mestreg postestimation — Postestimation tools for mestreg

Postestimation commands

The following postestimation commands are of special interest after mestreg:

<table>
<thead>
<tr>
<th>Command</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>stcurve</td>
<td>plot the survivor, hazard, and cumulative hazard functions</td>
</tr>
<tr>
<td>estat group</td>
<td>summarize the composition of the nested groups</td>
</tr>
<tr>
<td>estat sd</td>
<td>display variance components as standard deviations and correlations</td>
</tr>
</tbody>
</table>

The following standard postestimation commands are also available:

<table>
<thead>
<tr>
<th>Command</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>contrast</td>
<td>contrasts and ANOVA-style joint tests of estimates</td>
</tr>
<tr>
<td>estat ic</td>
<td>Akaike’s and Schwarz’s Bayesian information criteria (AIC and BIC)</td>
</tr>
<tr>
<td>estat summarize</td>
<td>summary statistics for the estimation sample</td>
</tr>
<tr>
<td>estat vce</td>
<td>variance–covariance matrix of the estimators (VCE)</td>
</tr>
<tr>
<td>estat (svy)</td>
<td>postestimation statistics for survey data</td>
</tr>
<tr>
<td>estimates</td>
<td>cataloging estimation results</td>
</tr>
<tr>
<td>etable</td>
<td>table of estimation results</td>
</tr>
<tr>
<td>*hausman</td>
<td>Hausman’s specification test</td>
</tr>
<tr>
<td>lincom</td>
<td>point estimates, standard errors, testing, and inference for linear combinations of coefficients</td>
</tr>
<tr>
<td>*lrtest</td>
<td>likelihood-ratio test</td>
</tr>
<tr>
<td>margins</td>
<td>marginal means, predictive margins, marginal effects, and average marginal effects</td>
</tr>
<tr>
<td>marginsplot</td>
<td>graph the results from margins (profile plots, interaction plots, etc.)</td>
</tr>
<tr>
<td>nlcem</td>
<td>point estimates, standard errors, testing, and inference for nonlinear combinations of coefficients</td>
</tr>
<tr>
<td>predict</td>
<td>means, medians, hazards, densities, REs, residuals, etc.</td>
</tr>
<tr>
<td>predictnl</td>
<td>point estimates, standard errors, testing, and inference for generalized predictions</td>
</tr>
<tr>
<td>pwcompare</td>
<td>pairwise comparisons of estimates</td>
</tr>
<tr>
<td>test</td>
<td>Wald tests of simple and composite linear hypotheses</td>
</tr>
<tr>
<td>testnl</td>
<td>Wald tests of nonlinear hypotheses</td>
</tr>
</tbody>
</table>

*hausman and lrtest are not appropriate with svy estimation results.
predict

Description for predict

predict creates a new variable containing predictions such as mean and median survival times, hazards, survivor functions, linear predictions, and standard errors.

Menu for predict

Statistics > Postestimation

Syntax for predict

Syntax for obtaining predictions of the outcome and other statistics

\[ \text{predict \{type\} \{stub*|newvarlist\} \{if\} \{in\}, \text{statistic \ options}\} \]

Syntax for obtaining estimated random effects and their standard errors

\[ \text{predict \{type\} \{stub*|newvarlist\} \{if\} \{in\}, \text{reffects \ re\_options}\} \]

Syntax for obtaining ML scores

\[ \text{predict \{type\} \{stub*|newvarlist\} \{if\} \{in\}, \text{scores}\} \]

