sspace postestimation — Postestimation tools for sspace

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Postestimation commands

The following standard postestimation commands are available after sspace:

Command	Description
estat ic	Akaike's, consistent Akaike's, corrected Akaike's, and Schwarz's Bayesian infor- mation criteria (AIC, CAIC, AICc, and BIC, respectively)
estat summarize	summary statistics for the estimation sample
estat vce	variance-covariance matrix of the estimators (VCE)
estimates	cataloging estimation results
etable	table of estimation results
forecast	dynamic forecasts and simulations
lincom	point estimates, standard errors, testing, and inference for linear combinations of parameters
lrtest	likelihood-ratio test
nlcom	point estimates, standard errors, testing, and inference for nonlinear combinations of parameters
predict	linear predictions, latent states, residuals, etc.
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. The root mean squared error is available for all predictions. All predictions are also 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] { stub* | newvarlist } [if] [in] [, statistic options]

statistic	Description
Main	
xb	observable variables
<u>st</u> ates	latent state variables
<u>r</u> esiduals	residuals
<u>rsta</u> ndard	standardized residuals
These statistics are available bot the estimation sample.	h in and out of sample; type predict if e(sample) if wanted only for
options	Description
Options	
equation(<i>eqnames</i>)	name(s) of equation(s) for which predictions are to be made
<pre>rmse(stub* newvarlist)</pre>	put estimated root mean squared errors of predicted statistics in new variables
<pre>dynamic(time_constant)</pre>	begin dynamic forecast at specified time
Advanced	
<pre>smethod(method)</pre>	method for predicting unobserved states
method	Description
onestep	predict using past information
<u>sm</u> ooth	predict using all sample information
<u>fi</u> lter	predict using past and contemporaneous information

Options for predict

Main

xb, states, residuals, and rstandard specify the statistic to be predicted.

xb, the default, calculates the linear predictions of the observed variables.

states calculates the linear predictions of the latent state variables.

- residuals calculates the residuals in the equations for observable variables. residuals may not be specified with dynamic().
- rstandard calculates the standardized residuals, which are the residuals normalized to be uncorrelated and to have unit variances. rstandard may not be specified with smethod(filter), smethod(smooth), or dynamic().

Options

equation(*eqnames*) specifies the equation(s) for which the predictions are to be calculated. If you do not specify equation() or *stub**, the results are the same as if you had specified the name of the first equation for the predicted statistic.

You specify a list of equation names, such as equation (income consumption) or equation (factor1 factor2), to identify the equations. Specify names of state equations when predicting states and names of observable equations in all other cases.

equation() may not be specified with stub*.

- rmse(stub* | newvarlist) puts the root mean squared errors of the predicted statistics into the specified new variables. The root mean squared errors measure the variances due to the disturbances but do not account for estimation error.
- dynamic(*time_constant*) specifies when predict starts producing dynamic forecasts. The specified *time_constant* must be in the scale of the time variable specified in tsset, and the *time_constant* must be inside a sample for which observations on the dependent variables are available. For example, dynamic(tq(2008q4)) causes dynamic predictions to begin in the fourth quarter of 2008, assuming that your time variable is quarterly; see [D] **Datetime**. If the model contains exogenous variables, they must be present for the whole predicted sample. dynamic() may not be specified with rstandard, residuals, or smethod(smooth).

Advanced

- smethod(method) specifies the method for predicting the unobserved states; smethod(onestep), smethod(filter), and smethod(smooth) cause different amounts of information on the dependent variables to be used in predicting the states at each time period.
 - smethod(onestep), the default, causes predict to estimate the states at each time period using previous information on the dependent variables. The Kalman filter is performed on previous periods, but only the one-step predictions are made for the current period.
 - smethod(smooth) causes predict to estimate the states at each time period using all the sample
 data by the Kalman smoother. smethod(smooth) may not be specified with rstandard.
 - smethod(filter) causes predict to estimate the states at each time period using previous and contemporaneous data by the Kalman filter. The Kalman filter is performed on previous periods and the current period. smethod(filter) may be specified only with states.

Remarks and examples

We assume that you have already read [TS] **sspace**. In this entry, we illustrate some of the features of predict after using sspace to estimate the parameters of a state-space model.

All the predictions after sspace depend on the unobserved states, which are estimated recursively. Changing the sample can alter the state estimates, which can change all other predictions.

