Syntax

**Basic syntax**

```
reg3 (depvar1 varlist1) (depvar2 varlist2) ... (depvarN varlistN) [if] [in] [weight]
```

**Full syntax**

```
reg3 ([eqname1:] depvar1a [depvar1b ... = ]varlist1 [ , noconstant ])
([eqname2:] depvar2a [depvar2b ... = ]varlist2 [ , noconstant ])
...
([eqnameN:] depvarNa [depvarNb ... = ]varlistN [ , noconstant ])
[if] [in] [weight] [ , options ]
```

<table>
<thead>
<tr>
<th>options</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>ireg3</code></td>
<td>iterate until estimates converge</td>
</tr>
<tr>
<td><code>constraints(constraints)</code></td>
<td>apply specified linear constraints</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model 2</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>exog(varlist)</code></td>
<td>exogenous variables not specified in system equations</td>
</tr>
<tr>
<td><code>endog(varlist)</code></td>
<td>additional right-hand-side endogenous variables</td>
</tr>
<tr>
<td><code>inst(varlist)</code></td>
<td>full list of exogenous variables</td>
</tr>
<tr>
<td><code>allexog</code></td>
<td>all right-hand-side variables are exogenous</td>
</tr>
<tr>
<td><code>noconstant</code></td>
<td>suppress constant from instrument list</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Est. method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>3sls</td>
<td>three-stage least squares; the default</td>
</tr>
<tr>
<td>2sls</td>
<td>two-stage least squares</td>
</tr>
<tr>
<td>ols</td>
<td>ordinary least squares (OLS)</td>
</tr>
<tr>
<td>sure</td>
<td>seemingly unrelated regression estimation (SURE)</td>
</tr>
<tr>
<td>mvreg</td>
<td>sure with OLS degrees-of-freedom adjustment</td>
</tr>
<tr>
<td><code>corr(correlation)</code></td>
<td>unstructured or independent correlation structure; default is unstructured</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>df adj.</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>small</td>
<td>report small-sample statistics</td>
</tr>
<tr>
<td>dfk</td>
<td>use small-sample adjustment</td>
</tr>
<tr>
<td>dfk2</td>
<td>use alternate adjustment</td>
</tr>
</tbody>
</table>
Reporting

- `level(#)`: set confidence level; default is `level(95)`
- `first`: report first-stage regression
- `nocnsreport`: do not display constraints
- `display_options`: control column formats, row spacing, line width, display of omitted variables and base and empty cells, and factor-variable labeling

Optimization

- `optimization_options`: control the optimization process; seldom used
- `noheader`: suppress display of header
- `notable`: suppress display of coefficient table
- `nofooter`: suppress display of footer
- `coeflegend`: display legend instead of statistics

- `varlist1,...,varlistN` and the `exog()` and the `inst()` varlist may contain factor variables; see [U] 11.4.3 Factor variables. You must have the same levels of factor variables in all equations that have factor variables.
- `depvar` and `varlist` may contain time-series operators; see [U] 11.4.4 Time-series varlists.
- `bootstrap`, `by`, `fp`, `jackknife`, `rolling`, and `statsby` are allowed; see [U] 11.1.10 Prefix commands.
- Weights are not allowed with the `bootstrap` prefix; see [R] `bootstrap`.
- `aweights` are not allowed with the `jackknife` prefix; see [R] `jackknife`.
- `aweights` and `fweights` are allowed; see [U] 11.1.6 Weight.
- `noheader`, `notable`, `nofooter`, and `coeflegend` do not appear in the dialog box.

See [U] 20 Estimation and postestimation commands for more capabilities of estimation commands.

Explicit equation naming (`eqname:`) cannot be combined with multiple dependent variables in an equation specification.

