Title

> **mestreg postestimation** — Postestimation tools for mestreg

Postestimation commands

The following postestimation commands are of special interest after `mestreg`:

Command	Description
stcurve	plot the survivor, hazard, and cumulative hazard functions
estat group	summarize the composition of the nested groups
estat sd	display variance components as standard deviations and correlations

The following standard postestimation commands are also available:

Command	Description
contrast	contrasts and ANOVA-style joint tests of estimates
estat ic	Akaike's, consistent Akaike's, corrected Akaike's, and Schwarz's Bayesian information criteria (AIC, CAIC, AICc, and BIC)
estat summarize	summary statistics for the estimation sample
estat vce	variance–covariance matrix of the estimators (VCE)
estat (svy)	postestimation statistics for survey data
estimates	cataloging estimation results
etable	table of estimation results
* hausman	Hausman's specification test
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	means, medians, hazards, densities, REs, residuals, etc.
predictnl	point estimates, standard errors, testing, and inference for generalized predictions
pwcompare	pairwise comparisons of estimates
test	Wald tests of simple and composite linear hypotheses
testnl	Wald tests of nonlinear hypotheses

* `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

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

Syntax for obtaining estimated random effects and their standard errors

> predict [*type*] { *stub** | *newvarlist* } [*if*] [*in*], reffects [*re_options*]

Syntax for obtaining ML scores

> predict [*type*] { *stub** | *newvarlist* } [*if*] [*in*], <u>sc</u>ores

statistic	Description
Main	
mean	mean survival time; the default
<u>med</u>ian	median survival time
<u>haz</u>ard	hazard
eta	fitted linear predictor
xb	linear predictor for the fixed portion of the model only
stdp	standard error of the fixed-portion linear prediction
<u>sur</u>v	predicted survivor function
<u>den</u>sity	predicted density function
<u>dis</u>tribution	predicted distribution function

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

options	Description
Main	
<u>condition</u>al(*ctype*)	compute *statistic* conditional on estimated random effects; default is conditional(ebmeans)
marginal	compute *statistic* marginally with respect to the random effects
<u>noo</u>ffset	make calculation ignoring offset or exposure
Integration	
int_options	integration options

median may not be combined with marginal.

ctype	Description
<u>ebmea</u>ns	empirical Bayes means of random effects; the default
<u>ebmod</u>es	empirical Bayes modes of random effects
<u>fixed</u>only	prediction for the fixed portion of the model only

re_options	Description
Main	
<u>ebmea</u>ns	use empirical Bayes means of random effects; the default
<u>ebmod</u>es	use empirical Bayes modes of random effects
reses(*stub** | *newvarlist*)	calculate standard errors of empirical Bayes estimates
Integration	
int_options	integration options

int_options	Description
<u>intp</u>oints(*#*)	use *#* quadrature points to compute marginal predictions and empirical Bayes means
<u>iter</u>ate(*#*)	set maximum number of iterations in computing statistics involving empirical Bayes estimators
<u>tol</u>erance(*#*)	set convergence tolerance for computing statistics involving empirical Bayes estimators

Options for predict

Main

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.

reffects, ebmeans, ebmodes, and reses(); see [ME] **meglm postestimation**.

┌─── Integration ───

intpoints(), iterate(), and tolerance(); see [ME] **meglm postestimation**.

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
surv	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   stata.com

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:

```
. use https://www.stata-press.com/data/r18/catheter
(Kidney data, McGilchrist and Aisbett, Biometrics, 1991)

. 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)
```

	patient	female	age	m_marg	m_cond
15.	29	0	53	52.79355	22.36027
16.	29	0	53	52.79355	22.36027
17.	16	0	60	50.67546	28.01295
18.	16	0	60	50.67546	28.01295
19.	38	0	60	50.67546	49.47013
20.	38	0	60	50.67546	49.47013

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   Number of obs = 76
Model VCE: OIM

Expression: Marginal predicted mean, predict(mean marginal)