Example 1: One-step predictions

In example 5 of [TS] sspace, we estimated the parameters of the dynamic-factor model

$$\begin{pmatrix} f_t \\ f_{t-1} \end{pmatrix} = \begin{pmatrix} \theta_1 & \theta_2 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} f_{t-1} \\ f_{t-2} \end{pmatrix} + \begin{pmatrix} \nu_t \\ 0 \end{pmatrix}$$

$$\begin{pmatrix} \Delta \text{ipman}_t \\ \Delta \text{income}_t \\ \Delta \text{hours}_t \\ \Delta \text{unemp}_t \end{pmatrix} = \begin{pmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \\ \gamma_4 \end{pmatrix} f_t + \begin{pmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \\ \epsilon_{4t} \end{pmatrix}$$

where

$$\operatorname{Var}\begin{pmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \\ \epsilon_{4t} \end{pmatrix} = \begin{pmatrix} \sigma_1^2 & 0 & 0 & 0 \\ 0 & \sigma_2^2 & 0 & 0 \\ 0 & 0 & \sigma_3^2 & 0 \\ 0 & 0 & 0 & \sigma_4^2 \end{pmatrix}$$

by typing

```
. use https://www.stata-press.com/data/r19/dfex
(St. Louis Fed (FRED) macro data)
. constraint 1 [lf]L.f = 1
. sspace (f L.f L.lf, state noconstant)
>
         (lf L.f, state noconstant noerror)
>
         (D.ipman f, noconstant)
>
         (D.income f, noconstant)
>
         (D.hours f, noconstant)
>
         (D.unemp f, noconstant),
>
         covstate(identity) constraints(1)
 (output omitted)
```

Below we obtain the one-step predictions for each of the four dependent variables in the model, and then we graph the actual and predicted ipman:



The graph shows that the one-step predictions account for only a small part of the swings in the realized ipman.

Example 2: Out-of-sample, dynamic predictions

We use the estimates from the previous example to make out-of-sample predictions. After using tsappend to extend the dataset by six periods, we use predict with the dynamic() option and graph the result.



The model predicts that the changes in industrial production will remain negative for the forecast horizon, although they increase toward zero.

Example 3: Estimating an unobserved factor

In this example, we want to estimate the unobserved factor instead of predicting a dependent variable. Specifying smethod(smooth) causes predict to use all sample information in estimating the states by the Kalman smoother.

Below we estimate the unobserved factor by using the estimation sample, and we graph ipman and the estimated factor:

- . predict fac if e(sample), states smethod(smooth) equation(f)
- . tsline D.ipman fac, lcolor(gs10) xtitle("") legend(rows(2))



Example 4: Calculating residuals

The residuals and the standardized residuals are frequently used to review the specification of the model.

Below we calculate the standardized residuals for each of the series and display them in a combined graph:



Methods and formulas

Estimating the unobserved states is key to predicting the dependent variables.

By default and with the smethod (onestep) option, predict estimates the states in each period by applying the Kalman filter to all previous periods and only making the one-step predictions to the current period. (See *Methods and formulas* of [TS] **sspace** for the Kalman filter equations.)

With the smethod(filter) option, predict estimates the states in each period by applying the Kalman filter on all previous periods and the current period. The computational difference between smethod(onestep) and smethod(filter) is that smethod(filter) performs the update step on the current period while smethod(onestep) does not. The statistical difference between smethod(onestep) and smethod(filter) is that smethod(filter) uses contemporaneous information on the dependent variables while smethod(onestep) does not. As noted in [TS] **sspace**, sspace has both a stationary and a diffuse Kalman filter. predict uses the same Kalman filter used for estimation.

With the smethod (smooth) option, predict estimates the states in each period using all the sample information by applying the Kalman smoother. predict uses the Harvey (1989, sec. 3.6.2) fixed-interval smoother with model-based initial values to estimate the states when the estimated parameters imply a stationary model. De Jong (1989) provides a computationally efficient method. Hamilton (1994) discusses the model-based initial values for stationary state-space models. When the model is nonstationary, the De Jong (1989) diffuse Kalman smoother is used to predict the states. The smoothed estimates of the states are subsequently used to predict the dependent variables.

The dependent variables are predicted by plugging in the estimated states. The residuals are calculated as the differences between the predicted and the realized dependent variables. The root mean squared errors are the square roots of the diagonal elements of the mean squared error matrices that are computed by the Kalman filter. The standardized residuals are the residuals normalized by the Cholesky factor of their mean squared error produced by the Kalman filter.

predict uses the Harvey (1989, sec. 3.5) methods to compute the dynamic forecasts and the root mean squared errors. Let τ be the period at which the dynamic forecasts begin; τ must either be in the specified sample or be in the period immediately following the specified sample.

The dynamic forecasts depend on the predicted states in the period $\tau - 1$, which predict obtains by running the Kalman filter or the diffuse Kalman filter on the previous sample observations. The states in the periods prior to starting the dynamic predictions may be estimated using smethod(onestep) or smethod(smooth).

Using an if or in qualifier to alter the prediction sample can change the estimate of the unobserved states in the period prior to beginning the dynamic predictions and hence alter the dynamic predictions. The initial states are estimated using e(b) and the prediction sample.

References

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- Hamilton, J. D. 1994. Time Series Analysis. Princeton, NJ: Princeton University Press. https://doi.org/10.2307/j. ctv14jx6sm.

Harvey, A. C. 1989. Forecasting, Structural Time Series Models and the Kalman Filter. Cambridge: Cambridge University Press.

Lütkepohl, H. 2005. New Introduction to Multiple Time Series Analysis. New York: Springer.

Also see

- [TS] sspace State-space models
- [TS] dfactor Dynamic-factor models
- [TS] dfactor postestimation Postestimation tools for dfactor
- [U] 20 Estimation and postestimation commands

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