Postestimation commands

The following postestimation commands for time series are available for `regress`:

Command	Description
estat archlm	test for ARCH effects in the residuals
estat bgodfrey	Breusch–Godfrey test for higher-order serial correlation
estat durbinalt	Durbin's alternative test for serial correlation
estat dwatson	Durbin–Watson d statistic to test for first-order serial correlation
estat sbcusum	perform cumulative sum test for parameter stability
estat sbknown	perform tests for a structural break with a known break date
estat sbsingle	perform tests for a structural break with an unknown break date

These commands provide regression diagnostic tools specific to time series. You must `tsset` your data before using these commands; see [TS] **tsset**.

estat archlm

Description for estat archlm

`estat archlm` performs Engle's Lagrange multiplier (LM) test for the presence of autoregressive conditional heteroskedasticity.

Menu for estat

Statistics > Postestimation

Syntax for estat archlm

estat archlm [, *archlm_options*]

archlm_options	Description
<u>lags</u>(*numlist*)	test *numlist* lag orders
force	allow test after `regress, vce(robust)`

`collect` is allowed; see [U] **11.1.10 Prefix commands**.

Options for estat archlm

lags(*numlist*) specifies a list of numbers, indicating the lag orders to be tested. The test will be performed separately for each order. The default is order one.

force allows the test to be run after regress, vce(robust). The command will not work if the vce(cluster *clustvar*) option is specified with regress; see [R] **regress**.

estat bgodfrey

Description for estat bgodfrey

estat bgodfrey performs the Breusch–Godfrey test for higher-order serial correlation in the disturbance. This test does not require that all the regressors be strictly exogenous.

Menu for estat

Statistics > Postestimation

Syntax for estat bgodfrey

estat <u>bgodfrey</u> [, *bgodfrey_options*]

bgodfrey_options	Description
<u>lags</u>(*numlist*)	test *numlist* lag orders
<u>nomiss0</u>	do not use Davidson and MacKinnon's approach
<u>small</u>	obtain p-values using the F or t distribution

collect is allowed; see [U] **11.1.10 Prefix commands**.

Options for estat bgodfrey

lags(*numlist*) specifies a list of numbers, indicating the lag orders to be tested. The test will be performed separately for each order. The default is order one.

nomiss0 specifies that Davidson and MacKinnon's approach (1993, 358), which replaces the missing values in the initial observations on the lagged residuals in the auxiliary regression with zeros, not be used.

small specifies that the p-values of the test statistics be obtained using the F or t distribution instead of the default χ^2 or normal distribution.

estat durbinalt

Description for estat durbinalt

estat durbinalt performs Durbin's alternative test for serial correlation in the disturbance. This test does not require that all the regressors be strictly exogenous.

Menu for estat

Statistics > Postestimation

Syntax for estat durbinalt

estat <u>dur</u>binalt [, *durbinalt_options*]

durbinalt_options	Description
<u>lags</u>(*numlist*)	test *numlist* lag orders
<u>nomiss0</u>	do not use Davidson and MacKinnon's approach
robust	compute standard errors using the robust/sandwich estimator
<u>small</u>	obtain *p*-values using the *F* or *t* distribution
force	allow test after regress, vce(robust) or after newey

collect is allowed; see **[U] 11.1.10 Prefix commands**.

Options for estat durbinalt

lags(*numlist*) specifies a list of numbers, indicating the lag orders to be tested. The test will be performed separately for each order. The default is order one.

nomiss0 specifies that Davidson and MacKinnon's approach (1993, 358), which replaces the missing values in the initial observations on the lagged residuals in the auxiliary regression with zeros, not be used.

robust specifies that the Huber/White/sandwich robust estimator for the variance–covariance matrix be used in Durbin's alternative test.

small specifies that the *p*-values of the test statistics be obtained using the *F* or *t* distribution instead of the default χ^2 or normal distribution. This option may not be specified with robust, which always uses an *F* or a *t* distribution.

force allows the test to be run after regress, vce(robust) and after newey (see [R] **regress** and [TS] **newey**). The command will not work if the vce(cluster *clustvar*) option is specified with regress.

estat dwatson

Description for estat dwatson

estat dwatson computes the Durbin–Watson d statistic (Durbin and Watson 1950) to test for first-order serial correlation in the disturbance when all the regressors are strictly exogenous.

Menu for estat

Statistics > Postestimation

Syntax for estat dwatson

estat <u>dwat</u>son

collect is allowed; see [U] **11.1.10 Prefix commands**.