Menu

Statistics > Endogenous covariates > Three-stage least squares

Description

`reg3` estimates a system of structural equations, where some equations contain endogenous variables among the explanatory variables. Estimation is via three-stage least squares (3SLS); see Zellner and Theil (1962). Typically, the endogenous explanatory variables are dependent variables from other equations in the system. `reg3` supports iterated GLS estimation and linear constraints.

`reg3` can also estimate systems of equations by seemingly unrelated regression estimation (SURE), multivariate regression (MVREG), and equation-by-equation ordinary least squares (OLS) or two-stage least squares (2SLS).

Nomenclature

Under 3SLS or 2SLS estimation, a structural equation is defined as one of the equations specified in the system. A dependent variable will have its usual interpretation as the left-hand-side variable in an equation with an associated disturbance term. All dependent variables are explicitly taken to be endogenous to the system and are treated as correlated with the disturbances in the system’s equations. Unless specified in an `endog()` option, all other variables in the system are treated as exogenous to the system and uncorrelated with the disturbances. The exogenous variables are taken to be instruments for the endogenous variables.
### Options

**Model**

- `ireg3` causes `reg3` to iterate over the estimated disturbance covariance matrix and parameter estimates until the parameter estimates converge. Although the iteration is usually successful, there is no guarantee that it will converge to a stable point. Under SURE, this iteration converges to the maximum likelihood estimates.

- `constraints(constraints)`; see [R] estimation options.

**Model 2**

- `exog(varlist)` specifies additional exogenous variables that are included in none of the system equations. This can occur when the system contains identities that are not estimated. If implicitly exogenous variables from the equations are listed here, `reg3` will just ignore the additional information. Specified variables will be added to the exogenous variables in the system and used in the first stage as instruments for the endogenous variables. By specifying dependent variables from the structural equations, you can use `exog()` to override their endogeneity.

- `endog(varlist)` identifies variables in the system that are not dependent variables but are endogenous to the system. These variables must appear in the variable list of at least one equation in the system. Again, the need for this identification often occurs when the system contains identities. For example, a variable that is the sum of an exogenous variable and a dependent variable may appear as an explanatory variable in some equations.

- `inst(varlist)` specifies a full list of all exogenous variables and may not be used with the `endog()` or `exog()` options. It must contain a full list of variables to be used as instruments for the endogenous regressors. Like `exog()`, the list may contain variables not specified in the system of equations. This option can be used to achieve the same results as the `endog()` and `exog()` options, and the choice is a matter of convenience. Any variable not specified in the `varlist` of the `inst()` option is assumed to be endogenous to the system. As with `exog()`, including the dependent variables from the structural equations will override their endogeneity.

- `allexog` indicates that all right-hand-side variables are to be treated as exogenous—even if they appear as the dependent variable of another equation in the system. This option can be used to enforce a SURE or MVREG estimation even when some dependent variables appear as regressors.

- `noconstant`; see [R] estimation options.

**Est. method**

- `3sls` specifies the full 3SLS estimation of the system and is the default for `reg3`.

- `2sls` causes `reg3` to perform equation-by-equation 2SLS on the full system of equations. This option implies `dfk`, `small`, and `corr(independent)`.

  Cross-equation testing should not be performed after estimation with this option. With `2sls`, no covariance is estimated between the parameters of the equations. For cross-equation testing, use `3sls`.

- `ols` causes `reg3` to perform equation-by-equation OLS on the system—even if dependent variables appear as regressors or the regressors differ for each equation; see [MV] `mvreg`. `ols` implies `allexog`, `dfk`, `small`, and `corr(independent)`; `nodfk` and `nosmall` may be specified to override `dfk` and `small`.

