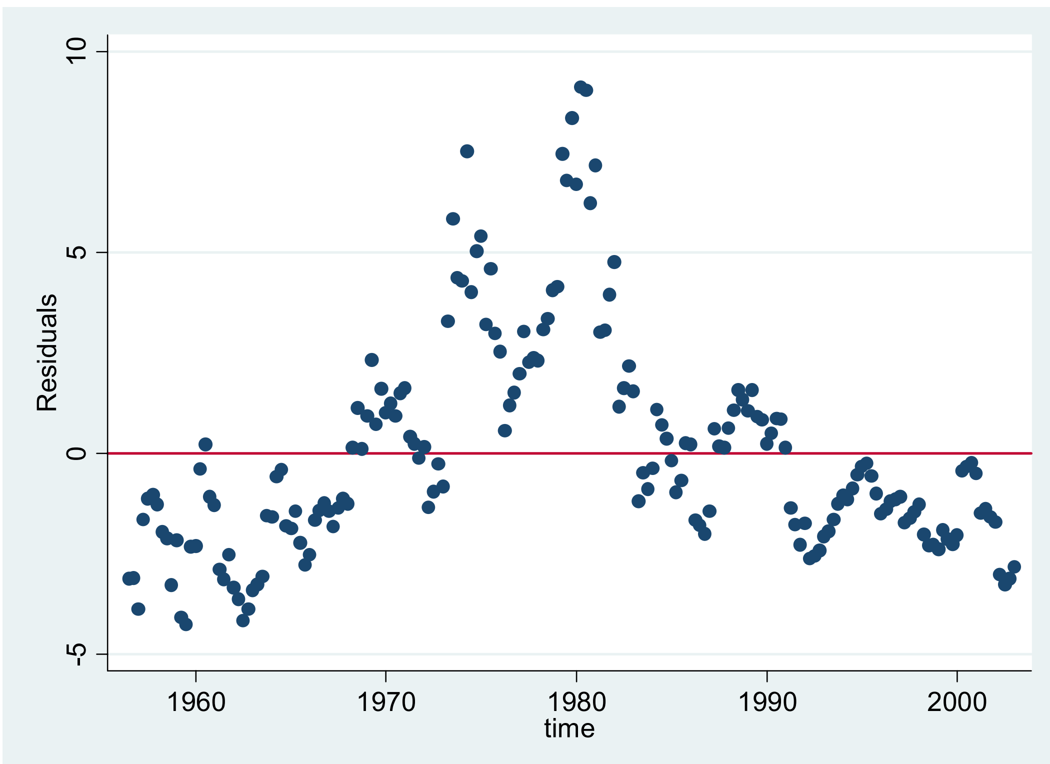
```
. tsset TIME
        time variable:  TIME, 1 to 188

. reg  usinf DG
      Source |       SS       df       MS              Number of obs =     187
-------------+------------------------------           F(  1,   185) =   13.98
       Model |  110.148815     1  110.148815           Prob > F      =  0.0002
    Residual |  1457.20779   185  7.87679889           R-squared     =  0.0703
-------------+------------------------------           Adj R-squared =  0.0653
       Total |  1567.35661   186  8.42664844           Root MSE      =  2.8066
------------------------------------------------------------------------------
       usinf |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          DG |  -.7576151   .2025973    -3.74   0.000    -1.157313    -.357917
       _cons |   4.650681   .2398357    19.39   0.000     4.177516    5.123845

. bgtest
Breusch-Godfrey LM statistic:  157.9169  Chi-sq( 1)  P-value =  3.2e-36
```

and a graph of the residuals also shows them to be (positively) autocorrelated

```
predict res, resid
two (scatter res time, yline(0) )
```



Now suppose decide to include the 1 period lag of inflation rate on the right hand side

```
. reg  usinf DG l.usinf
      Source |       SS       df       MS              Number of obs =     187
-------------+------------------------------           F(  2,   184) =  994.55
       Model |  1434.64607     2  717.323035           Prob > F      =  0.0000
    Residual |  132.710539   184  .721252931           R-squared     =  0.9153
-------------+------------------------------           Adj R-squared =  0.9144
       Total |  1567.35661   186  8.42664844           Root MSE      =  .84927

------------------------------------------------------------------------------
       usinf |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          DG |  -.0653697   .0633985    -1.03   0.304    -.1904512    .0597117
       usinf |
         L1. |   .9504842   .0221801    42.85   0.000     .9067242    .9942442
       _cons |   .2478525   .1257897     1.97   0.050    -.0003231     .496028
------------------------------------------------------------------------------

. bgtest
Breusch-Godfrey LM statistic:  .2578382  Chi-sq( 1)  P-value =  .6116
```

Now the pattern of autocorrelation seems to have become much less noticeable in the new specification compared to the original, (though there still may be endogeneity bias in the OLS estimates of the coefficients)

2. Can, in principle, manipulate the data to remove autocorrelation from the residuals.

Suppose you had

$$Y_t = b_0 + b_1X_t + u_t \qquad (1)$$

and **assumed** AR(1) behaviour in the residuals

$$u_t = \rho u_{t-1} + e_t \qquad (2)$$

(1) $\Rightarrow$ $Y_{t-1} = b_0 + b_1X_{t-1} + u_{t-1}$ (3)

