**Title**

**hart — Test linear hypotheses after har estimation**

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**Syntax**

Basic syntax

hart coeflist

hart exp=exp[=…]

options Description

Model

kernel(string) set the type of kernels: Bartlett; Parzen; Quadratic Spectral; Orthonormal Series

accumulate test the hypothesis jointly with previously tested hypotheses

level(#) set the confidence level; default is level(95)

kernel(string ) is required.

time-series operators are allowed.

Syntax 1 tests that the coefficients are 0.

Syntax 2 tests that the linear expressions are equal.

**Menu**

statistics>Postestimation>Tests> Test linear hypotheses after har estimation

**Description**

hart performs Wald tests of simple and composite linear hypotheses about the parameters in the most recently estimated har model. See Sun (2013) and Sun (2014).

**Options**

Model

kernel(string) specifies the type of kernels (Bartlett; Parzen; Quadratic Spectral; Orthonormal Series) to be used in the estimation of the long run covariance matrix.

accumulate allows a hypothesis to be tested jointly with the previously tested hypotheses.

Reporting

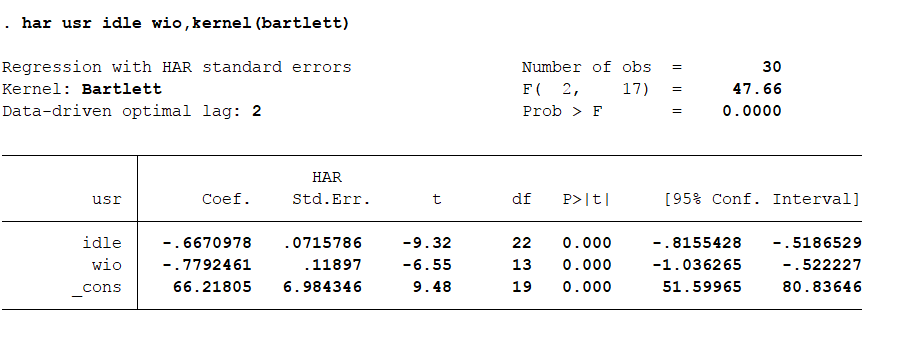
level(#); see [R] estimation options.

**Remarks and examples**

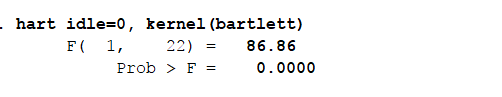
Sun (2013) and Sun (2014) introduce simple and trustworthy inference procedures that are robust to heteroskedasticity and autocorrelation. The HAR variance estimator in Sun (2013) is based on an orthonormal series long run variance matrix estimator. The optimal number K of orthonormal bases is selected by minimizing the type II error of the test subject to a control of the type I error. The tests in Sun (2013) are asymptotic F and t tests in an exact sense: the asymptotic distribution of the adjusted F statistic and t statistic are standard F and t distributions. The HAR variance estimator in Sun (2014) is based on the more conventional kernel long run variance matrix estimators. The F and t tests in Sun (2014) are approximate tests. The asymptotic distributions of the adjusted F and t statistic are not exactly F and t distribution, but they can be well approximated by the standard F and t distributions.

**ΔExample 1: Test for a single coefficient against zero**

We estimate the following regression:



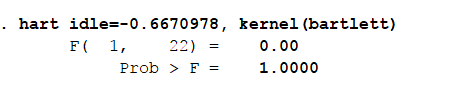
We can test the hypothesis that the coefficient on idle is zero by typing:



The F statistic is 86.86. The degrees of freedom of the approximating F distribution are (1,22). The p-value of the test is 0%. We can reject the null hypothesis at the 1% level.

**ΔExample 2: Testing that a coefficient is equal to a given value**

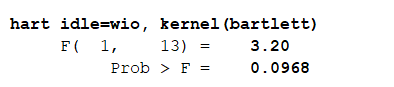
We can test the hypothesis that the coefficient on idle is -0.6670978 by typing:



We find that we cannot reject that hypothesis.