Remarks and examples

The Durbin–Watson test is used to determine whether the error term in a linear regression model follows an AR(1) process. For the linear model

$$y_t = \mathbf{x}_t \boldsymbol{\beta} + u_t$$

the AR(1) process can be written as

$$u_t = \rho u_{t-1} + \epsilon_t$$

In general, an AR(1) process requires only that ϵ_t be independent and identically distributed (i.i.d.). The Durbin–Watson test, however, requires ϵ_t to be distributed $N(0, \sigma^2)$ for the statistic to have an exact distribution. Also, the Durbin–Watson test can be applied only when the regressors are strictly exogenous. A regressor x is strictly exogenous if $\text{Corr}(x_s, u_t) = 0$ for all s and t, which precludes the use of the Durbin–Watson statistic with models where lagged values of the dependent variable are included as regressors.

The null hypothesis of the test is that there is no first-order autocorrelation. The Durbin–Watson d statistic can take on values between 0 and 4 and under the null d is equal to 2. Values of d less than 2 suggest positive autocorrelation ($\rho > 0$), whereas values of d greater than 2 suggest negative autocorrelation ($\rho < 0$). Calculating the exact distribution of the d statistic is difficult, but empirical upper and lower bounds have been established based on the sample size and the number of regressors. Extended tables for the d statistic have been published by Savin and White (1977). For example, suppose you have a model with 30 observations and three regressors (including the constant term). For a test of the null hypothesis of no autocorrelation versus the alternative of positive autocorrelation, the lower bound of the d statistic is 1.284, and the upper bound is 1.567 at the 5% significance level. You would reject the null if $d < 1.284$, and you would fail to reject if $d > 1.567$. A value falling within the range (1.284, 1.567) leads to no conclusion about whether or not to reject the null hypothesis.

When lagged dependent variables are included among the regressors, the past values of the error term are correlated with those lagged variables at time t, implying that they are not strictly exogenous regressors. The inclusion of covariates that are not strictly exogenous causes the d statistic to be biased toward the acceptance of the null hypothesis. Durbin (1970) suggested an alternative test for models with lagged dependent variables and extended that test to the more general AR(p) serial correlation process

$$u_t = \rho_1 u_{t-1} + \cdots + \rho_p u_{t-p} + \epsilon_t$$

where ϵ_t is i.i.d. with variance σ^2 but is not assumed or required to be normal for the test.

The null hypothesis of Durbin's alternative test is

$$H_0 : \rho_1 = 0, \ldots, \rho_p = 0$$

and the alternative is that at least one of the ρ's is nonzero. Although the null hypothesis was originally derived for an AR(p) process, this test turns out to have power against MA(p) processes as well. Hence, the actual null of this test is that there is no serial correlation up to order p because the MA(p) and the AR(p) models are locally equivalent alternatives under the null. See Godfrey (1988, 113–115) for a discussion of this result.

Durbin's alternative test is in fact a LM test, but it is most easily computed with a Wald test on the coefficients of the lagged residuals in an auxiliary OLS regression of the residuals on their lags and all the covariates in the original regression. Consider the linear regression model

$$y_t = \beta_1 x_{1t} + \cdots + \beta_k x_{kt} + u_t \tag{1}$$

in which the covariates x_1 through x_k are not assumed to be strictly exogenous and u_t is assumed to be i.i.d. and to have finite variance. The process is also assumed to be stationary. (See Wooldridge [2020, sec. 11.1] for a discussion of stationarity.) Estimating the parameters in (1) by OLS obtains the residuals $\hat{u}_t$. Next another OLS regression is performed of $\hat{u}_t$ on $\hat{u}_{t-1}, \ldots, \hat{u}_{t-p}$ and the other regressors,

$$\hat{u}_t = \gamma_1 \hat{u}_{t-1} + \cdots + \gamma_p \hat{u}_{t-p} + \beta_1 x_{1t} + \cdots + \beta_k x_{kt} + \epsilon_t \tag{2}$$

where ϵ_t stands for the random-error term in this auxiliary OLS regression. Durbin's alternative test is then obtained by performing a Wald test that $\gamma_1, \ldots, \gamma_p$ are jointly zero. The test can be made robust to an unknown form of heteroskedasticity by using a robust VCE estimator when estimating the regression in (2). When there are only strictly exogenous regressors and $p = 1$, this test is asymptotically equivalent to the Durbin–Watson test.

