

# quadchk — Check sensitivity of quadrature approximation

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## Syntax

```
quadchk [#1 #2] [, nooutput nofrom]
```

## Menu

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## Description

quadchk checks the quadrature approximation used in the random-effects estimators of the following commands:

```

xtcloglog
xtintreg
xtlogit
xtologit
xtoprobit
xtpoisson, re with the normal option
xtprobit
xttobit

```

quadchk refits the model for different numbers of quadrature points and then compares the different solutions.

#1 and #2 specify the number of quadrature points to use in the comparison runs of the previous model. The default is to use (roughly)  $2n_q/3$  and  $4n_q/3$  points, where  $n_q$  is the number of quadrature points used in the original estimation.

Most options supplied to the original model are respected by quadchk, but some are not. These are `or`, `vce()`, and the *maximize\_options*.

## Options

`nooutput` suppresses the iteration log and output of the refitted models.

`nofrom` forces the refitted models to start from scratch rather than starting from the previous estimation results. Specifying the `nofrom` option can level the playing field in testing estimation results.

## Remarks and examples

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Remarks are presented under the following headings:

*What makes a good random-effects model fit?*  
*How do I know whether I have a good quadrature approximation?*  
*What can I do to improve my results?*

## What makes a good random-effects model fit?

Some random-effects estimators in Stata use adaptive or nonadaptive Gauss–Hermite quadrature to compute the log likelihood and its derivatives. As a rule, adaptive quadrature, which is the default integration method, is much more accurate. The `quadchk` command provides a means to look at the numerical accuracy of either quadrature approximation. A good random-effects model fit depends on both the goodness of the quadrature approximation and the goodness of the data.

The accuracy of the quadrature approximation depends on three factors. The first and second are how many quadrature points are used and where the quadrature points fall. These two factors directly influence the accuracy of the quadrature approximation. The number of quadrature points may be specified with the `intpoints()` option. However, once the number of points is specified, their abscissas (locations) and corresponding weights are completely determined. Increasing the number of points expands the range of the abscissas and, to a lesser extent, increases the density of the abscissas. For this reason, a function that undulates between the abscissas can be difficult to approximate.

Third, the smoothness of the function being approximated influences the accuracy of the quadrature approximation. Gauss–Hermite quadrature estimates integrals of the type

$$\int_{-\infty}^{\infty} e^{-x^2} f(x) dx$$

and the approximation is exact if  $f(x)$  is a polynomial of degree less than the number of integration points. Therefore,  $f(x)$  that are well approximated by polynomials of a given degree have integrals that are well approximated by Gauss–Hermite quadrature with that given number of integration points. Both large panel sizes and high  $\rho$  can reduce the accuracy of the quadrature approximation.

A final factor affects the goodness of the random-effects model: the data themselves. For high  $\rho$ , for example, there is high intrapanel correlation, and panels look like observations. The model becomes unidentified. Here, even with exact quadrature, fitting the model would be difficult.

## How do I know whether I have a good quadrature approximation?

`quadchk` is intended as a tool to help you know whether you have a good quadrature approximation. As a rule of thumb, if the coefficients do not change by more than a relative difference of  $10^{-4}$  (0.01%), the choice of quadrature points does not significantly affect the outcome, and the results may be confidently interpreted. However, if the results do change appreciably—greater than a relative difference of  $10^{-2}$  (1%)—then quadrature is not reliably approximating the likelihood.

## What can I do to improve my results?

If the `quadchk` command indicates that the estimation results are sensitive to the number of quadrature points, there are several things you can do. First, if you are not using adaptive quadrature, switch to adaptive quadrature.

Adaptive quadrature can improve the approximation by transforming the integrand so that the abscissas and weights sample the function on a more suitable range. Details of this transformation are in *Methods and formulas* for the given commands; for example, see [\[XT\] xtprobit](#).

If the model still shows sensitivity to the number of quadrature points, increase the number of quadrature points with the `intpoints()` option. This option will increase the range and density of the sampling used for the quadrature approximation.

If neither of these works, you may then want to consider an alternative model, such as a fixed-effects, pooled, or population-averaged model. Alternatively, a different random-effects model whose likelihood is not approximated via quadrature (for example, `xtpoisson`, `re`) may be a better choice.