		Delta-method				
	Margin	std. err.	z	P>|z|	[95% conf.	interval]
_at						
1	64.03481	28.99882	2.21	0.027	7.19816	120.8715
2	62.18903	26.33284	2.36	0.018	10.57761	113.8005
3	60.39646	24.11456	2.50	0.012	13.13279	107.6601
4	58.65556	22.37001	2.62	0.009	14.81116	102.5
5	56.96484	21.11488	2.70	0.007	15.58043	98.34925
6	55.32285	20.34538	2.72	0.007	15.44663	95.19908
7	53.7282	20.03192	2.68	0.007	14.46635	92.99004
8	52.17951	20.12	2.59	0.010	12.74503	91.61398
9	50.67546	20.53852	2.47	0.014	10.42071	90.93021
10	49.21476	21.21134	2.32	0.020	7.64129	90.78823
11	47.79617	22.06715	2.17	0.030	4.545348	91.04698

```
. marginsplot
```
Variables that uniquely identify margins: **age**
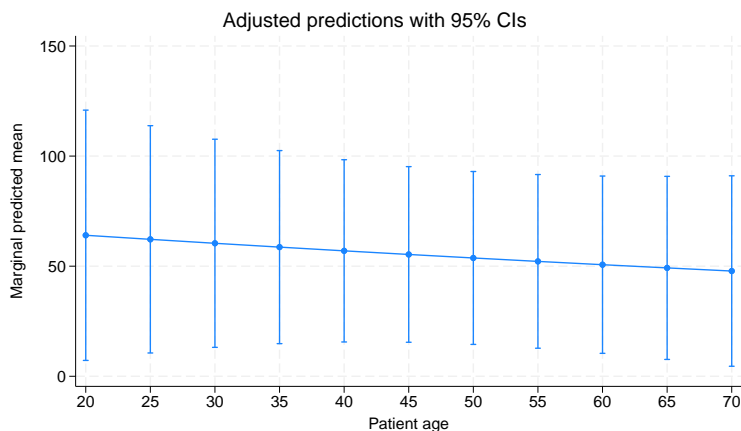
We see that the predicted marginal mean decreases with age; older patients are expected to have an event earlier. This is consistent with the findings from example 1 of [ME] **mestreg** that the hazard is increasing with age.

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▷ 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)
```

	patient	female	age	_t	S_marg	S_cond
15.	29	0	53	2	.9628581	.9564017
16.	29	0	53	25	.5165027	.3493623
17.	16	0	60	4	.9122225	.9230723
18.	16	0	60	17	.6273606	.6129264
19.	38	0	60	8	.8141544	.9107039
20.	38	0	60	63	.20487	.2900458

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)
note: function evaluated at specified values of selected covariates and
      overall means of other covariates (if any).
```


Mixed-effects Weibull PH regression
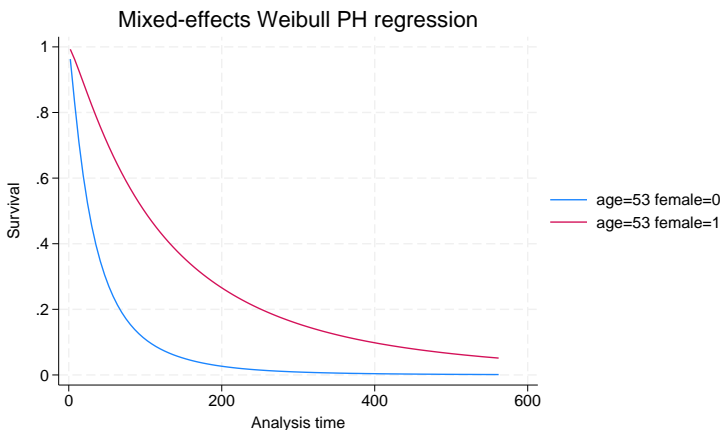
We see that the survivor function for females is above the survivor function for males, which means that females have a greater probability of not having an episode by study time _t.