  The covariance of the coefficients between equations is not estimated under this option, and cross-equation tests should not be performed after estimation with `ols`. For cross-equation testing, use `sure` or `3sls` (the default).
sure causes reg3 to perform a SURE of the system—even if dependent variables from some equations appear as regressors in other equations; see [R] sureg. sure is a synonym for allexog.

mvreg is identical to sure, except that the disturbance covariance matrix is estimated with an OLS degrees-of-freedom adjustment—the dfk option. If the regressors are identical for all equations, the parameter point estimates will be the standard MVREG results. If any of the regressors differ, the point estimates are those for SURE with an OLS degrees-of-freedom adjustment in computing the covariance matrix. nodfk and nosmall may be specified to override dfk and small.

corr(correlation) specifies the assumed form of the correlation structure of the equation disturbances and is rarely requested explicitly. For the family of models fit by reg3, the only two allowable correlation structures are unstructured and independent. The default is unstructured.

This option is used almost exclusively to estimate a system of equations by 2SLS or to perform OLS regression with reg3 on multiple equations. In these cases, the correlation is set to independent, forcing reg3 to treat the covariance matrix of equation disturbances as diagonal in estimating model parameters. Thus a set of two-stage coefficient estimates can be obtained if the system contains endogenous right-hand-side variables, or OLS regression can be imposed, even if the regressors differ across equations. Without imposing independent disturbances, reg3 would estimate the former by 3SLS and the latter by SURE.

Any tests performed after estimation with the independent option will treat coefficients in different equations as having no covariance; cross-equation tests should not be used after specifying corr(independent).

dfk specifies the use of an alternative divisor in computing the covariance matrix for the equation residuals. As an asymptotically justified estimator, reg3 by default uses the number of sample observations \( n \) as a divisor. When the dfk option is set, a small-sample adjustment is made, and the divisor is taken to be \( \sqrt{(n - k_i)(n - k_j)} \), where \( k_i \) and \( k_j \) are the numbers of parameters in equations \( i \) and \( j \), respectively.

dfk2 specifies the use of an alternative divisor in computing the covariance matrix for the equation errors. When the dfk2 option is set, the divisor is taken to be the mean of the residual degrees of freedom from the individual equations.

small specifies that small-sample statistics be computed. It shifts the test statistics from \( \chi^2 \) and \( z \) statistics to \( F \) statistics and \( t \) statistics. This option is intended primarily to support MVREG. Although the standard errors from each equation are computed using the degrees of freedom for the equation, the degrees of freedom for the \( t \) statistics are all taken to be those for the first equation. This approach poses no problem under MVREG because the regressors are the same across equations.

level(#) ; see [R] estimation options.

first requests that the first-stage regression results be displayed during estimation.

nocnsreport ; see [R] estimation options.

display_options: noomitted, vsquish, noemptycells, baselevels, allbaselevels, nolabel, fvwrap(#), fvwrapon(style), cformat(%fmt), pformat(%fmt), sformat(%fmt), and nolstretch; see [R] estimation options.
Optimization

`optimization_options` control the iterative process that minimizes the sum of squared errors when `ireg3` is specified. These options are seldom used.

`iterate(#)` specifies the maximum number of iterations. When the number of iterations equals #, the optimizer stops and presents the current results, even if the convergence tolerance has not been reached. The default value of `iterate()` is the current value of `set maxiter` (see [R] maximize), which is `iterate(16000)` if `maxiter` has not been changed.

`trace` adds to the iteration log a display of the current parameter vector.

`nolog` suppresses the display of the iteration log.

`tolerance(#)` specifies the tolerance for the coefficient vector. When the relative change in the coefficient vector from one iteration to the next is less than or equal to #, the optimization process is stopped. `tolerance(1e-6)` is the default.

The following options are available with `reg3` but are not shown in the dialog box:

`noheader` suppresses display of the header reporting the estimation method and the table of equation summary statistics.

`notable` suppresses display of the coefficient table.

`nofooter` suppresses display of the footer reporting the list of endogenous and exogenous variables in the model.

`coeflegend`; see [R] estimation options.