<table>
<thead>
<tr>
<th>statistic</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>mean survival time; the default</td>
</tr>
<tr>
<td>median</td>
<td>median survival time</td>
</tr>
<tr>
<td>hazard</td>
<td>hazard</td>
</tr>
<tr>
<td>eta</td>
<td>fitted linear predictor</td>
</tr>
<tr>
<td>xb</td>
<td>linear predictor for the fixed portion of the model only</td>
</tr>
<tr>
<td>stdp</td>
<td>standard error of the fixed-portion linear prediction</td>
</tr>
<tr>
<td>surv</td>
<td>predicted survivor function</td>
</tr>
<tr>
<td>density</td>
<td>predicted density function</td>
</tr>
<tr>
<td>distribution</td>
<td>predicted distribution function</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>conditional(ctype)</code></td>
<td>compute statistic conditional on estimated random effects; default is <code>conditional(ebmeans)</code></td>
</tr>
<tr>
<td><code>marginal</code></td>
<td>compute statistic marginally with respect to the random effects</td>
</tr>
<tr>
<td><code>nooffset</code></td>
<td>make calculation ignoring offset or exposure</td>
</tr>
</tbody>
</table>

### Integration

#### `int_options`

Integration options

- `median` may not be combined with `marginal`.

#### `ctype`

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>ebmeans</code></td>
<td>empirical Bayes means of random effects; the default</td>
</tr>
<tr>
<td><code>ebmodes</code></td>
<td>empirical Bayes modes of random effects</td>
</tr>
<tr>
<td><code>fixedonly</code></td>
<td>prediction for the fixed portion of the model only</td>
</tr>
</tbody>
</table>

### `re_options`

#### Main

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>ebmeans</code></td>
<td>use empirical Bayes means of random effects; the default</td>
</tr>
<tr>
<td><code>ebmodes</code></td>
<td>use empirical Bayes modes of random effects</td>
</tr>
<tr>
<td><code>reses(stub* newvarlist)</code></td>
<td>calculate standard errors of empirical Bayes estimates</td>
</tr>
</tbody>
</table>

#### Integration

Integration options

### `int_options`

#### Main

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>intpoints(#)</code></td>
<td>use # quadrature points to compute marginal predictions and empirical Bayes means</td>
</tr>
<tr>
<td><code>iterate(#)</code></td>
<td>set maximum number of iterations in computing statistics involving empirical Bayes estimators</td>
</tr>
<tr>
<td><code>tolerance(#)</code></td>
<td>set convergence tolerance for computing statistics involving empirical Bayes estimators</td>
</tr>
</tbody>
</table>

---

### Options for predict

- `mean`, the default, calculates the mean survival time.
- `median` calculates the median survival time.
- `hazard` calculates the hazard. When `marginal` is specified, marginal hazard is calculated as a ratio of the marginal density to the marginal survivor function.
- `surv` calculates the predicted survivor function.
- `eta`, `xb`, `stdp`, `density`, `distribution`, `scores`, `conditional()`, `marginal`, and `nooffset`; see [ME] `meglm postestimation`. marginal may not be specified with median.
margins

Description for margins

margins estimates margins of response for mean and median survival times and linear predictions.

Menu for margins

Statistics > Postestimation

Syntax for margins

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

statistic Description
mean mean survival time; the default
median median survival time
xb linear predictor for the fixed portion of the model only
hazard not allowed with margins
eta not allowed with margins
stdp not allowed with margins
density not allowed with margins
distribution not allowed with margins
reffects not allowed with margins
scores not allowed with margins

Options conditional(ebmeans) and conditional(ebmodes) are not allowed with margins.
Option marginal is assumed where applicable if conditional(fixedonly) is not specified.

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

For the full syntax, see [R] margins.

Remarks and examples

Various predictions, statistics, and diagnostic measures are available after fitting a mixed-effects parametric survival model with mestreg. For the most part, predictions center on obtaining estimates of the survival times or hazard functions. Conditional predictions are based on the computation of the group-specific random effects, and marginal predictions are obtained by numerically integrating out the random effects.
Example 1: Predicting conditional and marginal mean survival time

In example 1 of [ME] mestreg, we analyzed the time to infection of the catheter insertion point for 38 kidney dialysis patients. We fit the following model:

```
. stset time, failure(infect) (output omitted)
. mestreg age female || patient:, distribution(weibull) (output omitted)
```

