

example 24 — Reliability

[Description](#) [Remarks and examples](#) [Also see](#)

Description

Below we demonstrate `sem`'s `reliability()` option with the following data:

```
. use http://www.stata-press.com/data/r15/sem_rel
(measurement error with known reliabilities)
. summarize
```

Variable	Obs	Mean	Std. Dev.	Min	Max
y	1,234	701.081	71.79378	487	943
x1	1,234	100.278	14.1552	51	149
x2	1,234	100.2066	14.50912	55	150

```
. notes
_dta:
1. Fictional data.
2. Variables x1 and x2 each contain a test score designed to measure X. The
   test is scored to have mean 100.
3. Variables x1 and x2 are both known to have reliability 0.5.
4. Variable y is the outcome, believed to be related to X.
```

See [\[SEM\] sem and gsem option reliability\(\)](#) for background.

Remarks and examples

Remarks are presented under the following headings:

- Baseline model (reliability ignored)*
- Model with reliability*
- Model with two measurement variables and reliability*

Baseline model (reliability ignored)

```

. sem (y <- x1)
Endogenous variables
Observed:  y
Exogenous variables
Observed:  x1
Fitting target model:
Iteration 0:  log likelihood = -11629.745
Iteration 1:  log likelihood = -11629.745
Structural equation model          Number of obs      =      1,234
Estimation method = ml
Log likelihood      = -11629.745

```

	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
Structural						
y						
x1	3.54976	.1031254	34.42	0.000	3.347637	3.751882
_cons	345.1184	10.44365	33.05	0.000	324.6492	365.5876
var(e.y)	2627.401	105.7752			2428.053	2843.115

```
LR test of model vs. saturated: chi2(0) = 0.00, Prob > chi2 = .
```

Notes:

1. In these data, variable x1 is measured with error.
2. If we ignore that, we obtain a path coefficient for $y \leftarrow x1$ of 3.55.
3. We also ran this model for $y \leftarrow x2$. We obtained a path coefficient of 3.48.

Model with reliability

```
. sem (x1<-X) (y<-X), reliability(x1 .5)
```

Endogenous variables

Measurement: x1 y

Exogenous variables

Latent: X

Fitting target model:

Iteration 0: log likelihood = -11745.845

Iteration 1: log likelihood = -11661.626

Iteration 2: log likelihood = -11631.469

Iteration 3: log likelihood = -11629.755

Iteration 4: log likelihood = -11629.745

Iteration 5: log likelihood = -11629.745

Structural equation model

Number of obs = 1,234

Estimation method = ml

Log likelihood = -11629.745

(1) [x1]X = 1

(2) [/]var(e.x1) = 100.1036

		OIM				
		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
Measurement x1	X	1 (constrained)				
	_cons	100.278	.4027933	248.96	0.000	99.4885 101.0674
y	X	7.09952	.352463	20.14	0.000	6.408705 7.790335
	_cons	701.081	2.042929	343.17	0.000	697.077 705.0851
var(e.x1)		100.1036 (constrained)				
var(e.y)		104.631	207.3381			2.152334 5086.411
var(X)		100.1036	8.060038			85.48963 117.2157

LR test of model vs. saturated: chi2(0) = 0.00, Prob > chi2 = .

Notes:

1. We wish to estimate the effect of $y \leftarrow x_1$ when x_1 is measured with error (0.50 reliability). To do that, we introduce latent variable X and write our model as $(x_1 \leftarrow X) (y \leftarrow X)$.
2. When we ignored the measurement error of x_1 , we obtained a path coefficient for $y \leftarrow x_1$ of 3.55. Taking into account the measurement error, we obtain a coefficient of 7.1.

Model with two measurement variables and reliability

```

. sem (x1 x2<-X) (y<-X), reliability(x1 .5 x2 .5)
Endogenous variables
Measurement:  x1 x2 y
Exogenous variables
Latent:      X
Fitting target model:
Iteration 0:  log likelihood = -16258.636
Iteration 1:  log likelihood = -16258.401
Iteration 2:  log likelihood = -16258.4

Structural equation model          Number of obs      =      1,234
Estimation method = ml
Log likelihood      = -16258.4
( 1) [x1]X = 1
( 2) [ / ]var(e.x1) = 100.1036
( 3) [ / ]var(e.x2) = 105.1719

```

		OIM			[95% Conf. Interval]	
		Coef.	Std. Err.	z	P> z	
Measurement x1	X	1	(constrained)			
	_cons	100.278	.4037851	248.34	0.000	99.48655 101.0694
x2	X	1.030101	.0417346	24.68	0.000	.9483029 1.1119
	_cons	100.2066	.4149165	241.51	0.000	99.39342 101.0199
y	X	7.031299	.2484176	28.30	0.000	6.544409 7.518188
	_cons	701.081	2.042928	343.17	0.000	697.077 705.0851
var(e.x1)		100.1036	(constrained)			
var(e.x2)		105.1719	(constrained)			
var(e.y)		152.329	105.26			39.31868 590.1553
var(X)		101.0907	7.343656			87.67509 116.5591

```
LR test of model vs. saturated: chi2(2) = 0.59, Prob > chi2 = 0.7430
```

Notes:

1. We wish to estimate the effect of $y \leftarrow X$. We have two measures of X — x_1 and x_2 —both measured with error (0.50 reliability).
2. In the [previous section](#), we used just x_1 . We obtained path coefficient 7.1 with standard error 0.4. Using both x_1 and x_2 , we obtain path coefficient 7.0 and standard error 0.2.
3. We at StataCorp created these fictional data. The true coefficient is 7.

Also see

[\[SEM\] sem and gsem option reliability\(\)](#) — Fraction of variance not due to measurement error

[\[SEM\] example 1](#) — Single-factor measurement model