# What is the interpretation of $\mathrm{R}^{2}$ ? 

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Consider a regression equation between a dependent variable $y$ and a set of explanatory variables $\mathbf{x}^{\prime}=\left(x_{1}, x_{2}, \ldots, x_{q}\right)$ :

$$
\begin{equation*}
y=\alpha+\gamma_{1} x_{1}+\gamma_{2} x_{2}+\ldots+\gamma_{q} x_{q}+z, \tag{1}
\end{equation*}
$$

or in matrix form

$$
\begin{equation*}
y=\alpha+\gamma^{\prime} x+z \tag{2}
\end{equation*}
$$

where $\alpha$ is an intercept parameter, $z$ is a random error term assumed to be uncorrelated with the explanatory variables, and $\gamma^{\prime}=\left(\gamma_{1}, \gamma_{2}, \ldots, \gamma_{q}\right)$ is a vector of coefficients to be estimated. As most textbooks on statistics or econometrics covering the topic of regression analysis will explain (see, for example, Goldberger, 1964), the squared multiple correlation also called the coefficient of determination is defined as

$$
\begin{equation*}
\mathrm{R}^{2}=1-\operatorname{Var}(z) / \operatorname{Var}(y) \tag{3}
\end{equation*}
$$

In practice, we may estimate $R^{2}$ by substituting the estimated variance of $z$ for $\operatorname{Var}(z)$ and the estimated variance of $y$ for $\operatorname{Var}(y)$ in (3). For the calculation of $R^{2}$ there are several equivalent formulas. It is common practice to provide an $\mathrm{R}^{2}$ for every linear relationship estimated and LISREL has been doing so from version 5 .

The usual interpretation of $R^{2}$ is as the relative amount of variance of the dependent variable $y$ explained or accounted for by the explanatory variables $x_{1}, x_{2}, \ldots, x_{q}$. For example, if $R^{2}=0.762$ we say that the explanatory variables "explains" $76.2 \%$ of the variance of $y$.

The main point here is that this interpretation of $R^{2}$ is not valid if we use definition (3) for relationships in a non-recursive system. For this reason, the definition of $R^{2}$ has been changed in LISREL 8.30, with the release of the released August 1999 (Patch 3) version.

To explain this let $\mathbf{y}=\left(y_{1}, y_{2}, \ldots, y_{p}\right)$ be a set of jointly dependent (endogenous) variables and let $\mathbf{x}=\left(x_{1}, x_{2}, \ldots, x_{q}\right)$ be a set of independent (exogenous) variables. Consider a model of the form

$$
\begin{equation*}
y=\alpha+B y+\Gamma x+z \tag{4}
\end{equation*}
$$

where $\alpha=\left(\alpha_{1}, \alpha_{2}, \ldots, \alpha_{p}\right)$ is a vector of intercept terms, $B$ and $\Gamma$ are matrices of coefficients to be estimated, and $\mathbf{z}=\left(z_{1}, z_{2}, \ldots, z_{p}\right)$ is a vector of error terms assumed to be uncorrelated with $\mathbf{x}$. The matrix I-B is assumed to be non-singular. There are no latent variables in the model. Suppose the system is non-recursive so that the equations cannot be ordered in such a way that $\mathbf{B}$ is subdiagonal (see Jöreskog \& Sörbom, 1996a, pp 143-145).

In scalar notation, equation (4) is

$$
\begin{equation*}
y_{i}=\alpha_{i}+\beta_{i 1} y_{1}+\beta_{i 2} y_{2}+\ldots+\beta_{i p} y_{\mathrm{p}}+\gamma_{i 1} x_{1}+\gamma_{i 2} x_{2}+\ldots+\gamma_{i q} x_{q}+z_{i}, i=1,2, \ldots, p, \tag{5}
\end{equation*}
$$

where some of the $\beta$ 's and $\gamma$ 's may be zero. If $\beta_{\text {im }}=0, y_{i}$ does not depend on $y_{m}$ and if $\gamma_{i n}=0, y_{i}$ does not depend on $x_{n}$. For this equation to be identified, some of the $\beta$ 's and $\gamma$ 's must be zero. A simple neccessary but not sufficient condition for identification is the following. For each $y$ variable included on the right side of (5) there must be at least one x-variable excluded from the same equation. This is the so called order condition. There is also a rank condition which is both necessary and sufficient for identification (see for example, Goldberger, 1964, p.316), but this is difficult to apply in practice.