The `predict` command allows us to compute marginal and conditional predictions. Unless stated differently, we use the word “conditional” to mean “conditional on the empirical Bayes predictions of the random effects”. Below we compute marginal and conditional means for the mean survival time.

```
. predict m_marg, mean marginal
. predict m_cond, mean conditional (predictions based on fixed effects and posterior means of random effects) (using 7 quadrature points)
```

Now, we can display the predictions for some of the patients.

```
. sort female age patient
. list patient female age m_* in 15/20, sepby(patient)

<table>
<thead>
<tr>
<th>patient</th>
<th>female</th>
<th>age</th>
<th>m_marg</th>
<th>m_cond</th>
</tr>
</thead>
<tbody>
<tr>
<td>15.</td>
<td>29</td>
<td>53</td>
<td>52.79355</td>
<td>22.36027</td>
</tr>
<tr>
<td>16.</td>
<td>29</td>
<td>53</td>
<td>52.79355</td>
<td>22.36027</td>
</tr>
<tr>
<td>17.</td>
<td>16</td>
<td>60</td>
<td>50.67546</td>
<td>28.01295</td>
</tr>
<tr>
<td>18.</td>
<td>16</td>
<td>60</td>
<td>50.67546</td>
<td>28.01295</td>
</tr>
<tr>
<td>19.</td>
<td>38</td>
<td>60</td>
<td>50.67546</td>
<td>49.47013</td>
</tr>
<tr>
<td>20.</td>
<td>38</td>
<td>60</td>
<td>50.67546</td>
<td>49.47013</td>
</tr>
</tbody>
</table>
```

We see in the output that the predicted expected conditional mean for patient 29 is equal to 22.36 (shown in `m_cond`). This is the expected time to infection for this patient. However, the predicted marginal mean for this patient is 52.79 (shown in `m_marg`). This is the expected time to infection for a patient from the population who is male and is 53 years old. This particular patient seems to be more prone to infection than would be expected based on his age and gender.

Conditional predictions are specific to each group, while marginal predictions are the same within each covariate pattern through the data. Patients 16 and 38 have the same covariate patterns; therefore, their marginal predicted means are the same. However, conditional predicted means differ.
margins and marginsplot show the changes in the marginal means for different ages.

```
. margins, predict(mean marginal) at(female=0 age=(20(5)70)) noatlegend
```

**Adjusted predictions**

Model VCE: OIM

Expression: Marginal predicted mean, predict(mean marginal)

<table>
<thead>
<tr>
<th></th>
<th>Delta-method</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Margin std. err.</td>
<td>z</td>
<td>P&gt;</td>
<td>z</td>
<td></td>
</tr>
<tr>
<td>_at</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>64.03481</td>
<td>28.99882</td>
<td>2.21</td>
<td>0.027</td>
<td>7.19816</td>
</tr>
<tr>
<td>2</td>
<td>62.18903</td>
<td>26.33284</td>
<td>2.36</td>
<td>0.018</td>
<td>10.57761</td>
</tr>
<tr>
<td>3</td>
<td>60.39646</td>
<td>24.11456</td>
<td>2.50</td>
<td>0.012</td>
<td>13.13279</td>
</tr>
<tr>
<td>4</td>
<td>58.65556</td>
<td>22.37001</td>
<td>2.62</td>
<td>0.009</td>
<td>14.81116</td>
</tr>
<tr>
<td>5</td>
<td>56.96484</td>
<td>21.11488</td>
<td>2.70</td>
<td>0.007</td>
<td>15.58043</td>
</tr>
<tr>
<td>6</td>
<td>55.32285</td>
<td>20.34538</td>
<td>2.72</td>
<td>0.007</td>
<td>15.44663</td>
</tr>
<tr>
<td>7</td>
<td>53.7282</td>
<td>20.03192</td>
<td>2.68</td>
<td>0.007</td>
<td>14.46635</td>
</tr>
<tr>
<td>8</td>
<td>52.17951</td>
<td>20.12</td>
<td>2.59</td>
<td>0.010</td>
<td>12.74503</td>
</tr>
<tr>
<td>9</td>
<td>50.67546</td>
<td>20.53852</td>
<td>2.47</td>
<td>0.014</td>
<td>10.42071</td>
</tr>
<tr>
<td>10</td>
<td>49.21476</td>
<td>21.21134</td>
<td>2.32</td>
<td>0.020</td>
<td>7.64129</td>
</tr>
<tr>
<td>11</td>
<td>47.79617</td>
<td>22.06715</td>
<td>2.17</td>
<td>0.030</td>
<td>4.545348</td>
</tr>
</tbody>
</table>

```
. marginsplot
```