**ΔExample 3: Testing the equality of two coefficients**

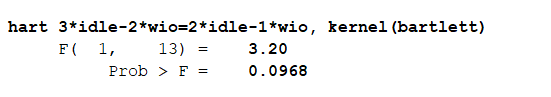
Now let’s test something a bit more difficult: whether the coefficient on idle is the same as the coefficient on wio:



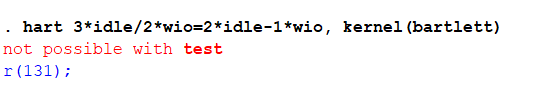
We find that we cannot reject the equality hypothesis at the 5% level, but we can at the 10% level.

**ΔExample 4:**

hart allows us to test any linear restrictions. For example,



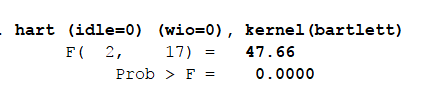
However, hart does not deal with nonlinear restrictions directly. If you attempt to test a nonlinear hypothesis, you will be told that it is not possible.



This is not a problem specific to the command hart. Stata’s command “test” exhibits the same behavior. In fact, hart uses Stata’s command “test” to parse the null hypothesis. To test nonlinear restrictions, we have to convert them into linear ones before using hart.

**ΔExample 5: Testing joint hypotheses**

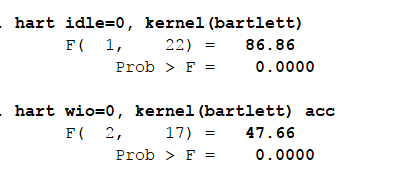
We wish to test whether idle and wio, taken as a whole, are significant by testing whether the coefficients on idle and wio are simultaneously zero. The command hart allows us to specify multiple conditions to be tested, each embedded within parentheses.



hart displays the set of conditions and reports an F statistic of 47.66. hart also reports the degrees of freedom of the approximating F distribution, which are 2 and 17. The p-value of the test is reported to be around 0. So we can strongly reject the hypothesis of no difference between the two coefficients.

**□Technical note**

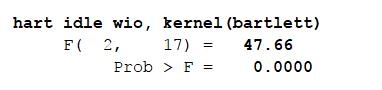
An alternative method to test simultaneous hypotheses is to specify a test for the first constraint and then accumulate it with the second constraint:



We first test the hypothesis that the coefficient on idle is zero by typing hart idle=0. We then test whether the coefficient on wio is also zero by typing hart wio=0, accumulate. The accumulate option tells hart that this is not the start of a new test but a continuation of the previous one. hart responds by showing us the two equations and reporting an F statistic of 47.66. The p-value is about 0%.

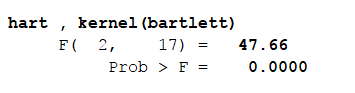
**ΔExample 6: Quickly testing coefficients against zero**

It is very common to test whether some coefficents are jointly zero in applied research. The command hart has a more convenient syntax to accommodate this common case:



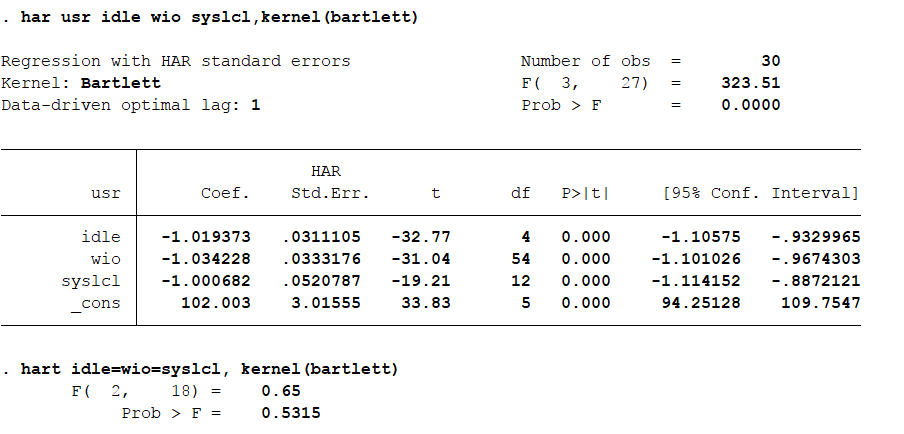
**ΔExample 7: Replaying the previous test**

We can review our last test by typing hart without arguments.