Consider the following simple example with $p=2$ and $q=3$ :

$$
\begin{align*}
& y_{1}=y_{2}+x_{1}+z_{1}  \tag{6}\\
& y_{2}=0.5 y_{1}+x_{2}+x_{3}+z_{2} \tag{7}
\end{align*}
$$

It is obvious that the order condition is satisfied.

The previous versions of LISREL (prior to August 1999) used the definition

$$
\begin{equation*}
\mathrm{R}_{1}{ }^{2}=1-\operatorname{Var}\left(z_{1}\right) / \operatorname{Var}\left(y_{1}\right) \tag{8}
\end{equation*}
$$

for the first equation, and

$$
\begin{equation*}
\mathrm{R}_{2}^{2}=1-\operatorname{Var}\left(z_{2}\right) / \operatorname{Var}\left(y_{2}\right) \tag{9}
\end{equation*}
$$

for the second equation.

The problem is that $z_{1}$ in (6) is not uncorrelated with $y_{2}$ appearing in that equation. So (6) is not a regression equation as in (1). To put it differently, the right side of (6) is not the conditional expectation of $y_{1}$ for given $y_{2}$ and $x_{1}$. Therefore, we cannot divide the variance of $y_{1}$ between $z_{1}$ and the other variables on the right side of (6). Also, this definition includes all of the variance of $y_{2}$ in the calculation of $\operatorname{Var}\left(y_{1}\right)$ although some of the variance of $y_{2}$ is due to error. The variance of $y_{1}$ depends on the variance $y_{2}$ and vice versa. The interpretation of $R_{1}{ }^{2}$ is therefore unclear. The same kind of argument applies to the second equation as well.

A better definition of $R^{2}$ for non-recursive systems can be obtained by using the reduced form, see Jöreskog \& Sörbom (1996a, pp 143-145). The reduced form is obtained by first noting that (4) can be written as

$$
\begin{equation*}
(\mathbf{I}-\mathbf{B}) \mathbf{y}=\alpha+\Gamma \mathrm{x}+\mathrm{z}, \tag{10}
\end{equation*}
$$

and then premultiplying this by $(\mathbf{I}-\mathbf{B})^{-1}$. This gives the reduced form as

$$
\begin{equation*}
y=(I-B)^{-1} \alpha+(I-B)^{-1} \Gamma x+z^{\star} \tag{11}
\end{equation*}
$$

where $\mathbf{z}^{*}=(\mathbf{I}-\mathbf{B})^{-1} \mathbf{z}$. This equation is the multivariate regression (as implied by the model) of $\mathbf{y}$ on $\mathbf{x}$. Since $\mathbf{z}^{\star}$ is a linear combination of $\mathbf{z}, \mathbf{z}^{\star}$ is uncorrelated with $\mathbf{x}$.

We can now define the new $\mathrm{R}_{\mathrm{i}}{ }^{* 2}$ for the $i$-th equation in (11) as

$$
\begin{equation*}
\mathrm{R}_{\mathrm{i}}^{* 2}=1-\operatorname{Var}\left(z_{\mathrm{i}}^{*}\right) / \operatorname{Var}\left(y_{\mathrm{i}}\right) \tag{12}
\end{equation*}
$$

This $R_{i}^{* 2}$ can be interpreted as the relative variance of $y_{i}$ explained or accounted for by all explanatory variables jointly.