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▷ Example 3 : Comparing marginal hazards

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

```
. mestreg age female || patient:, dist(weibull) time
(output omitted)
. stcurve, hazard at(female=1)
(option unconditional assumed)
note: function evaluated at specified values of selected covariates and
      overall means of other covariates (if any).
. graph save g1
file g1.gph saved
. mestreg age female || patient:, dist(gamma)
(output omitted)
. stcurve, hazard at(female=1)
(option unconditional assumed)
note: function evaluated at specified values of selected covariates and
      overall means of other covariates (if any).
. graph save g2
file g2.gph saved
. graph combine g1.gph g2.gph
```
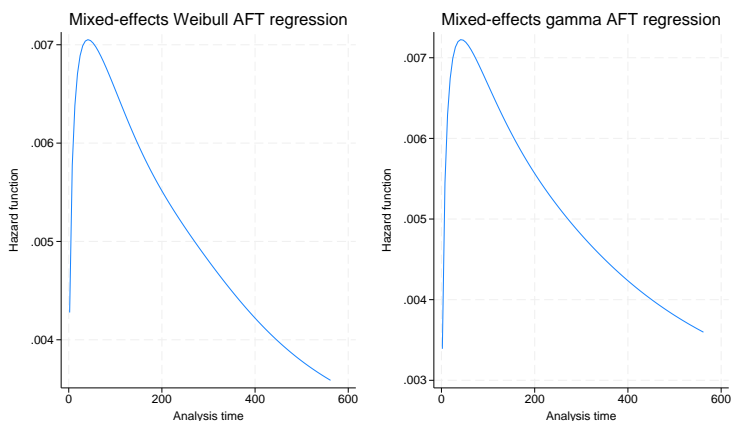
The two estimated marginal hazards are similar. The marginal hazard has a very different shape from the conditional hazards. The conditional hazard function for a Weibull or a gamma distribution are both monotonic (increasing, constant, or decreasing, depending on the parameters).

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▷ 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/r18/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, ytitle(EB means for random coefficient)
> xtitle(EB means for random intercept)
```
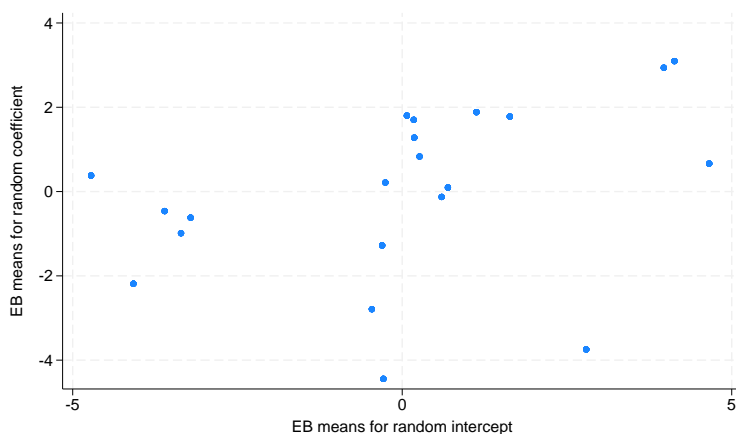

Individuals with large random intercepts have individual hazards that are larger than those of other individuals with the same covariate patterns. Also, individuals with large random coefficients have individual conditional hazard ratios for treatment that are larger than those of other individuals with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

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▷ 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 = loghcond0 + β_x. If the PH assumption is satisfied, then the plotted values of zcond will be superimposed on those of loghcond1.

```
. use https://www.stata-press.com/data/r18/weibre, clear
. mestreg i.x || group:, distribution(weibull) nolog
        Failure _d: 1 (meaning all fail)
  Analysis time _t: t
Mixed-effects Weibull PH regression              Number of obs     =     100,000
Group variable: group                            Number of groups  =         500

                                                 Obs per group:
                                                             min =         200
                                                             avg =       200.0
                                                             max =         200
Integration method: mvaghermite                  Integration pts.  =           7

                                                 Wald chi2(1)      =    21447.86
Log likelihood = 175196.47                       Prob > chi2       =      0.0000
```

_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	2.725281
/ln_p	-.6925791	.0024746			-.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
. 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
```

```
. twoway line loghcond0 loghcond1 zcond _t if group==1
```
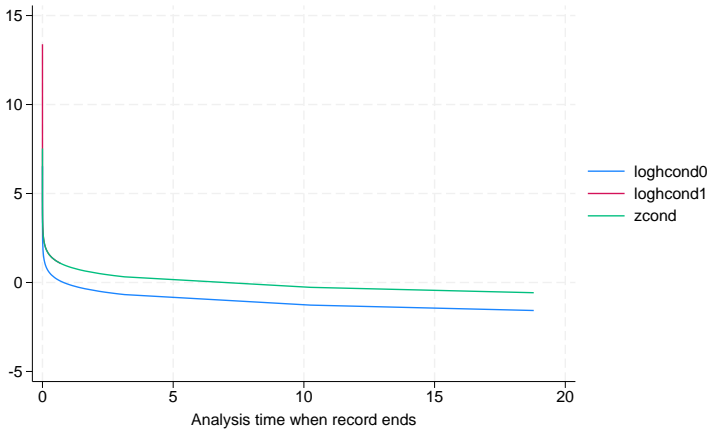