Remarks and examples

`reg3` estimates systems of structural equations where some equations contain endogenous variables among the explanatory variables. Generally, these endogenous variables are the dependent variables of other equations in the system, though not always. The disturbance is correlated with the endogenous variables—violating the assumptions of OLS. Further, because some of the explanatory variables are the dependent variables of other equations in the system, the error terms among the equations are expected to be correlated. `reg3` uses an instrumental-variables approach to produce consistent estimates and generalized least squares (GLS) to account for the correlation structure in the disturbances across the equations. Good general references on three-stage estimation include Davidson and MacKinnon (1993, 651–661) and Greene (2012, 331–334).

Three-stage least squares can be thought of as producing estimates from a three-step process.

**Step 1.** Develop instrumented values for all endogenous variables. These instrumented values can simply be considered as the predicted values resulting from a regression of each endogenous variable on all exogenous variables in the system. This stage is identical to the first step in 2SLS and is critical for the consistency of the parameter estimates.

**Step 2.** Obtain a consistent estimate for the covariance matrix of the equation disturbances. These estimates are based on the residuals from a 2SLS estimation of each structural equation.

**Step 3.** Perform a GLS-type estimation using the covariance matrix estimated in the second stage and with the instrumented values in place of the right-hand-side endogenous variables.
The estimation and use of the covariance matrix of disturbances in three-stage estimation is almost identical to the SURE method—sureg. As with SURE, using this covariance matrix improves the efficiency of the three-stage estimator. Even without the covariance matrix, the estimates would be consistent. (They would be 2SLS estimates.) This improvement in efficiency comes with a caveat. All the parameter estimates now depend on the consistency of the covariance matrix estimates. If one equation in the system is misspecified, the disturbance covariance estimates will be inconsistent, and the resulting coefficients will be biased and inconsistent. Alternatively, if each equation is estimated separately by 2SLS ([R] regress), only the coefficients in the misspecified equation are affected.

If an equation is just identified, the 3SLS point estimates for that equation are identical to the 2SLS estimates. However, as with sureg, even if all equations are just identified, fitting the model via reg3 has at least one advantage over fitting each equation separately via ivregress; by using reg3, tests involving coefficients in different equations can be performed easily using test or testnl.

Example 1

A simple macroeconomic model relates consumption (consump) to private and government wages paid (wagepriv and wagegovt). Simultaneously, private wages depend on consumption, total government expenditures (govt), and the lagged stock of capital in the economy (capital1). Although this is not a plausible model, it does meet the criterion of being simple. This model could be written as

\[
\text{consump} = \beta_0 + \beta_1 \text{wagepriv} + \beta_2 \text{wagegovt} + \epsilon_1 \\
\text{wagepriv} = \beta_3 + \beta_4 \text{consump} + \beta_5 \text{govt} + \beta_6 \text{capital1} + \epsilon_2
\]

If we assume that this is the full system, consump and wagepriv will be endogenous variables, with wagegovt, govt, and capital1 exogenous. Data for the U.S. economy on these variables are taken from Klein (1950). This model can be fit with reg3 by typing
. use http://www.stata-press.com/data/r13/klein
. reg3 (consump wagepriv wagegovt) (wagepriv consump govt capital1)

Three-stage least-squares regression

<table>
<thead>
<tr>
<th>Equation</th>
<th>Obs</th>
<th>Parms</th>
<th>RMSE</th>
<th>&quot;R-sq&quot;</th>
<th>chi2</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>consump</td>
<td>22</td>
<td>2</td>
<td>1.78</td>
<td>0.94</td>
<td>208</td>
<td>0.00</td>
</tr>
<tr>
<td>wagepriv</td>
<td>22</td>
<td>3</td>
<td>2.37</td>
<td>0.85</td>
<td>80</td>
<td>0.00</td>
</tr>
</tbody>
</table>

|                | Coef.  | Std. Err. | z     | P>|z|  | [95% Conf. Interval] |
|----------------|--------|-----------|-------|-----|-----------------------|
| consump        | .80    | .13       | 6.26  | 0.00| .55 -.10 .90          |
| wagepriv       | 1.03   | .30       | 3.43  | 0.00| .43 .11 .63          |
| wagegovt_cons  | 19     | 3.6       | 5.4   | 0.00| 12 .26 14           |
| wagepriv       | .41    | .26       | 1.60  | 0.11| -.10 .92          |
| consump        | 1.18   | .54       | 2.17  | 0.03| .11 .22            |
| capital1_con   | .02    | .06       | -.49  | 0.62| -.14 .08          |
| cons           | 14     | 10        | 1.42  | 0.15| -.50 .34         |