For the simple example, the reduced form is

$$
\begin{gather*}
y_{1}=2 x_{1}+2 x_{2}+2 x_{3}+z_{1}^{*}  \tag{13}\\
y_{2}=x_{1}+2 x_{2}+2 x_{3}+z_{2}^{*} \tag{14}
\end{gather*}
$$

where $z_{1}{ }^{*}$ and $z_{2}{ }^{*}$ are linear combinations of $z_{1}$ and $z_{2}$ and therefore uncorrelated with all the explanatory variables. Hence,

$$
\begin{align*}
& \mathrm{R}_{1}{ }^{* 2}=1-\operatorname{Var}\left(z_{1}{ }^{*}\right) / \operatorname{Var}\left(y_{1}\right)  \tag{15}\\
& \mathrm{R}_{2}{ }^{* 2}=1-\operatorname{Var}\left(z_{2}{ }^{*}\right) / \operatorname{Var}\left(y_{2}\right) \tag{16}
\end{align*}
$$

and each $\mathrm{R}^{\star 2}$ can be interpreted as the relative variance of the dependent variable explained or accounted for by all three $x$-variables jointly.

To simplify the calculations, I assume that $x_{1}, x_{2}, x_{3}, z_{1_{k}}$ and $z_{2}$ are independent, each with a variance of 1. From the reduced form it follows that $R_{1}{ }^{* 2}=0.60$ and $R_{2}{ }^{* 2}=0.64$. With previous definitions we obtain $R_{1}{ }^{2}=0.95$ and $R_{2}{ }^{2}=0.93$. We should therefore expect large differences in $R^{2}$ between the previous and the current version of LISREL.

To verify these results run the following SIMPLIS command file :

```
Test of Small SEM
Observed Variables: Y1 Y2 X1 X2 X3
Covariance Matrix
20 16 14 2 1 1 2 2 0 1 2 2 0 0 1
Sample Size: 101
Relationships
Y1 = Y2 X1
Y2 = Y1 X2 X3
End of Problem
```

This gives the following results:


The previous version (prior to August 1999) of LISREL gave the following results:


```
Y2 = 0.50*Y1 + 1.00*X2 + 1.00*X3, Errorvar.= 1.00, R2 = 0.93
    (0.039) (0.13) (0.13) (0.21)
    12.71 7.79 7.79 4.70
```

Note that parameter estimates, standard errors, and $t$-values are all the same. Only $R^{2}$ is different. The previous version overestimates the strength of the relationships.

All of the above applies to latent non-recursive models as well. Replacing y by $\eta, x$ by $\xi$, and $z$ by $\zeta$, we get the structural equation model in LISREL:

$$
\begin{equation*}
\eta=\alpha+B \eta+\Gamma \xi+\zeta . \tag{17}
\end{equation*}
$$

The $R^{2} s$ for these structural equations will also be different if $\mathbf{B}$ is not subdiagonal.
As a second example, consider the Hypothetical Model on pp. 133-135 in Jöreskog \& Sörbom (1996b). For example, run the following SIMPLIS command file (adapted from the file EX17A.SPL in the SPLEX subdirectory):

```
Hypothetical Model
Observed Variables: Y1-Y4 X1-X7
Correlation Matrix from File EX17.C0V
Sample Size: 100
Latent Variables: Eta1 Eta2 Ksi1-Ksi3
Relationships
    Eta1 = Eta2 Ksi1 Ksi2
    Eta2 = Eta1 Ksi1 Ksi3
Let the Errors of Eta1 and Eta2 Correlate
    Y1 = 1*Eta1
    Y2 = Eta1
    Y3 = 1*Eta2
    Y4 = Eta2
    X1 = 1*Ksi1
    X2 X3 = Ksi1
    X4 = 1*Ksi2
    X3 X5 = Ksi2
    X6 = 1*Ksi3
    X7 = Ksi3
!LISREL Output: RS MI SC EF WP
End of Problem
```

This gives the following results:


The previous version (prior to August 1999) of LISREL gave the following results:


Again note that parameter estimates, standard errors, and $t$-values are all the same. Only $R^{2}$ is different. The previous version overestimates the strength of the relationships.

## References

Goldberger, A.S. (1964) Econometric theory. New York: Wiley.
Jöreskog, K.G. \& Sörbom, D. (1996a) LISREL8: User's Reference Guide. Chicago: Scientific Software International.

Jöreskog, K.G. \& Sörbom, D. (1996b) LISREL8: Structural Equation Modeling with the SIMPLIS Command Language. Chicago: Scientific Software International.