Variables that uniquely identify margins: age

We see that the predicted marginal mean decreases with age; older patients are expected to have an event earlier. This is consistent with the findings from example 1 of [ME] mestreg that the hazard is increasing with age.
Example 2: Predicting survivor functions

Continuing with example 1, we now predict survivor functions.

. predict S_marg, surv marginal
   (using 7 quadrature points)
. predict S_cond, surv conditional
   (predictions based on fixed effects and posterior means of random effects)
   (using 7 quadrature points)
. sort female age patient _t
. list patient female age _t S_* in 15/20, sepby(patient)

<table>
<thead>
<tr>
<th>patient</th>
<th>female</th>
<th>age</th>
<th>_t</th>
<th>S_marg</th>
<th>S_cond</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>29</td>
<td>0</td>
<td>53</td>
<td>.9628581</td>
<td>.9564017</td>
</tr>
<tr>
<td>16</td>
<td>29</td>
<td>0</td>
<td>53</td>
<td>.5165027</td>
<td>.3493623</td>
</tr>
<tr>
<td>17</td>
<td>16</td>
<td>0</td>
<td>60</td>
<td>.9122225</td>
<td>.9230723</td>
</tr>
<tr>
<td>18</td>
<td>16</td>
<td>0</td>
<td>60</td>
<td>.6273606</td>
<td>.6129264</td>
</tr>
<tr>
<td>19</td>
<td>38</td>
<td>0</td>
<td>60</td>
<td>.8141544</td>
<td>.9107039</td>
</tr>
<tr>
<td>20</td>
<td>38</td>
<td>0</td>
<td>60</td>
<td>.20487</td>
<td>.2900458</td>
</tr>
</tbody>
</table>

Survival predictions vary with the value of the study time variable because they are predictions of the survivor function at the study time \( t \). For example, patient 29 has a 0.96 probability that a new insertion remains at least 2 days without infection and a 0.35 probability that a new insertion remains at least 25 days without infection. For a randomly chosen 53-year-old male patient from the population, the probabilities to remain at least 2 or 25 days without infection are, respectively, 0.96 and 0.52.

We can use stcurve to plot these predictions simultaneously for males and females of the same age.

. stcurve, surv at1(female=0 age=53) at2(female=1 age=53)
   (option unconditional assumed)

We see that the survivor function for females is above the survivor function for males, which means that females have a greater probability of not having an episode by study time \( t \).
Example 3: Comparing marginal hazards

In example 2 of \texttt{mestreg}, we estimated two different distributions with random effects on patient and covariates age and female. Here we compare the marginal hazards using \texttt{stcurve}. By default, \texttt{stcurve} plots predictions at the mean of the covariates, computed over the whole estimation sample. We plot the predictions for \texttt{female==1}.

\begin{verbatim}
mestreg age female || patient: , dist(weibull) time
(output omitted)
.mestreg age female || patient: , dist(gamma)
(output omitted)
\end{verbatim}

The two estimated marginal hazards are similar. The marginal hazard has a very different shape from the conditional hazards. The conditional hazard function for a Weibull or a gamma distribution are both monotonic (increasing, constant, or decreasing, depending on the parameters).
Example 4 : Obtaining predictions of random effects