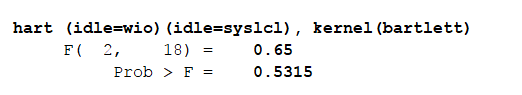
**ΔExample 8: Testing the equality of multiple coefficients**

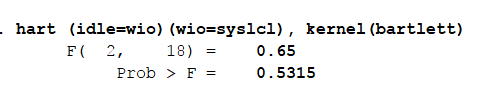
Let’s test the hypothesis that idle, wio and syslcl have the same coefficient.



The syntax idle=wio=syslcl with multiple = operators is just a convenient shorthand for typing that the first expression equals the second expression and that the first expression equals the third expression.

We can perform the same test by using either of the following





**Stored results**

hart stores the following results in r()：

Scalars

r(firdf) the first degrees of freedom

r(secdf) the second degrees of freedom

r(lag) the data-driven optimal truncation lag

r(kopt) the data-driven optimal K

r(F) the adjusted F statistic

Matrices

r(thetaiv) the IV coefficient vector

**Methods and formulas**

Consider the regression model:

where is a zero-mean process that may be correlated with the covariate process

There are instruments such that the moment conditions:

hold if and only if . We allow the process to have the autocorrelation of unknown forms. The model may be over-identified with the degree of over-identification .

Define:

, ,

Then the IV estimator of is

where , .

We are interested in testing the null against the alternative , where and is a matrix of full row rank. Nonlinear restrictions can be converted into linear ones via the delta method. Under some standard high-level conditions, we have

where and is the transformed moment

process. It then follows that , where is the long run variance of . The Wald statistic for testing against is

Let and. We consider the estimator of the form

where is a weighting function, and is the smoothing parameter. The above estimator includes the kernel HAR variance estimators and the orthonormal series HAR variance estimator as special cases.

For the kernel HAR variance estimator, we let and for a kernel function with being the so-called truncation lag. Define

, .

For the Bartlett kernel, , ; For the Parzen kernel, , For the Quadratic Spectral kernel,, . Let

,

where is the ceiling function, and

.

Based on the kernel estimator , Sun (2014) shows that

where is the 100 quantile of the standard distribution.

Sun (2014) obtains the testing-optimal bandwidth :

where is the permitted tolerance,is the pdf of the noncentral distribution with degrees of freedom and noncentrality parameter . In the above formula, is the quantile of the distribution with degrees of freedom and is chosen to satisfy, where . In addition,

where *q* is the order of the kernel used, and is the Parzen characteristic exponent of the kernel. For the Bartlett kernel, ; For the Parzen kernel, ; For the QS kernel, .

The parameter is estimated by a standard VAR(1) plug-in procedure. This is what we opt for in the new command. Plugging the estimate of into yields The data-driven choice of is then given by We do not use a *b* larger than 0.5 in order to avoid large power loss.

For the OS HAR variance estimator, we let , and ,

where are orthonormal basis functions on satisfying for

. Sun (2013) shows that the usual Wald statistic satisfies

where is the distribution with degrees of freedom).

Sun (2013) obtains the testing-optimal as follows

As before, the parameter is estimated by a standard VAR(1) plug-in procedure. Plugging the estimate of into yields .We truncate to be between and *T*. That is, we take

Imposing the lower bound ensures that the variance of the approximating distribution is finite and that power loss is not very large. Finally, we round to the greatest even number less than . We take this greatest even number, denoted by to be our data-driven and testing-optimal choice for *K*.

**References**

Sun, Y., 2013. A heteroskedasticity and autocorrelation robust F test using an orthonormal series variance estimator. Econometrics Journal, 16: 1-26.

Sun, Y., 2014. Let’s fix it: Fixed-b asymptotics versus small-b asymptotics in heteroskedasticity and autocorrelation robust inference. Journal of Econometrics, 178: 660-677.

**Also see**

[TS]tsset—Declare data to be time-series data.