

quadchk — Check sensitivity of quadrature approximation

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
xtstreg
xttobit
```

`quadchk` refits the model for different numbers of quadrature points and then compares the different solutions. `quadchk` respects all options supplied to the original model except `or`, `vce()`, and the *maximize_options*.

Quick start

Check quadrature approximation using the default range of quadrature points

```
quadchk
```

As above, but use 8 and 16 quadrature points

```
quadchk 8 16
```

As above, but suppress the iteration log and output of the refitted models

```
quadchk 8 16, nooutput
```

Refit the model instead of using original estimates

```
quadchk 8 16, nooutput nofrom
```

Menu

Statistics > Longitudinal/panel data > Setup and utilities > Check sensitivity of quadrature approximation

Syntax

quadchk [#$_1$ #$_2$] [, nooutput nofrom]

#$_1$ and #$_2$ specify the number of quadrature points to use in the comparison runs of the previous model. The default is to use approximately $2n_q/3$ and $4n_q/3$ points, where n_q is the number of quadrature points used in the original estimation.

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?

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 ρ can reduce the accuracy of the quadrature approximation.

A final factor affects the goodness of the random-effects model: the data themselves. For high ρ, 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/r14/quad1
. xtset id
       panel variable:  id (balanced)
. xtprobit z x1-x6
```

(output omitted)

```
Random-effects probit regression                Number of obs     =      6,000
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 pts.  =         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

```
LR 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        Comparison      Comparison
               quadrature       quadrature      quadrature
               12 points        8 points        16 points

Log            -3347.1097      -3347.1153      -3347.1099
likelihood                     -.00561484      -.00014288   Difference
                                1.678e-06       4.269e-08   Relative difference

z:               .0043068        .0043068       .00430541
      x1                        8.983e-15      -1.388e-06   Difference
                                2.086e-12      -.00032222   Relative difference

z:              .10007418       .10007418       .10007431
      x2                        2.540e-15       1.362e-07   Difference
                                2.538e-14       1.361e-06   Relative difference

z:              .15035391       .15035391       .15035406
      x3                        6.356e-15       1.520e-07   Difference
                                4.227e-14       1.011e-06   Relative difference

z:              .12301495       .12301495       .12301506
      x4                        4.149e-15       1.099e-07   Difference
                                3.373e-14       8.931e-07   Relative difference

z:              .13429881       .13429881       .13429896
      x5                        4.913e-15       1.471e-07   Difference
                                3.658e-14       1.096e-06   Relative difference

z:              .08799332       .08799332       .08799346
      x6                        3.345e-15       1.363e-07   Difference
                                3.801e-14       1.549e-06   Relative difference

z:              .07570675       .07570675       .07570423
   _cons                        1.964e-14      -2.516e-06   Difference
                                2.594e-13      -.00003323   Relative difference

lnsig2u:       -.03299164      -.03299164      -.03298184
   _cons                        7.268e-14       9.798e-06   Difference
                               -2.203e-12      -.00029699   Relative difference
```

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     =      6,000
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 pts.  =         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
------------------------------------------------------------------------------
LR 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      Comparison     Comparison
               quadrature     quadrature     quadrature
               12 points      8 points       16 points
─────────────────────────────────────────────────────
Log            -3349.6926     -3354.6372     -3348.3881
likelihood                    -4.9446636      1.3045063   Difference
                               .00147615     -.00038944   Relative difference
─────────────────────────────────────────────────────
z:              .11567633      .16153998      .07007833
      x1                       .04586365       -.045598   Difference
                               .39648262     -.39418608   Relative difference
─────────────────────────────────────────────────────
z:              .10055552      .10317831      .09937417
      x2                       .00262279     -.00118135   Difference
                               .02608297     -.01174825   Relative difference
─────────────────────────────────────────────────────
z:               .1542187      .15465369      .15150516
      x3                       .00043499     -.00271354   Difference
                               .00282062      -.0175954   Relative difference
─────────────────────────────────────────────────────
z:              .12576159      .12880254       .1243974
      x4                       .00304096     -.00136418   Difference
                               .02418032     -.01084739   Relative difference
─────────────────────────────────────────────────────
z:              .13660028      .13475211      .13707075
      x5                      -.00184817      .00047047   Difference
                              -.01352978      .00344411   Relative difference
─────────────────────────────────────────────────────
z:              .08703252      .08568342      .08738135
      x6                       -.0013491      .00034883   Difference
                               -.0155011      .00400809   Relative difference
─────────────────────────────────────────────────────
z:              .10983928      .11031299      .09654975
   _cons                       .00047371     -.01328953   Difference
                               .00431274     -.12099067   Relative difference
─────────────────────────────────────────────────────
lnsig2u:       -.07918212     -.18133821     -.05815644
   _cons                      -.10215609      .02102568   Difference
                               1.2901408     -.26553572   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     =      6,000
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 pts.  =        120

                                                Wald chi2(6)      =      29.24
Log likelihood  = -3347.1099                    Prob > chi2       =     0.0001

------------------------------------------------------------------------------
           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
------------------------------------------------------------------------------
LR 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      Comparison     Comparison
                quadrature    quadrature     quadrature
                120 points    80 points      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/r14/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                Number of obs     =      6,000
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 pts.  =         12
                                                Wald chi2(6)      =      39.43
Log likelihood  = -4065.3144                    Prob > chi2       =     0.0000
```

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

```
LR 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      Comparison    Comparison
            quadrature    quadrature    quadrature
            12 points     8 points      16 points
─────────────────────────────────────────────────────
Log         -4065.3144    -4065.3144    -4065.3144
likelihood                -2.268e-08     6.366e-12   Difference
                           5.578e-12    -1.566e-15   Relative difference
─────────────────────────────────────────────────────
z:           .02469427     .02469427     .02469427
      x1                  -7.290e-12    -8.007e-12   Difference
                          -2.952e-10    -3.242e-10   Relative difference
─────────────────────────────────────────────────────
z:           .13001229     .13001229     .13001229
      x2                  -3.131e-11    -6.880e-13   Difference
                          -2.408e-10    -5.292e-12   Relative difference
─────────────────────────────────────────────────────
z:           .11904089     .11904089     .11904089
      x3                  -1.291e-11    -3.030e-13   Difference
                          -1.085e-10    -2.545e-12   Relative difference
─────────────────────────────────────────────────────
z:           .13919697     .13919697     .13919697
      x4                   2.885e-12     1.693e-13   Difference
                           2.072e-11     1.216e-12   Relative difference
─────────────────────────────────────────────────────
z:           .07736398     .07736398     .07736398
      x5                  -1.160e-11    -4.556e-13   Difference
                          -1.500e-10    -5.890e-12   Relative difference
─────────────────────────────────────────────────────
z:           .08620282     .08620282     .08620282
      x6                   1.181e-11     3.190e-13   Difference
                           1.370e-10     3.701e-12   Relative difference
─────────────────────────────────────────────────────
z:           .09226527     .09226527     .09226527
   _cons                  -5.700e-12    -1.837e-11   Difference
                          -6.177e-11    -1.991e-10   Relative difference
─────────────────────────────────────────────────────
lnsig2u:    -2.3439389    -2.3439389    -2.3439389
   _cons                  -5.892e-09    -2.172e-10   Difference
                           2.514e-09     9.267e-11   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.

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