In example 3 of [ME] mestreg, we fit a Weibull model with random intercepts and random coefficients at the subject level. We obtained a positive covariance between the random effects. We refit the model here and then use predict with the option reffects to obtain predictions of the random effects based on the empirical Bayes posterior means.

```
use https://www.stata-press.com/data/r17/angina, clear
(Angina drug data, Rabe-Hesketh and Skrondal (2021, ch. 15.7))
mestreg occasion##treat || pid: i.treat, distribution(weibull)
> covariance(unstructured) nofvlabel
(output omitted)
predict re*, reffects
(calculating posterior means of random effects)
(using 7 quadrature points)
```

Plotting the predictions of the predicted random coefficient versus the random intercept shows the pattern we discussed in the main section: individuals with a larger random slope tend also to have a larger random intercept.

```
twoway scatter re1 re2
```

Individuals with large random intercepts have individual hazards that are larger than those of other individuals with the same covariate patterns. Also, individuals with large random coefficients have individual conditional hazard ratios for treatment that are larger than those of other individuals with the same covariate pattern.

In other words, if the aim of the treatment is to decrease the hazard, then the positive correlation means that the treatment tends to be less effective for individuals who have a higher individual hazard (within the same occasion number).

Example 5 : Conditional and marginal hazards

In example 1 of [ME] mestreg, we mentioned that hazard ratios should be interpreted as conditional on the random effects. Here we use predict to illustrate this concept. We use a simulated dataset for a Weibull model with random effects for group and a binary covariate x.
We show that for a given group, the conditional hazard function satisfies the proportional-hazards (PH) assumption. That is, for a given group \( j \),

\[
h(t|x = 1,\text{group} = j) = \exp(\beta x) \times h(t|x = 0,\text{group} = j)
\]

is equivalent to

\[
\log\{h(t|x = 1,\text{group} = j)\} = \beta x + \log\{h(t|x = 0,\text{group} = j)\}
\]

This property of the log hazard-function translates to one curve being a shifted version of the other, which is easier to see than the proportionality of the (untransformed) hazard function.

After fitting the model, we use `predict` to compute the conditional prediction of the hazard function for group 1; we create the variables `hcond0` and `hcond1`. `hcond0` will contain the conditional hazard for group 1 when \( x==0 \); `hcond1` will contain the conditional hazard for group 1 when \( x==1 \).

We also create `zcond = \log hcond0 + \beta x`. If the PH assumption is satisfied, then the plotted values of `zcond` will be superimposed on those of `\log hcond1`.

```
. use https://www.stata-press.com/data/r17/weibre, clear
. mestreg i.x || group:, distribution(weibull) nolog
    Analysis time _t: t
    Mixed-effects Weibull PH regression
    Number of obs = 100,000
    Group variable: group
    Number of groups = 500
    Integration method: mvaghermite
    Integration pts. = 7
    Log likelihood = 175196.47
    Wald chi2(1) = 21447.86
    Number of obs = 100,000
    Number of groups = 500
    Obs per group:  min   200     avg  200.0     max   200
    Integration method: mvaghermite
    Integration pts. = 7
    Log likelihood = 175196.47
    Wald chi2(1) = 21447.86

    _t   Haz. ratio   Std. err.     z   P>|z|    [95% conf. interval]
----------   ----------   --------   -----   -----   ------------------
      1.x   2.713138   .0184908   146.45   0.000    2.677137    2.749622
      _cons   2.564135   .0797385    30.28   0.000    2.412518    2.715851
      /ln_p  -.6925791   .0024746  -287.86   0.000   -.6974291   -.687729
      group  var(_cons)   .472804   .0303096    .4169789   .536103

Note: Estimates are transformed only in the first equation to hazard ratios.
Note: _cons estimates baseline hazard (conditional on zero random effects).
LR test vs. Weibull model: chibar2(01) = 35800.39   Prob >= chibar2 = 0.0000
```