In the graph above, the line for `loghcond1` cannot be distinguished from the line for `zcond` for most of the distribution. This illustrates that the PH assumption is satisfied for the conditional hazard. Notice that you can still see a part of `loghcond1` near the origin. This is because the two variables correspond to different values of `_t` and only `loghcond1` happens to be defined at the early values.

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

```
. 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
```
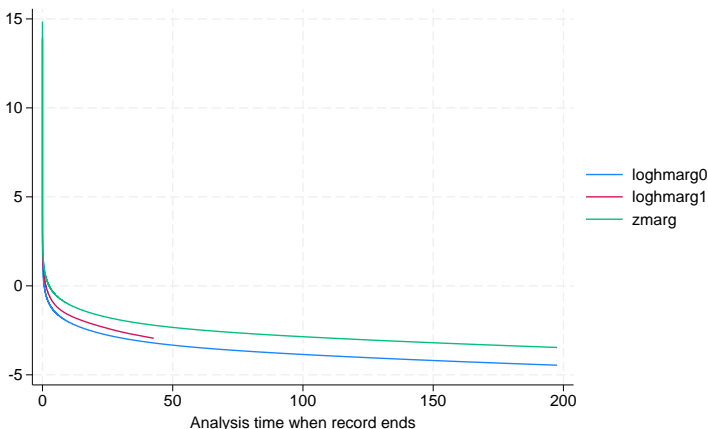
The curve for zmarg is clearly different from the curve for loghmarg1, demonstrating that the marginal distribution does not meet the PH assumption. Notice that the line for loghmarg1 is shorter than the others. This is because predictions are obtained at the values of _t in the dataset. These values of _t were simulated based on the model, which determines that observations with x==1 fail earlier.

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Methods and formulas

Methods and formulas for predicting random effects and other statistics are given in *Methods and formulas* of [ME] **meglm postestimation**. Statistics of special interest for survival analysis are described below.

predict *newvar* with the conditional() option computes the following predictions:

median:
$$newvar_{ji} = \{t : \widehat{S}(t|\mathbf{x}_{ji}, \widehat{u}_{ji}) = 1/2\}$$

where $\widehat{S}(t|\mathbf{x}_{ji}, \widehat{u}_{ji})$ is $S(t|\mathbf{x}_{ji}\widehat{\boldsymbol{\beta}} + \widehat{u}_{ji})$, where $\widehat{u}_{ji}$ are the empirical Bayes predictions for u_{ji}. If conditional(fixedonly) is specified, then 0 is substituted for $\widehat{u}_{ji}$.

mean:
$$newvar_{ji} = \int_0^\infty \widehat{S}(t|\mathbf{x}_{ji}, u_{ji})dt$$

surv:
$$newvar_{ji} = \widehat{S}(t_{ji}|\mathbf{x}_{ji}, \widehat{u}_{ji})$$

hazard:
$$newvar_{ji} = \widehat{g}(t_{ji}|\mathbf{x}_{ji}, \widehat{u}_{ji})/\widehat{S}(t_{ji}|\mathbf{x}_{ji}, \widehat{u}_{ji})$$

where $\widehat{g}(t|\mathbf{x}_{ji}, u_{ji})$ is the density $g(t|\mathbf{x}_{ji}\widehat{\boldsymbol{\beta}} + \widehat{u}_{ji})$.

When the marginal option is used with mean or 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 marginal option is used with 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

[ME] **mestreg** — Multilevel mixed-effects parametric survival models

[ME] **meglm postestimation** — Postestimation tools for meglm

[ME] **mixed postestimation** — Postestimation tools for mixed

[ST] **stcurve** — Plot the survivor or related function after streg, stcox, and more

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

For suggested citations, see the FAQ on citing Stata documentation.