The Breusch–Godfrey test is also an LM test of the null hypothesis of no autocorrelation versus the alternative that u_t follows an AR(p) or MA(p) process. Like Durbin's alternative test, it is based on the auxiliary regression (2), and it is computed as NR^2, where N is the number of observations and R^2 is the simple R^2 from the regression. This test and Durbin's alternative test are asymptotically equivalent. The test statistic NR^2 has an asymptotic χ^2 distribution with p degrees of freedom. It is valid with or without the strict exogeneity assumption but is not robust to conditional heteroskedasticity, even if a robust VCE is used when fitting (2).

In fitting (2), the values of the lagged residuals will be missing in the initial periods. As noted by Davidson and MacKinnon (1993), the residuals will not be orthogonal to the other covariates in the model in this restricted sample, which implies that the R^2 from the auxiliary regression will not be zero when the lagged residuals are left out. Hence, Breusch and Godfrey's NR^2 version of the test may overreject in small samples. To correct this problem, Davidson and MacKinnon (1993) recommend setting the

missing values of the lagged residuals to zero and running the auxiliary regression in (2) over the full sample used in (1). This small-sample correction has become conventional for both the Breusch–Godfrey and Durbin's alternative test, and it is the default for both commands. Specifying the `nomiss0` option overrides this default behavior and treats the initial missing values generated by regressing on the lagged residuals as missing. Hence, `nomiss0` causes these initial observations to be dropped from the sample of the auxiliary regression.

Durbin's alternative test and the Breusch–Godfrey test were originally derived for the case covered by `regress` without the `vce(robust)` option. However, after `regress, vce(robust)` and `newey`, Durbin's alternative test is still valid and can be invoked if the `robust` and `force` options are specified.

▷ Example 1: tests for serial correlation

Using data from Klein (1950), we first fit an OLS regression of consumption on the government wage bill:

```
. use https://www.stata-press.com/data/r19/klein
. tsset yr
Time variable: yr, 1920 to 1941
        Delta: 1 unit
. regress consump wagegovt
```

Source	SS	df	MS		Number of obs	=	22
					F(1, 20)	=	17.72
Model	532.567711	1	532.567711		Prob > F	=	0.0004
Residual	601.207167	20	30.0603584		R-squared	=	0.4697
					Adj R-squared	=	0.4432
Total	1133.77488	21	53.9892799		Root MSE	=	5.4827

consump	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]
wagegovt	2.50744	.5957173	4.21	0.000	1.264796 3.750085
_cons	40.84699	3.192183	12.80	0.000	34.18821 47.50577

If we assume that `wagegov` is a strictly exogenous variable, we can use the Durbin–Watson test to check for first-order serial correlation in the errors.

```
. estat dwatson
Durbin-Watson d-statistic(  2,    22) =  .3217998
```

The Durbin–Watson d statistic, 0.32, is far from the center of its distribution ($d = 2.0$). Given 22 observations and two regressors (including the constant term) in the model, the lower 5% bound is about 0.997, much greater than the computed d statistic. Assuming that `wagegov` is strictly exogenous, we can reject the null of no first-order serial correlation. Rejecting the null hypothesis does not necessarily mean an AR process; other forms of misspecification may also lead to a significant test statistic. If we are willing to assume that the errors follow an AR(1) process and that `wagegov` is strictly exogenous, we could refit the model using `arima` or `prais` and model the error process explicitly; see [TS] **arima** and [TS] **prais**.

If we are not willing to assume that `wagegov` is strictly exogenous, we could instead use Durbin's alternative test or the Breusch–Godfrey to test for first-order serial correlation. Because we have only 22 observations, we will use the `small` option.

```
. estat durbinalt, small
Durbin's alternative test for autocorrelation
```

lags(p)	F	df	Prob > F
1	35.035	(1, 19)	0.0000

H0: no serial correlation

```
. estat bgodfrey, small
Breusch–Godfrey LM test for autocorrelation
```

lags(p)	F	df	Prob > F
1	14.264	(1, 19)	0.0013

H0: no serial correlation

Both tests strongly reject the null of no first-order serial correlation, so we decide to refit the model with two lags of `consump` included as regressors and then rerun `estat durbinalt` and `estat bgodfrey`. Because the revised model includes lagged values of the dependent variable, the Durbin–Watson test is not applicable.

```
. regress consump wagegovt L.consump L2.consump
```

Source	SS	df	MS			
Model	702.660311	3	234.220104	Number of obs	=	20
Residual	85.1596011	16	5.32247507	F(3, 16)	=	44.01
				Prob > F	=	0.0000
				R-squared	=	0.8919
Total	787.819912	19	41.4642059	Adj R-squared	=	0.8716
				Root MSE	=	2.307

consump	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
wagegovt	.6904282	.3295485	2.10	0.052	−.0081835	1.38904
consump						
L1.	1.420536	.197024	7.21	0.000	1.002864	1.838208
L2.	−.650888	.1933351	−3.37	0.004	−1.06074	−.241036
_cons	9.209073	5.006701	1.84	0.084	−1.404659	19.82281

```
. estat durbinalt, small lags(1/2)
```