(ie relationship holds in any time period)

Multiplying (3) by ρ

$$\rho Y_{t-1} = \rho b_0 + \rho b_1X_{t-1} + \rho u_{t-1} \qquad (4)$$

(1) – (4)

$$Y_t-\rho Y_{t-1} = b_0 -\rho b_0 + b_1X_t -\rho b_1X_{t-1} + u_t-\rho u_{t-1}$$

or

$$Y_t = b_0 -\rho b_0 + \rho Y_{t-1} + b_1X_t -\rho b_1X_{t-1} + u_t-\rho u_{t-1}$$

or

$$Y_t = (b_0 -\rho b_0) + \rho Y_{t-1} + b_1X_t -\rho b_1X_{t-1} + e_t \qquad (5)$$

$$Y_t - \rho Y_{t-1} = (b_0 -\rho b_0) + b_1(Xt -\rho X_{t-1}) + e_t \qquad (6)$$

Since $e_t = u_t - \rho u_{t-1}$ from (2), then if estimate (5) by OLS there should be no autocorrelation.

This is called Feasible Generalised Least Squares (FGLS)

Ok **if** assumption (2) is correct. If not may make things worse.

Also if the X variables are endogenous then this technique is not valid

Note to get the coefficient on the original constant b_0 from (6) need an estimate of ρ

3. If don't know exact form of autocorrelation (highly likely) it may be preferable to fix up the OLS standard errors so they are no longer biased but remain inefficient - in the sense that if you knew the precise form of autocorrelation you could write down the exact formula for the standard errors

Newey-West standard errors do this and are valid in presence of lagged dependent variables **if** have large sample (ie fix-up is only valid asymptotically though it has been used on sample sizes of around 50).

In absence of autocorrelation we know OLS estimate of variance on any coefficient is

$$Var(\hat{\beta}_{ols}) = \frac{s^2{}_u}{N * Var(X)}$$

In presence of autocorrelation, can show the Newey-West standard errors (unbiased but inefficient) are

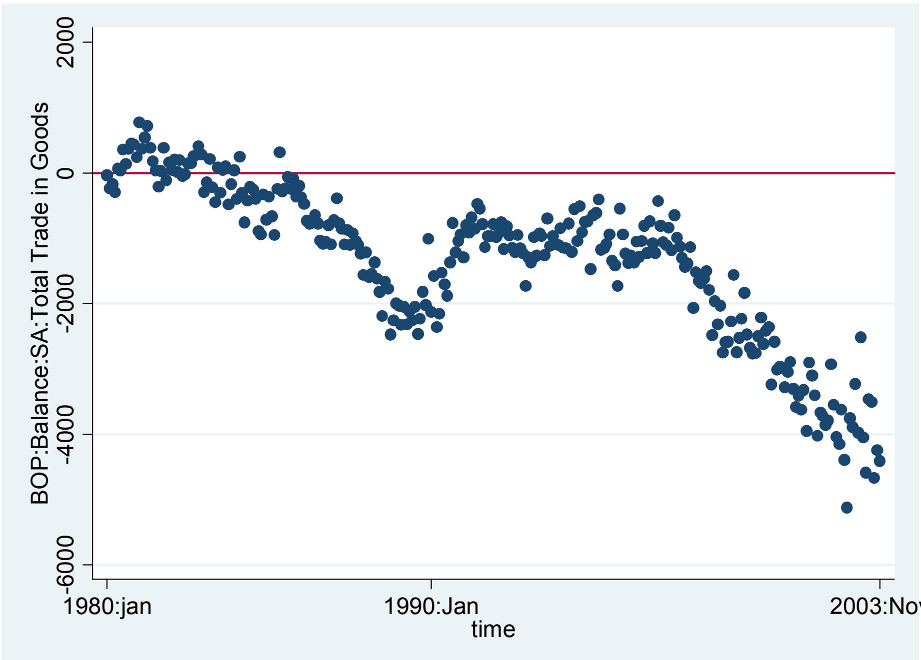
$$Var(\hat{\beta}_{ols}) = \frac{Var(\hat{\beta}_{ols})}{s_u} * v$$

where v is a (complicated) function of the maximum number of lags you believe could be correlated with current residuals (in annual data 1 or 2 lags should be enough)