## ▷ Example 1

Here we synthesize data according to the model

$$E(y) = 0.05 x_1 + 0.08 x_2 + 0.08 x_3 + 0.1 x_4 + 0.1 x_5 + 0.1 x_6 + 0.1\epsilon$$

$$z = \begin{cases} 1 & \text{if } y \geq 0 \\ 0 & \text{if } y < 0 \end{cases}$$

where the intrapanel correlation is 0.5 and the x1 variable is constant within panels. We first fit a random-effects probit model, and then we check the stability of the quadrature calculation:

```
. use http://www.stata-press.com/data/r13/quad1
. xtset id
      panel variable:  id (balanced)
. xtprobit z x1-x6
      (output omitted)
Random-effects probit regression           Number of obs   =       6000
Group variable: id                       Number of groups =       300
Random effects u_i ~ Gaussian            Obs per group: min =        20
                                           avg   =       20.0
                                           max   =        20
Integration method: mvaghermite          Integration points =        12
                                           Wald chi2(6)    =       29.24
Log likelihood = -3347.1097              Prob > chi2     =       0.0001
```

z	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	.0043068	.0607058	0.07	0.943	-.1146743	.1232879
x2	.1000742	.066331	1.51	0.131	-.0299323	.2300806
x3	.1503539	.0662503	2.27	0.023	.0205057	.2802021
x4	.123015	.0377089	3.26	0.001	.0491069	.196923
x5	.1342988	.0657222	2.04	0.041	.0054856	.263112
x6	.0879933	.0455753	1.93	0.054	-.0013325	.1773192
_cons	.0757067	.060359	1.25	0.210	-.0425948	.1940083
/lnsig2u	-.0329916	.1026847			-.23425	.1682667
sigma_u	.9836395	.0505024			.889474	1.087774
rho	.4917528	.0256642			.4417038	.5419677

Likelihood-ratio test of rho=0: chibar2(01) = 1582.67 Prob >= chibar2 = 0.000

```

. quadchk
Refitting model intpoints() = 8
(output omitted)
Refitting model intpoints() = 16
(output omitted)

```

Quadrature check				
	Fitted quadrature 12 points	Comparison quadrature 8 points	Comparison quadrature 16 points	
Log likelihood	-3347.1097	-3347.1153 -.00561484 1.678e-06	-3347.1099 -.00014288 4.269e-08	Difference Relative difference
z:	.0043068	.0043068 8.983e-15 2.086e-12	.00430541 -1.388e-06 -.00032222	Difference Relative difference
x1				
z:	.10007418	.10007418 2.540e-15 2.538e-14	.10007431 1.362e-07 1.361e-06	Difference Relative difference
x2				
z:	.15035391	.15035391 6.356e-15 4.227e-14	.15035406 1.520e-07 1.011e-06	Difference Relative difference
x3				
z:	.12301495	.12301495 4.149e-15 3.373e-14	.12301506 1.099e-07 8.931e-07	Difference Relative difference
x4				
z:	.13429881	.13429881 4.913e-15 3.658e-14	.13429896 1.471e-07 1.096e-06	Difference Relative difference
x5				
z:	.08799332	.08799332 3.358e-15 3.817e-14	.08799346 1.363e-07 1.549e-06	Difference Relative difference
x6				
z:	.07570675	.07570675 1.962e-14 2.592e-13	.07570423 -2.516e-06 -.00003323	Difference Relative difference
_cons				
lnsig2u:	-.03299164	-.03299164 7.268e-14 -2.203e-12	-.03298184 9.798e-06 -.00029699	Difference Relative difference
_cons				

We see that the largest difference is in the x1 variable with a relative difference of 0.03% between the model with 12 integration points and 16. This example is somewhat rare in that the differences between eight quadrature points and 12 are smaller than those between 12 and 16. Usually the opposite occurs: the model results converge as you add quadrature points. Here we have an indication that perhaps some minor feature of the model was missed with eight points and 12 but seen with 16. Because all differences are very small, we could accept this model as is. We would like to have a largest relative difference of about 0.01%, and this is close. The differences and relative differences are small, indicating that refitting the random-effects probit model with a few more integration points will yield a satisfactory result. Indeed, refitting the model with the `intpoints(20)` option yields completely satisfactory results when checked with `quadchk`.

Nonadaptive Gauss–Hermite quadrature does not yield such robust results.

```

. xtprobit z x1-x6, intmethod(ghermite) nolog
Random-effects probit regression      Number of obs      =      6000
Group variable: id                   Number of groups   =       300
Random effects u_i ~ Gaussian        Obs per group: min =       20
                                       avg =      20.0
                                       max =       20
Integration method: ghermite          Integration points =       12
                                       Wald chi2(6)       =      36.15
Log likelihood = -3349.6926           Prob > chi2        =      0.0000

```

z	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	.1156763	.0554925	2.08	0.037	.0069131	.2244396
x2	.1005555	.066227	1.52	0.129	-.0292469	.230358
x3	.1542187	.0660852	2.33	0.020	.0246941	.2837433
x4	.1257616	.0375776	3.35	0.001	.0521108	.1994123
x5	.1366003	.0654696	2.09	0.037	.0082823	.2649182
x6	.0870325	.0453489	1.92	0.055	-.0018497	.1759147
_cons	.1098393	.0500514	2.19	0.028	.0117404	.2079382
/lnsig2u	-.0791821	.0971063			-.2695071	.1111428
sigma_u	.9611824	.0466685			.8739313	1.057145
rho	.4802148	.0242386			.4330281	.5277571