Durbin's alternative test for autocorrelation

lags(p)	F	df	Prob > F
1	0.080	(1, 15)	0.7805
2	0.260	(2, 14)	0.7750

H0: no serial correlation

```
. estat bgodfrey, small lags(1/2)
```

Breusch–Godfrey LM test for autocorrelation

lags(p)	F	df	Prob > F
1	0.107	(1, 15)	0.7484
2	0.358	(2, 14)	0.7056

H0: no serial correlation

Although wagegov and the constant term are no longer statistically different from zero at the 5% level, the output from estat durbinalt and estat bgodfrey indicates that including the two lags of consump has removed any serial correlation from the errors.

◁

Engle (1982) suggests an LM test for checking for autoregressive conditional heteroskedasticity (ARCH) in the errors. The pth-order ARCH model can be written as

$$\sigma_t^2 = E(u_t^2 | u_{t-1}, \dots, u_{t-p})$$
$$= \gamma_0 + \gamma_1 u_{t-1}^2 + \cdots + \gamma_p u_{t-p}^2$$

To test the null hypothesis of no autoregressive conditional heteroskedasticity (that is, $\gamma_1 = \cdots = \gamma_p = 0$), we first fit the OLS model (1), obtain the residuals $\hat{u}_t$, and run another OLS regression on the lagged residuals:

$$\hat{u}_t^2 = \gamma_0 + \gamma_1 \hat{u}_{t-1}^2 + \cdots + \gamma_p \hat{u}_{t-p}^2 + \epsilon \qquad (3)$$

The test statistic is NR^2, where N is the number of observations in the sample and R^2 is the R^2 from the regression in (3). Under the null hypothesis, the test statistic follows a χ_p^2 distribution.

▷ Example 2: estat archlm

We refit the original model that does not include the two lags of consump and then use estat archlm to see if there is any evidence that the errors are autoregressive conditional heteroskedastic.

```
. regress consump wagegovt
```

Source	SS	df	MS		
Model	532.567711	1	532.567711		
Residual	601.207167	20	30.0603584		
Total	1133.77488	21	53.9892799		

Number of obs	=	22
F(1, 20)	=	17.72
Prob > F	=	0.0004
R-squared	=	0.4697
Adj R-squared	=	0.4432
Root MSE	=	5.4827

consump	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
wagegovt	2.50744	.5957173	4.21	0.000	1.264796	3.750085
_cons	40.84699	3.192183	12.80	0.000	34.18821	47.50577

```
. estat archlm, lags(1 2 3)
LM test for autoregressive conditional heteroskedasticity (ARCH)
```

lags(p)	chi2	df	Prob > chi2
1	5.543	1	0.0186
2	9.431	2	0.0090
3	9.039	3	0.0288

HO: no ARCH effects   *vs.* H1: ARCH(p) disturbance

estat archlm shows the results for tests of ARCH(1), ARCH(2), and ARCH(3) effects, respectively. At the 5% significance level, all three tests reject the null hypothesis that the errors are not autoregressive conditional heteroskedastic. See [TS] **arch** for information on fitting ARCH models.

◁

Stored results

estat archlm stores the following in r():

Scalars
    r(N)   number of observations
    r(k)   number of regressors
    r(N_gaps)   number of gaps

Macros
    r(lags)   lag order

Matrices
    r(arch)   test statistic for each lag order
    r(df)   degrees of freedom
    r(p)   two-sided p-values

estat bgodfrey stores the following in r():

Scalars
    r(N)   number of observations
    r(k)   number of regressors
    r(N_gaps)   number of gaps

Macros
    r(lags)   lag order

Matrices
    r(chi2) χ^2 statistic for each lag order
    r(F) F statistic for each lag order (small only)
    r(df_r)   residual degrees of freedom (small only)
    r(df)   degrees of freedom
    r(p)   two-sided p-values

`estat durbinalt` stores the following in `r()`:

Scalars
    `r(N)`   number of observations
    `r(k)`   number of regressors
    `r(N_gaps)`   number of gaps

Macros
    `r(lags)`   lag order

Matrices
    `r(chi2)` χ^2 statistic for each lag order
    `r(F)` F statistic for each lag order (`small` only)
    `r(df_r)`   residual degrees of freedom (`small` only)
    `r(df)`   degrees of freedom
    `r(p)`   two-sided p-values

`estat dwatson` stores the following in `r()`:

Scalars
    `r(N)`   number of observations
    `r(k)`   number of regressors
    `r(N_gaps)`   number of gaps
    `r(dw)`   Durbin–Watson statistic

Methods and formulas

Consider the regression

$$y_t = \beta_1 x_{1t} + \cdots + \beta_k x_{kt} + u_t \tag{4}$$

in which some of the covariates are not strictly exogenous. In particular, some of the x_{it} may be lags of the dependent variable. We are interested in whether the u_t are serially correlated.