Endogenous variables: consump wagepriv
Exogenous variables: wagegovt govt capital1

Without showing the 2SLS results, we note that the consumption function in this system falls under the conditions noted earlier. That is, the 2SLS and 3SLS coefficients for the equation are identical.

Example 2

Some of the most common simultaneous systems encountered are supply-and-demand models. A simple system could be specified as

\[
q_{Demand} = \beta_0 + \beta_1 price + \beta_2 pcompete + \beta_3 income + \epsilon_1 \\
q_{Supply} = \beta_4 + \beta_5 price + \beta_6 praw + \epsilon_2
\]

Equilibrium condition: quantity = q Demand = q Supply

where

- **quantity** is the quantity of a product produced and sold,
- **price** is the price of the product,
- **pcompete** is the price of a competing product,
- **income** is the average income level of consumers, and
- **praw** is the price of raw materials used to produce the product.

In this system, price is assumed to be determined simultaneously with demand. The important statistical implications are that price is not a predetermined variable and that it is correlated with the disturbances of both equations. The system is somewhat unusual: quantity is associated with two disturbances. This fact really poses no problem because the disturbances are specified on the behavioral demand and supply equations—two separate entities. Often one of the two equations is rewritten to place price on the left-hand side, making this endogeneity explicit in the specification.
To provide a concrete illustration of the effects of simultaneous equations, we can simulate data for the above system by using known coefficients and disturbance properties. Specifically, we will simulate the data as

\[
q_{\text{Demand}} = 40 - 1.0 \text{price} + 0.25 \text{pcompete} + 0.5 \text{income} + \epsilon_1 \\
q_{\text{Supply}} = 0.5 \text{price} - 0.75 \text{praw} + \epsilon_2
\]

where

\[
\epsilon_1 \sim N(0, 3.8) \\
\epsilon_2 \sim N(0, 2.4)
\]

For comparison, we can estimate the supply and demand equations separately by OLS. The estimates for the demand equation are

```
use http://www.stata-press.com/data/r13/supDem
regress quantity price pcompete income
```

```
<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>Number of obs = 49</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>23.16</td>
<td>3</td>
<td>7.72</td>
<td>F( 3, 45) = 1.00</td>
</tr>
<tr>
<td>Residual</td>
<td>346.46</td>
<td>45</td>
<td>7.70</td>
<td>Prob &gt; F = 0.4004</td>
</tr>
<tr>
<td>Total</td>
<td>369.62</td>
<td>48</td>
<td>7.70</td>
<td>R-squared = 0.0627</td>
</tr>
</tbody>
</table>
```

| quantity | Coef. | Std. Err. | t     | P>|t| | [95% Conf. Interval] |
|----------|-------|-----------|-------|------|---------------------|
| price    | .119  | .172      | 0.69  | 0.493| -.227 to .462       |
| pcompete | .095  | .120      | 0.79  | 0.435| -.147 to .337       |
| income   | .079  | .116      | 0.68  | 0.502| -.156 to .321       |
| _cons    | 7.56  | 5.02      | 1.51  | 0.139| -2.5 to 17.7       |

