# mestreg postestimation — Postestimation tools for mestreg

Postestimation commands	predict	margins
Remarks and examples	Methods and formulas	Also see

# **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 parameters
estat ic	Akaike's, consistent Akaike's, corrected Akaike's, and Schwarz's Bayesian in- formation criteria (AIC, CAIC, AICc, and BIC, respectively)
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 parameters
* 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 combina- tions of parameters
predict	means, medians, hazards, densities, REs, residuals, etc.
predictnl	point estimates, standard errors, testing, and inference for generalized predic- tions
pwcompare	pairwise comparisons of parameters
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], scores

statistic	Description
Main	
mean	mean survival time; the default
<u>med</u> ian	median survival time
<u>ha</u> zard	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
surv	predicted survivor function
<u>den</u> sity	predicted density function
<u>dist</u> ribution	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.

mestreg postestimation — Pos	testimation tools for mestreg 3
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options	Description
Main	
<pre>conditional(ctype)</pre>	<pre>compute statistic conditional on estimated random effects; default is     conditional(ebmeans)</pre>
marginal	compute statistic marginally with respect to the random effects
<u>nooff</u> set	make calculation ignoring offset or exposure
Integration	
int_options	integration options
median may not be combined w	ith marginal.
ctype	Description
ebmeans	empirical Bayes means of random effects; the default
<u>ebmode</u> s	empirical Bayes modes of random effects
<u>fixed</u> only	prediction for the fixed portion of the model only
re_options	Description
Main	
<u>ebmean</u> s	use empirical Bayes means of random effects; the default
<u>ebmode</u> s	use empirical Bayes modes of random effects
<pre>reses(stub* newvarlist)</pre>	calculate standard errors of empirical Bayes estimates
Integration	
int_options	integration options
int_options	Description
<pre>intpoints(#)</pre>	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]	, <u>pr</u> edict	(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
<u>ha</u> zard	not allowed with margins
eta	not allowed with margins
stdp	not allowed with margins
<u>s</u> urv	not allowed with margins
<u>den</u> sity	not allowed with margins
<u>dist</u> ribution	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 groupspecific 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/r19/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,	<pre>sepby(patient</pre>	;)
	patient	female	age	m_marg	g m_cond	
15.	29	0	53	52.79355	22.36027	
16.	29	0	53	52.79355	5 22.36027	
17.	16	0	60	50.67546	28.01295	
18.	16	0	60	50.67546	6 28.01295	
19.	38	0	60	50.67546	6 49.47013	
20.	38	0	60	50.67546	6 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)

	Margin	Delta-method	-	PNI	[QE% conf	intorwoll
-	Haigin	stu. ell.	Z	r / 21	[95% CON1.	Incervarj
_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	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.

#### 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
```

· borto romaro ago patronto \_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
             1
             .8
             .6
         Survival
                                                                        age=53 female=0
                                                                        age=53 female=1
             .4
             .2
             0
                               200
                                               4\dot{0}0
                                                               600
                Ó
                                   Analysis time
```

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.

4

## 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
                 Mixed-effects Weibull AFT regression
                                                         Mixed-effects gamma AFT regression
             .007
                                                     .007
                                                     .006
             .006
                                                  Hazard function
          Hazard function
                                                     .005
             .005
                                                     .004
             .004
                                                     .003
                                                                                      600
                          200
                                    400
                                              600
                                                                  200
                                                                            400
                            Analysis time
                                                                    Analysis time
```

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/r19/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.



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).

4

#### 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,

$$h(t|\mathbf{x} = 1, \texttt{group} = j) = \exp(\beta_x) \times h(t|\mathbf{x} = 0, \texttt{group} = j)$$

is equivalent to

$$\log\{h(t|\mathbf{x}=1, \texttt{group}=j)\} = \beta_x + \log\{h(t|\mathbf{x}=0, \texttt{group}=j)\}$$

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

. use https://	/www.stata-pre	ess.com/data	/r19/weib	ore, clear		
. mestreg i.x	group:, d:	istribution(	weibull)	nolog		
Failur Analysis tin	re <b>_d</b> : 1 (mean ne <b>_t</b> : t	ning all fai	.1)			
Mixed-effects Weibull PH regression				Number of	f obs =	100,000
Group variable: group				Number of	f groups =	500
				Obs per group:		
					min =	200
					avg =	200.0
					max =	200
Integration method: mvaghermite				Integration pts. =		7
				Wald chi	2(1) =	21447.86
Log likelihood = 175196.47				Prob > c	hi2 =	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



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.



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

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.

4

# 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:

$$\textit{newvar}_{ji} = \{t: \hat{S}(t|\mathbf{x}_{ji}, \hat{u}_{ji}) = 1/2\}$$

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

mean:

$$\textit{newvar}_{ji} = \int_0^\infty \hat{S}(t | \mathbf{x}_{ji}, u_{ji}) dt$$

surv:

$$\mathit{newvar}_{ji} = \hat{S}(t_{ji} | \mathbf{x}_{ji}, \hat{u}_{ji})$$

hazard:

$$\textit{newvar}_{ji} = \hat{g}(t_{ji} | \mathbf{x}_{ji}, \hat{u}_{ji}) / S(t_{ji} | \mathbf{x}_{ji}, \hat{u}_{ji})$$

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

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

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