Likelihood-ratio test of rho=0: chibar2(01) = 1577.50 Prob >= chibar2 = 0.000

```

. quadchk, nooutput
Refitting model intpoints() = 8
Refitting model intpoints() = 16

```

Quadrature check				
	Fitted quadrature 12 points	Comparison quadrature 8 points	Comparison quadrature 16 points	
Log likelihood	-3349.6926	-3354.6372 -4.9446636 .00147615	-3348.3881 1.3045063 -.00038944	Difference Relative difference
z: x1	.11567633	.16153998 .04586365 .39648262	.07007833 -.045598 -.39418608	Difference Relative difference
z: x2	.10055552	.10317831 .00262279 .02608297	.09937417 -.00118135 -.01174825	Difference Relative difference
z: x3	.1542187	.15465369 .00043499 .00282062	.15150516 -.00271354 -.0175954	Difference Relative difference
z: x4	.12576159	.12880254 .00304096 .02418032	.1243974 -.00136418 -.01084739	Difference Relative difference
z: x5	.13660028	.13475211 -.00184817 -.01352978	.13707075 .00047047 .00344411	Difference Relative difference
z: x6	.08703252	.08568342 -.0013491 -.0155011	.08738135 .00034883 .00400809	Difference Relative difference
z: _cons	.10983928	.11031299 .00047371 .00431274	.09654975 -.01328953 -.12099067	Difference Relative difference
lnsig2u: _cons	-.07918212	-.18133821 -.10215609 1.2901408	-.05815644 .02102568 -.26553572	Difference Relative difference

Here we see that the x1 variable (the one that was constant within panel) changed with a relative difference of nearly 40%! This example clearly demonstrates the benefit of adaptive quadrature methods.

## ▷ Example 2

Here we rerun the [previous](#) nonadaptive quadrature model, but using the `intpoints(120)` option to increase the number of integration points to 120. We get results close to those from adaptive quadrature and an acceptable `quadchk`. This example demonstrates the efficacy of increasing the number of integration points to improve the quadrature approximation.

```
. xtprobit z x1-x6, intmethod(ghermite) intpoints(120) nolog
Random-effects probit regression      Number of obs      =      6000
Group variable: id                   Number of groups   =       300
Random effects u_i ~ Gaussian        Obs per group: min =        20
                                       avg =       20.0
                                       max =        20

Integration method: ghermite          Integration points =       120
Wald chi2(6)                          =       29.24
Prob > chi2                             =       0.0001

Log likelihood = -3347.1099
```

	z	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
	x1	.0043059	.0607087	0.07	0.943	-.114681 .1232929
	x2	.1000743	.0663311	1.51	0.131	-.0299322 .2300808
	x3	.1503541	.0662503	2.27	0.023	.0205058 .2802023
	x4	.1230151	.0377089	3.26	0.001	.049107 .1969232
	x5	.134299	.0657223	2.04	0.041	.0054856 .2631123
	x6	.0879935	.0455753	1.93	0.054	-.0013325 .1773194
	_cons	.0757054	.0603621	1.25	0.210	-.0426021 .1940128
	/lnsig2u	-.0329832	.1026863			-.2342446 .1682783
	sigma_u	.9836437	.0505034			.8894764 1.08778
	rho	.491755	.0256646			.4417052 .5419706

Likelihood-ratio test of rho=0: `chibar2(01) = 1582.67 Prob >= chibar2 = 0.000`

```

. quadchk, nooutput
Refitting model intpoints() = 80
Refitting model intpoints() = 160

```

		Quadrature check				
		Fitted quadrature 120 points	Comparison quadrature 80 points	Comparison quadrature 160 points		
Log		-3347.1099	-3347.1099	-3347.1099		
likelihood			-.00007138	2.440e-07	Difference	
			2.133e-08	-7.289e-11	Relative difference	
z:		.00430592	.00431318	.00430553		
	x1		7.259e-06	-3.871e-07	Difference	
			.00168592	-.00008991	Relative difference	
z:		.10007431	.10007415	.10007431		
	x2		-1.519e-07	5.585e-09	Difference	
			-1.517e-06	5.580e-08	Relative difference	
z:		.15035406	.15035407	.15035406		
	x3		1.699e-08	7.636e-09	Difference	
			1.130e-07	5.078e-08	Relative difference	
z:		.12301506	.12301512	.12301506		
	x4		6.036e-08	5.353e-09	Difference	
			4.907e-07	4.352e-08	Relative difference	
z:		.13429895	.13429962	.13429896		
	x5		6.646e-07	4.785e-09	Difference	
			4.949e-06	3.563e-08	Relative difference	
z:		.08799345	.08799334	.08799346		
	x6		-1.123e-07	3.049e-09	Difference	
			-1.276e-06	3.465e-08	Relative difference	
z:		.07570536	.07570205	.07570442		
	_cons		-3.305e-06	-9.405e-07	Difference	
			-.00004365	-.00001242	Relative difference	
lnsig2u:		-.03298317	-.03298909	-.03298186		
	_cons		-5.919e-06	1.304e-06	Difference	
			.00017945	-.00003952	Relative difference	