The OLS estimates for the supply equation are

```
regress quantity price praw
```

```
<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>Number of obs = 49</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>224.8</td>
<td>2</td>
<td>112.4</td>
<td>F( 2, 46) = 35.71</td>
</tr>
<tr>
<td>Residual</td>
<td>144.8</td>
<td>46</td>
<td>3.17</td>
<td>Prob &gt; F = 0.0000</td>
</tr>
<tr>
<td>Total</td>
<td>369.6</td>
<td>48</td>
<td>7.70</td>
<td>R-squared = 0.5912</td>
</tr>
</tbody>
</table>
```

| quantity | Coef. | Std. Err. | t     | P>|t| | [95% Conf. Interval] |
|----------|-------|-----------|-------|------|---------------------|
| price    | .72   | .110      | 6.61  | 0.000| .504 to .945       |
| praw     | -.87  | .107      | -8.14 | 0.000| -.11 to -.653      |
| _cons    | -6.97 | 3.32      | -2.10 | 0.041| -13.7 to -3.2      |

Examining the coefficients from these regressions, we note that they are not close to the known parameters used to generate the simulated data. In particular, the positive coefficient on price in the demand equation stands out. We constructed our simulated data to be consistent with economic theory—people demand less of a product if its price rises and more if their personal income rises. Although the price coefficient is statistically insignificant, the positive value contrasts starkly with what is predicted from economic price theory and the −1.0 value that we used in the simulation. Likewise, we are disappointed with the insignificance and level of the coefficient on average income. The supply equation has correct signs on the two main parameters, but their levels are different from the known values. In fact, the coefficient on price (0.724675) is different from the simulated parameter (0.5) at the 5% level of significance.
All of these problems are to be expected. We explicitly constructed a simultaneous system of equations that violated one of the assumptions of least squares. Specifically, the disturbances were correlated with one of the regressors—price.

Two-stage least squares can be used to address the correlation between regressors and disturbances. Using instruments for the endogenous variable, price, 2SLS will produce consistent estimates of the parameters in the system. Let’s use `ivregress` (see [R ivregress]) to see how our simulated system behaves when fit using 2SLS.

```
.ivregress 2sls quantity (price = praw) pcompete income
```

```
Instrumental variables (2SLS) regression
Number of obs = 49
Wald chi2(3) = 8.77
Prob > chi2 = 0.0326
R-squared = .
Root MSE = 3.7333
```

```
| quantity  | Coef.   | Std. Err. | z     | P>|z|    | [95% Conf. Interval] |
|-----------|---------|-----------|-------|--------|----------------------|
| price     | -1.015817 | .374209  | -2.71 | 0.007  | -1.749253, -.282381  |
| pcompete  | .3319504  | .172912  | 1.92  | 0.055  | -.0069508, .6708517  |
| income    | .5090607  | .1919482 | 2.65  | 0.008  | .1328491, .8852723   |
| _cons     | 39.89988  | 10.77378 | 3.70  | 0.000  | 18.78366, 61.01611   |
```

Instrumented: price
Instruments: pcompete income praw

```
.ivregress 2sls quantity (price = pcompete income) praw
```

```
Instrumental variables (2SLS) regression
Number of obs = 49
Wald chi2(2) = 39.25
Prob > chi2 = 0.0000
R-squared = 0.5928
Root MSE = 1.7525
```

```
| quantity  | Coef.   | Std. Err. | z     | P>|z|    | [95% Conf. Interval] |
|-----------|---------|-----------|-------|--------|----------------------|
| price     | .5773133 | .1749974 | 3.30  | 0.001  | .2343247, .9203019   |
| praw      | -.7835496 | .1312414 | -5.97 | 0.000  | -1.040778, -.5263213 |
| _cons     | -2.550694 | 5.273067 | -0.48 | 0.629  | -12.88571, 7.784327  |
```

Instrumented: price
Instruments: praw pcompete income

We are now much happier with the estimation results. All the coefficients from both equations are close to the true parameter values for the system. In particular, the coefficients are all well within 95% confidence intervals for the parameters. The missing $R^2$ in the demand equation seems unusual; we will discuss that more later.