The Durbin–Watson d statistic reported by `estat dwatson` is

$$d = \frac{\sum\limits_{t=1}^{n-1} (\hat{u}_{t+1} - \hat{u}_t)^2}{\sum\limits_{t=1}^{n} \hat{u}_t^2}$$

where $\hat{u}_t$ represents the residual of the tth observation.

To compute Durbin's alternative test and the Breusch–Godfrey test against the null hypothesis that there is no pth order serial correlation, we fit the regression in (4), compute the residuals, and then fit the following auxiliary regression of the residuals $\hat{u}_t$ on p lags of $\hat{u}_t$ and on all the covariates in the original regression in (4):

$$\hat{u}_t = \gamma_1 \hat{u}_{t-1} + \cdots + \gamma_p \hat{u}_{t-p} + \beta_1 x_{1t} + \cdots + \beta_k x_{kt} + \epsilon \tag{5}$$

Durbin's alternative test is computed by performing a Wald test to determine whether the coefficients of $\hat{u}_{t-1}, \ldots, \hat{u}_{t-p}$ are jointly different from zero. By default, the statistic is assumed to be distributed $\chi^2(p)$. When `small` is specified, the statistic is assumed to follow an $F(p, N - p - k)$ distribution. The reported p-value is a two-sided p-value. When `robust` is specified, the Wald test is performed using the Huber/White/sandwich estimator of the variance–covariance matrix, and the test is robust to an unspecified form of heteroskedasticity.

The Breusch–Godfrey test is computed as NR^2, where N is the number of observations in the auxiliary regression (5) and R^2 is the R^2 from the same regression (5). Like Durbin's alternative test, the Breusch–Godfrey test is asymptotically distributed $\chi^2(p)$, but specifying small causes the p-value to be computed using an $F(p, N - p - k)$.

By default, the initial missing values of the lagged residuals are replaced with zeros, and the auxiliary regression is run over the full sample used in the original regression of (4). Specifying the nomiss0 option causes these missing values to be treated as missing values, and the observations are dropped from the sample.

Engle's LM test for ARCH(p) effects fits an OLS regression of $\hat{u}_t^2$ on $\hat{u}_{t-1}^2, \ldots, \hat{u}_{t-p}^2$:

$$\hat{u}_t^2 = \gamma_0 + \gamma_1 \hat{u}_{t-1}^2 + \cdots + \gamma_p \hat{u}_{t-p}^2 + \epsilon$$

The test statistic is nR^2 and is asymptotically distributed $\chi^2(p)$.

Acknowledgment

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James Durbin (1923–2012) was a British statistician who was born in Wigan, near Manchester. He studied mathematics at Cambridge and after military service and various research posts joined the London School of Economics in 1950. Later in life, he was also affiliated with University College London. His many contributions to statistics centered on serial correlation, time series (including major contributions to structural or unobserved components models), sample survey methodology, goodness-of-fit tests, and sample distribution functions, with emphasis on applications in the social sciences. He served terms as president of the Royal Statistical Society and the International Statistical Institute.

Geoffrey Stuart Watson (1921–1998) was born in Victoria, Australia, and earned degrees at Melbourne University and North Carolina State University. After a visit to the University of Cambridge, he returned to Australia, working at Melbourne and then the Australian National University. Following periods at Toronto and Johns Hopkins, he settled at Princeton. Throughout his wide-ranging career, he made many notable accomplishments and important contributions, including the Durbin–Watson test for serial correlation, the Nadaraya–Watson estimator in nonparametric regression, and methods for analyzing directional data.

Leslie G. Godfrey (1946–) was born in London and earned degrees at the Universities of Exeter and London. He is now a professor of econometrics at the University of York. His interests center on implementation and interpretation of tests of econometric models, including nonnested models.

Trevor Stanley Breusch (1953–) was born in Queensland and earned degrees at the University of Queensland and Australian National University (ANU). After a post at the University of Southampton, he returned to work at ANU. His background is in econometric methods and his recent interests include political values and social attitudes, earnings and income, and measurement of underground economic activity.

Also see