◀

### ▷ Example 3

Here we synthesize data the same way as in the [previous example](#), but we make the intrapanel correlation equal to 0.1 instead of 0.5. We again fit a random-effects probit model and check the quadrature:



```
. use http://www.stata-press.com/data/r13/quad2
. xtset id
      panel variable:  id (balanced)
. xtprobit z x1-x6
```

Fitting comparison model:

```
Iteration 0:  log likelihood = -4142.2915
Iteration 1:  log likelihood = -4120.4109
Iteration 2:  log likelihood = -4120.4099
Iteration 3:  log likelihood = -4120.4099
```

Fitting full model:

```
rho = 0.0      log likelihood = -4120.4099
rho = 0.1      log likelihood = -4065.7986
rho = 0.2      log likelihood = -4087.7703

Iteration 0:  log likelihood = -4065.7986
Iteration 1:  log likelihood = -4065.3157
Iteration 2:  log likelihood = -4065.3144
Iteration 3:  log likelihood = -4065.3144
```

```
Random-effects probit regression
Group variable:  id
Random effects u_i ~ Gaussian
```

```
Number of obs      =      6000
Number of groups   =       300
Obs per group: min =        20
                  avg  =       20.0
                  max  =        20
Integration points =       12
Wald chi2(6)       =       39.43
Prob > chi2        =       0.0000
```

Integration method: mvaghermite

Log likelihood = -4065.3144

z	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	.0246943	.025112	0.98	0.325	-.0245243	.0739129
x2	.1300123	.0587906	2.21	0.027	.0147847	.2452398
x3	.1190409	.0579539	2.05	0.040	.0054533	.2326284
x4	.139197	.0331817	4.19	0.000	.0741621	.2042319
x5	.077364	.0578454	1.34	0.181	-.036011	.1907389
x6	.0862028	.0401185	2.15	0.032	.007572	.1648336
_cons	.0922653	.0244392	3.78	0.000	.0443653	.1401652
/lnsig2u	-2.343939	.1575275			-2.652687	-2.035191
sigma_u	.3097563	.0243976			.2654461	.3614631
rho	.0875487	.0125839			.0658236	.1155574

Likelihood-ratio test of rho=0: chibar2(01) = 110.19 Prob >= chibar2 = 0.000

```

. quadchk, nooutput
Refitting model intpoints() = 8
Refitting model intpoints() = 16

```

Quadrature check				
	Fitted quadrature 12 points	Comparison quadrature 8 points	Comparison quadrature 16 points	
Log likelihood	-4065.3144	-4065.3144 -2.268e-08 5.578e-12	-4065.3144 5.457e-12 -1.342e-15	Difference Relative difference
z: x1	.02469427	.02469427 -3.645e-12 -1.476e-10	.02469427 -8.007e-12 -3.242e-10	Difference Relative difference
z: x2	.13001229	.13001229 -1.566e-11 -1.204e-10	.13001229 -6.880e-13 -5.292e-12	Difference Relative difference
z: x3	.11904089	.11904089 -6.457e-12 -5.425e-11	.11904089 -3.030e-13 -2.545e-12	Difference Relative difference
z: x4	.13919697	.13919697 1.442e-12 1.036e-11	.13919697 1.693e-13 1.216e-12	Difference Relative difference
z: x5	.07736398	.07736398 -5.801e-12 -7.499e-11	.07736398 -4.557e-13 -5.890e-12	Difference Relative difference
z: x6	.08620282	.08620282 5.903e-12 6.848e-11	.08620282 3.191e-13 3.701e-12	Difference Relative difference
z: _cons	.09226527	.09226527 -2.850e-12 -3.089e-11	.09226527 -1.837e-11 -1.991e-10	Difference Relative difference
lnsig2u: _cons	-2.3439389	-2.3439389 -2.946e-09 1.257e-09	-2.3439389 -2.172e-10 9.267e-11	Difference Relative difference

Here we see that the quadrature approximation is stable. With this result, we can confidently interpret the results. Satisfactory results are also obtained in this case with nonadaptive quadrature.