Finally, this system could be estimated using 3SLS. To demonstrate how large systems might be handled and to avoid multiline commands, we will use global macros (see [P macro]) to hold the specifications for our equations.

```
.global demand "(qDemand: quantity price pcompete income)"
.global supply "(qSupply: quantity price praw)"
.reg3 $demand $supply, endog(price)
```

We must specify price as endogenous because it does not appear as a dependent variable in either equation. Without this option, `reg3` would assume that there are no endogenous variables in the system and produce seemingly unrelated regression (`sureg`) estimates. The `reg3` output from our series of commands is
Three-stage least-squares regression

<table>
<thead>
<tr>
<th>Equation</th>
<th>Obs</th>
<th>Parms</th>
<th>RMSE</th>
<th>&quot;R-sq&quot;</th>
<th>chi2</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>qDemand</td>
<td>49</td>
<td>3</td>
<td>3.739686</td>
<td>-0.8540</td>
<td>8.68</td>
<td>0.0338</td>
</tr>
<tr>
<td>qSupply</td>
<td>49</td>
<td>2</td>
<td>1.752501</td>
<td>0.5928</td>
<td>39.25</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

| Coef.     | Std. Err. | z   | P>|z| | [95% Conf. Interval] |
|-----------|-----------|-----|------|----------------------|
| qDemand   |           |     |      |                      |
| price     | -1.014345 | .3742036 | -2.71  | 0.007 | -1.74777 | -.2809194 |
| pcompete  | .2647206 | .1464194 | 1.81   | 0.071 | -.0222561 | .5516973  |
| income    | .5299146 | .1898161 | 2.79   | 0.005 | .1578819  | .9019472  |
| _cons     | 40.08749 | 10.77072 | 3.72   | 0.000 | 18.97726  | 61.19772  |

| Coef.     | Std. Err. | z   | P>|z| | [95% Conf. Interval] |
|-----------|-----------|-----|------|----------------------|
| qSupply   |           |     |      |                      |
| price     | .5773133 | .1749974 | 3.30   | 0.001 | .2343247  | .9203019  |
| praw      | -.7835496 | .1312414 | -5.97  | 0.000 | -1.040778 | -.5263213 |
| _cons     | -2.550694 | 5.273067 | -0.48  | 0.629 | -12.88571 | 7.784327  |

Endogenous variables: quantity price
Exogenous variables: pcompete income praw

The use of 3SLS over 2SLS is essentially an efficiency issue. The coefficients of the demand equation from 3SLS are close to the coefficients from two-stage least squares, and those of the supply equation are identical. The latter case was mentioned earlier for systems with some exactly identified equations. However, even for the demand equation, we do not expect the coefficients to change systematically. What we do expect from three-stage least squares are more precise estimates of the parameters given the validity of our specification and reg3’s use of the covariances among the disturbances.

Let’s summarize the results. With OLS, we got obviously biased estimates of the parameters. No amount of data would have improved the OLS estimates—they are inconsistent in the face of the violated OLS assumptions. With 2SLS, we obtained consistent estimates of the parameters, and these would have improved with more data. With 3SLS, we obtained consistent estimates of the parameters that are more efficient than those obtained by 2SLS.

Technical note

We noted earlier that the $R$-squared was missing from the two-stage estimates of the demand equation. Now we see that the $R$-squared is negative for the three-stage estimates of the same equation. How can we have a negative $R$-squared?

In most estimators, other than least squares, the $R$-squared is no more than a summary measure of the overall in-sample predictive power of the estimator. The computational formula for $R$-squared is $R$-squared $= 1 - \text{RSS}/\text{TSS}$, where RSS is the residual sum of squares (sum of squared residuals) and TSS is the total sum of squared deviations about the mean of the dependent variable. In a standard linear model with a constant, the model from which the TSS is computed is nested within the full model from which RSS is computed—they both have a constant term based on the same data. Thus it must be that $\text{TSS} \geq \text{RSS}$ and $R$-squared is constrained between 0 and 1.

