Title

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arch postestimation — Postestimation tools for arch

Postestimation commands

The following postestimation commands are available after `arch`:

Command	Description
`estat ic`	Akaike's and Schwarz's Bayesian information criteria (AIC and BIC)
`estat summarize`	summary statistics for the estimation sample
`estat vce`	variance–covariance matrix of the estimators (VCE)
`estimates`	cataloging estimation results
`forecast`	dynamic forecasts and simulations
`lincom`	point estimates, standard errors, testing, and inference for linear combinations of coefficients
`lrtest`	likelihood-ratio test
`margins`	marginal means, predictive margins, marginal effects, and average marginal effects
`marginsplot`	graph the results from margins (profile plots, interaction plots, etc.)
`nlcom`	point estimates, standard errors, testing, and inference for nonlinear combinations of coefficients
`predict`	predictions, residuals, influence statistics, and other diagnostic measures
`predictnl`	point estimates, standard errors, testing, and inference for generalized predictions
`test`	Wald tests of simple and composite linear hypotheses
`testnl`	Wald tests of nonlinear hypotheses

predict

Description for predict

`predict` creates a new variable containing predictions such as expected values and residuals. All predictions are available as static one-step-ahead predictions or as dynamic multistep predictions, and you can control when dynamic predictions begin.

Menu for predict

Statistics > Postestimation

Syntax for predict

`predict` [*type*] *newvar* [*if*] [*in*] [, *statistic options*]

statistic	Description
Main	
`xb`	predicted values for mean equation—the differenced series; the default
`y`	predicted values for the mean equation in y—the undifferenced series
`variance`	predicted values for the conditional variance
`het`	predicted values of the variance, considering only the multiplicative heteroskedasticity
`residuals`	residuals or predicted innovations
`yresiduals`	residuals or predicted innovations in y—the undifferenced series

These statistics are available both in and out of sample; type `predict ... if e(sample) ...` if wanted only for the estimation sample.

options	Description
Options	
`dynamic(`*time_constant*`)`	how to handle the lags of y_t
`at(`*varname*$_\epsilon$ | #$_\epsilon$ *varname*$_{\sigma^2}$ | #$_{\sigma^2}$`)`	make static predictions
`t0(`*time_constant*`)`	set starting point for the recursions to *time_constant*
`structural`	calculate considering the structural component only

time_constant is a # or a time literal, such as `td(1jan1995)` or `tq(1995q1)`, etc.; see *Conveniently typing SIF values* in [D] **datetime**.

Options for predict

Six statistics can be computed by using `predict` after `arch`: the predictions of the mean equation (option `xb`, the default), the undifferenced predictions of the mean equation (option `y`), the predictions of the conditional variance (option `variance`), the predictions of the multiplicative heteroskedasticity component of variance (option `het`), the predictions of residuals or innovations (option `residuals`), and the predictions of residuals or innovations in terms of y (option `yresiduals`). Given the dynamic nature of ARCH models and because the dependent variable might be differenced, there are other ways of computing each statistic. We can use all the data on the dependent variable available right up to the time of each prediction (the default, which is often called a one-step prediction), or we can use the data up to a particular time, after which the predicted value of the dependent variable is used recursively to make later predictions (option `dynamic()`). Either way, we can consider or ignore the ARMA disturbance component, which is considered by default and is ignored if you specify the `structural` option. We might also be interested in predictions at certain fixed points where we specify the prior values of ϵ_t and σ_t^2 (option `at()`).

Main

`xb`, the default, calculates the predictions from the mean equation. If `D.`*depvar* is the dependent variable, these predictions are of `D.`*depvar* and not of *depvar* itself.

`y` specifies that predictions of *depvar* are to be made even if the model was specified for, say, `D.`*depvar*.

`variance` calculates predictions of the conditional variance $\widehat{\sigma}_t^2$.

`het` calculates predictions of the multiplicative heteroskedasticity component of variance.

`residuals` calculates the residuals. If no other options are specified, these are the predicted innovations ϵ_t; that is, they include any ARMA component. If the `structural` option is specified, these are the residuals from the mean equation, ignoring any ARMA terms; see `structural` below. The residuals are always from the estimated equation, which may have a differenced dependent variable; if *depvar* is differenced, they are not the residuals of the undifferenced *depvar*.

`yresiduals` calculates the residuals for *depvar*, even if the model was specified for, say, `D.`*depvar*. As with `residuals`, the `yresiduals` are computed from the model, including any ARMA component. If the `structural` option is specified, any ARMA component is ignored and `yresiduals` are the residuals from the structural equation; see `structural` below.

Options

`dynamic(`*time_constant*`)` specifies how lags of y_t in the model are to be handled. If `dynamic()` is not specified, actual values are used everywhere lagged values of y_t appear in the model to produce one-step-ahead forecasts.

`dynamic(`*time_constant*`)` produces dynamic (also known as recursive) forecasts. *time_constant* specifies when the forecast is to switch from one step ahead to dynamic. In dynamic forecasts, references to y_t evaluate to the prediction of y_t for all periods at or after *time_constant*; they evaluate to the actual value of y_t for all prior periods.

`dynamic(10)`, for example, would calculate predictions where any reference to y_t with $t < 10$ evaluates to the actual value of y_t and any reference to y_t with $t \geq 10$ evaluates to the prediction of y_t. This means that one-step-ahead predictions would be calculated for $t < 10$ and dynamic predictions would be calculated thereafter. Depending on the lag structure of the model, the dynamic predictions might still refer to some actual values of y_t.