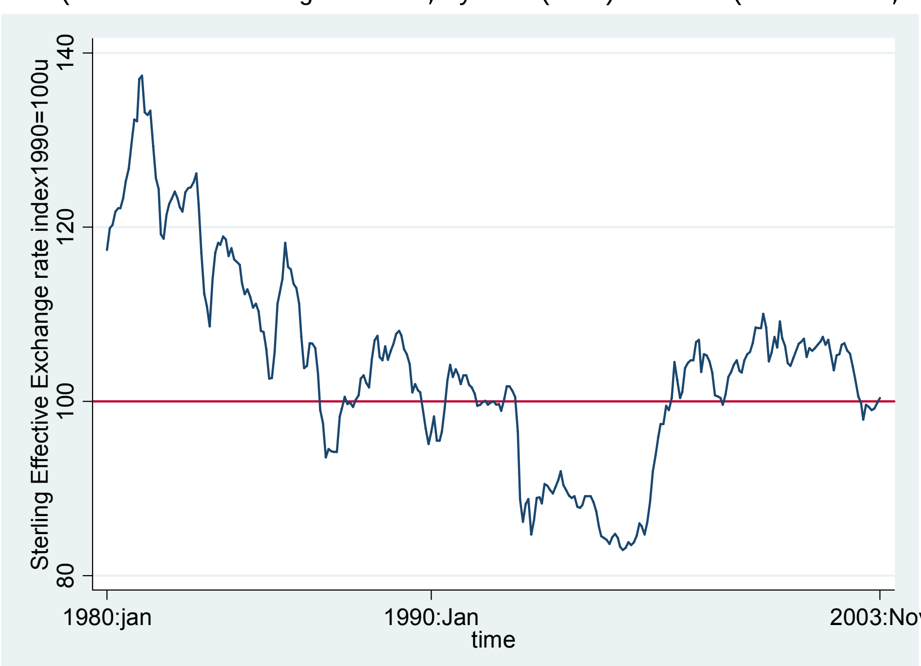
Example

The data set *bop.dta* contains monthly time series data on the UK Balance of Trade in goods (measured in £billion) and the effective exchange rate – a weighted average of sterling's value against a basket of foreign currencies which is centred on the value 100 in January 1990. A value above zero indicates the Balance of Trade is in surplus, a value below zero indicates a deficit. A value > 100 indicates sterling has appreciated, a value<100 indicates that sterling has depreciated

```
two (scatter bop time, yline(0) xlabel(1 121 287, value) )
```




```
two (scatter  xchanger time, yline(100) xlabel(1 121 287, value) )
```



Can see that over time the balance of trade has deteriorated, whilst the value of sterling has generally been high over the same period

To see if the 2 events are related, run a simple regression of the trade balance on sterling's value (lagged by one month to reduce endogeneity concerns)

```
. u bop                             /* read data in */

tsset time                    /* declare data is time series */
        time variable:  time, 1 to 287
                delta:  1 unit
. sort time
. g xchange1=xchange[_n-1]          /* set up 1 period lag of exchange rate */

. reg bop xchange1
      Source |       SS       df       MS              Number of obs =     286
-------------+------------------------------           F(  1,   284) =   28.08
       Model |  37414954.7     1  37414954.7           Prob > F      =  0.0000
    Residual |   378396350   284  1332381.51           R-squared     =  0.0900
-------------+------------------------------           Adj R-squared =  0.0868
       Total |   415811305   285  1458987.03           Root MSE      =  1154.3
------------------------------------------------------------------------------
         bop |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    xchange1 |   31.56233   5.956083     5.30   0.000     19.83866      43.286
       _cons |  -4646.285   623.5585    -7.45   0.000    -5873.667   -3418.902
```

regressions suggests a high exchange rate is positively correlated with the trade balance

Check for 1st and 12th order autocorrelation (this is monthly data so residuals could be related to last month's value and/or previous 12 month's value)

```
. bgtest,lags(1)
Breusch-Godfrey LM statistic:  249.0974  Chi-sq( 1)  P-value =  4.1e-56

. bgtest,lags(12)
Breusch-Godfrey LM statistic:  250.9979  Chi-sq(12)  P-value =  8.5e-47
```

Results suggest presence of both types of autocorrelation

To fix up standard errors using newey west procedure

```
. newey bop xchange1, lag(1)
Regression with Newey-West standard errors          Number of obs  =       286
maximum lag : 1                                     F(  1,   284)  =     23.81
                                                    Prob > F       =    0.0000
------------------------------------------------------------------------------
             |             Newey-West
         bop |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    xchange1 |   31.56233   6.468508     4.88   0.000     18.83003    44.29463
       _cons |  -4646.285   674.1623    -6.89   0.000    -5973.274   -3319.296
```

and to allow for an AR(12) process

```
. newey bop xchange1, lag(12)
Regression with Newey-West standard errors          Number of obs  =       286
maximum lag : 12                                    F(  1,   284)  =      4.23
                                                    Prob > F       =    0.0406
------------------------------------------------------------------------------
             |             Newey-West
         bop |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    xchange1 |   31.56233   15.34144     2.06   0.041     1.364981    61.75968
       _cons |  -4646.285   1593.395    -2.92   0.004    -7782.646   -1509.923
```

Note the coefficients are unchanged but the standard errors are different, (uncorrected OLS t statistics much larger as expected, particularly when compared to the model that allows for autocorrelation of up to 12 lags)

Note also that this test is robust to the inclusion of lagged dependent variables (and potentially endogenous regressors) whilst the FGLS procedure is not.

However, the Newey-West technique is only valid asymptotically. In small samples the results could be misleading.

How can fix up by specifying number of lags, if test is supposed to account for unknown form of autocorrelation? - can be shown that Newey-West test works for unknown forms of autocorrelation as long as number of lags is allowed to rise with number of observations/type of data (monthly, daily etc)