Note: Estimates are transformed only in the first equation to hazard ratios.
Note: _cons estimates baseline hazard (conditional on zero random effects).
LR test vs. Weibull model: chibar2(01) = 35800.39   Prob >= chibar2 = 0.0000

```
. predict hcond, hazard conditional(ebmeans)
      (predictions based on fixed effects and posterior means of random effects)
. gen loghcond0 = \log(hcond) if x==0
      (49,991 missing values generated)
. gen loghcond1 = \log(hcond) if x==1
      (50,009 missing values generated)
. gen zcond = loghcond0 + _b[_t:1.x]
      (49,991 missing values generated)
. sort _t group
```
In the graph above, the line for $\log h_{cond1}$ cannot be distinguished from the line for $z_{cond}$ for most of the distribution. This illustrates that the PH assumption is satisfied for the conditional hazard. Notice that you can still see a part of $\log h_{cond1}$ near the origin. This is because the two variables correspond to different values of $t$ and only $\log h_{cond1}$ happens to be defined at the early values.

Now, we make the same computation for the marginal hazard.

```stata
. predict hmarg, hazard marginal
. gen loghmarg0 = log(hmarg) if x==0
   (49,991 missing values generated)
. gen loghmarg1 = log(hmarg) if x==1
   (50,009 missing values generated)
. gen zmarg = loghmarg0 + _b[_t:1.x]
   (49,991 missing values generated)
. sort _t group
. twoway line loghmarg0 loghmarg1 zmarg _t
```
The curve for \texttt{zmarg} is clearly different from the curve for \texttt{loghmarg1}, demonstrating that the marginal distribution does not meet the PH assumption. Notice that the line for \texttt{loghmarg1} is shorter than the others. This is because predictions are obtained at the values of \_t in the dataset. These values of \_t were simulated based on the model, which determines that observations with \texttt{x==1} fail earlier.

Methods and formulas

Methods and formulas for predicting random effects and other statistics are given in Methods and formulas of \texttt{mestreg}. Statistics of special interest for survival analysis are described below.

\texttt{predict} \texttt{newvar} with the \texttt{conditional()} option computes the following predictions:

\textbf{median}:
\[
\texttt{newvar}_{ji} = \{t : \hat{S}(t|x_{ji}, \hat{u}_{ji}) = 1/2\}
\]
where \(\hat{S}(t|x_{ji}, \hat{u}_{ji}) = S(t|x_{ji}\hat{\beta} + \hat{u}_{ji})\), where \(\hat{u}_{ji}\) are the empirical Bayes predictions for \(u_{ji}\). If \texttt{conditional(fixedonly)} is specified, then 0 is substituted for \(\hat{u}_{ji}\).

\textbf{mean}:
\[
\texttt{newvar}_{ji} = \int_0^\infty \hat{S}(t|x_{ji}, u_{ji})dt
\]

\textbf{surv}:
\[
\texttt{newvar}_{ji} = \hat{S}(t_{ji}|x_{ji}, \hat{u}_{ji})
\]

\textbf{hazard}:
\[
\texttt{newvar}_{ji} = \hat{g}(t_{ji}|x_{ji}, \hat{u}_{ji})/\hat{S}(t_{ji}|x_{ji}, \hat{u}_{ji})
\]
where \(\hat{g}(t|x_{ji}, u_{ji})\) is the density \(g(t|x_{ji}\hat{\beta} + \hat{u}_{ji})\).

When the \texttt{marginal} option is used with \texttt{mean} or \texttt{surv}, the prediction is computed marginally with respect to the random effects. That is, the prediction is integrated over the random-effects distributions. When the \texttt{marginal} option is used with \texttt{hazard}, the hazard for the marginal distribution is computed. That is, the predicted hazard is computed as the quotient of the marginal hazard and the marginal survivor function.

Also see

- \texttt{mestreg} — Multi-level mixed-effects parametric survival models
- \texttt{meglm postestimation} — Postestimation tools for \texttt{meglm}
- \texttt{mixed postestimation} — Postestimation tools for \texttt{mixed}
- \texttt{stcurve} — Plot the survivor or related function after \texttt{streg}, \texttt{stcox}, and others
- \texttt{20 Estimation and postestimation commands}