You may also specify `dynamic(.)` to have `predict` automatically switch from one-step-ahead to dynamic predictions at $p + q$, where p is the maximum AR lag and q is the maximum MA lag.

`at(`*varname*$_\epsilon$ `|` `#`$_\epsilon$ *varname*$_{\sigma^2}$ `|` `#`$_{\sigma^2}$`)` makes static predictions. `at()` and `dynamic()` may not be specified together.

Specifying `at()` allows static evaluation of results for a given set of disturbances. This is useful, for instance, in generating the news response function. `at()` specifies two sets of values to be used for ϵ_t and σ_t^2, the dynamic components in the model. These specified values are treated as given. Also, any lagged values of *depvar* in the model are obtained from the real values of the dependent variable. All computations are based on actual data and the given values.

`at()` requires that you specify two arguments, which can be either a variable name or a number. The first argument supplies the values to be used for ϵ_t; the second supplies the values to be used for σ_t^2. If σ_t^2 plays no role in your model, the second argument may be specified as '`.`' to indicate missing.

`t0(`*time_constant*`)` specifies the starting point for the recursions to compute the predicted statistics; disturbances are assumed to be 0 for $t <$ `t0()`. The default is to set `t0()` to the minimum t observed in the estimation sample, meaning that observations before that are assumed to have disturbances of 0.

`t0()` is irrelevant if `structural` is specified because then all observations are assumed to have disturbances of 0.

`t0(5)`, for example, would begin recursions at $t = 5$. If your data were quarterly, you might instead type `t0(tq(1961q2))` to obtain the same result.

Any ARMA component in the mean equation or GARCH term in the conditional-variance equation makes `arch` recursive and dependent on the starting point of the predictions. This includes one-step-ahead predictions.

`structural` makes the calculation considering the structural component only, ignoring any ARMA terms, and producing the steady-state equilibrium predictions.

margins

Description for margins

`margins` estimates margins of response for expected values.

Menu for margins

Statistics > Postestimation

Syntax for margins

`margins` [*marginlist*] [`,` *options*]

`margins` [*marginlist*] `,` `predict(`*statistic* ...`)` [`predict(`*statistic* ...`)` ...] [*options*]

statistic	Description
`xb`	predicted values for mean equation—the differenced series; the default
`y`	predicted values for the mean equation in y—the undifferenced series
`variance`	predicted values for the conditional variance
`het`	predicted values of the variance, considering only the multiplicative heteroskedasticity
`residuals`	not allowed with `margins`
`yresiduals`	not allowed with `margins`

Statistics not allowed with `margins` are functions of stochastic quantities other than `e(b)`.

For the full syntax, see [R] **margins**.

Remarks and examples

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▷ Example 1

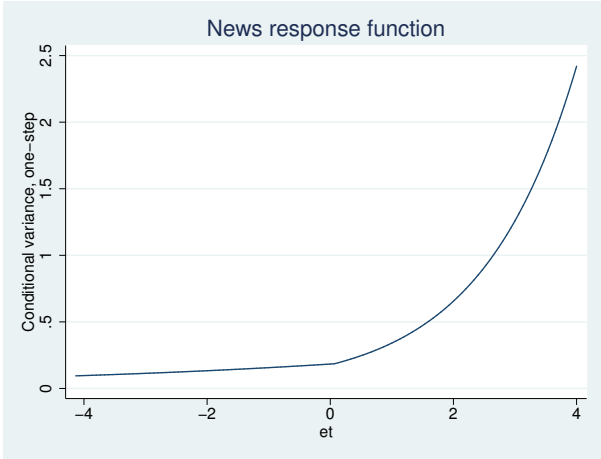
Continuing with our EGARCH model example (example 3) in [TS] **arch**, we can see that `predict, at()` calculates σ_t^2 given a set of specified innovations $(\epsilon_t, \epsilon_{t-1}, \ldots)$ and prior conditional variances $(\sigma_{t-1}^2, \sigma_{t-2}^2, \ldots)$. The syntax is

```
. predict newvar, variance at(epsilon sigma2)
```

epsilon and *sigma2* are either variables or numbers. Using *sigma2* is a little tricky because you specify values of σ_t^2, which `predict` is supposed to predict. *predict* does not simply copy variable *sigma2* into *newvar* but uses the lagged values contained in *sigma2* to produce the predicted value of σ_t^2. It does this for all t, and those results are saved in *newvar*. (If you are interested in dynamic predictions of σ_t^2, see *Options for predict*.)

We will generate predictions for σ_t^2, assuming that the lagged values of σ_t^2 are 1, and we will vary ϵ_t from -4 to 4. First, we will create variable `et` containing ϵ_t, and then we will create and graph the predictions:

```
. generate et = (_n-64)/15
. predict sigma2, variance at(et 1)
. line sigma2 et in 2/l, m(i) c(l) title(News response function)
```



The positive asymmetry does indeed dominate the shape of the news response function. In fact, the response is a monotonically increasing function of news. The form of the response function shows that, for our simple model, only positive, unanticipated price increases have the destabilizing effect that we observe as larger conditional variances.

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▷ Example 2

Continuing with our ARCH model with constraints example (example 6) in [TS] **arch**, using `lincom` we can recover the α parameter from the original specification.

```
. lincom [ARCH]l1.arch/.4
 ( 1)  2.5*[ARCH]L.arch = 0
```

D.ln_wpi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
(1)	.5450344	.1844468	2.95	0.003	.1835253	.9065436

Any `arch` parameter could be used to produce an identical estimate.

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Also see

[TS] **arch** — Autoregressive conditional heteroskedasticity (ARCH) family of estimators

[U] **20 Estimation and postestimation commands**