For 2SLS and 3SLS, some of the regressors enter the model as instruments when the parameters are estimated. However, because our goal is to fit the structural model, the actual values, not the instruments for the endogenous right-hand-side variables, are used to determine $R$-squared. The model residuals are computed over a different set of regressors from those used to fit the model. The two-
or three-stage estimates are no longer nested within a constant-only model of the dependent variable, and the residual sum of squares is no longer constrained to be smaller than the total sum of squares.

A negative $R^2$-squared in 3SLS should be taken for exactly what it is—an indication that the structural model predicts the dependent variable worse than a constant-only model. Is this a problem? It depends on the application. Three-stage least squares applied to our contrived supply-and-demand example produced good estimates of the known true parameters. Still, the demand equation produced an $R^2$-squared of $-0.854$. How do we feel about our parameter estimates? This should be determined by the estimates themselves, their associated standard errors, and the overall model significance. On this basis, negative $R^2$-squared and all, we feel pretty good about all the parameter estimates for both the supply and demand equations. Would we want to make predictions about equilibrium quantity by using the demand equation alone? Probably not. Would we want to make these quantity predictions by using the supply equation? Possibly, because based on in-sample predictions, they seem better than those from the demand equations. However, both the supply and demand estimates are based on limited information. If we are interested in predicting quantity, a reduced-form equation containing all our independent variables would usually be preferred.

Technical note

As a matter of syntax, we could have specified the supply-and-demand model on one line without using global macros.

```
. reg3 (quantity price pcompete income) (quantity price praw), endog(price)
```

<table>
<thead>
<tr>
<th>Equation</th>
<th>Obs</th>
<th>Parms</th>
<th>RMSE</th>
<th>&quot;R-sq&quot;</th>
<th>chi2</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>quantity</td>
<td>49</td>
<td>3</td>
<td>3.739686</td>
<td>-0.8540</td>
<td>8.68</td>
<td>0.0338</td>
</tr>
<tr>
<td>2quantity</td>
<td>49</td>
<td>2</td>
<td>1.752501</td>
<td>0.5928</td>
<td>39.25</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

|                      | Coef. | Std. Err. | z     | P>|z| | [95% Conf. Interval] |
|----------------------|-------|-----------|-------|------|---------------------|
| quantity             |       |           |       |      |                     |
| price                | -1.014345 | .3742036 | -2.71 | 0.007 | -1.74777 - .2809194 |
| pcompete             | .2647206 | .1464194  | 1.81  | 0.071 | -.0222561 .5516973 |
| income               | .5299146 | .1898161  | 2.79  | 0.005 | .1578819 .9019472  |
| _cons                | 40.08749 | 10.77072 | 3.72  | 0.000 | 18.97726 61.19772 |
| 2quantity            |       |           |       |      |                     |
| price                | .5773133 | .1749974 | 3.30  | 0.001 | .2343247 .9203019  |
| praw                 | -.7835496 | .1312414 | -5.97 | 0.000 | -1.040778 -.5263213 |
| _cons                | -2.550694 | 5.273067 | -0.48 | 0.629 | -12.88571 7.784327 |

Endogenous variables: quantity price
Exogenous variables: pcompete income praw

However, here `reg3` has been forced to create a unique equation name for the supply equation—2quantity. Both the supply and demand equations could not be designated as quantity, so a number was prefixed to the name for the supply equation.
We could have specified

```
.reg3 (qDemand: quantity price pcompete income) (qSupply: quantity price praw), > endog(price)
```

and obtained the same results and equation labeling as when we used global macros to hold the equation specifications.

Without explicit equation names, `reg3` always assumes that the dependent variable should be used to name equations. When each equation has a different dependent variable, this rule causes no problems and produces easily interpreted result tables. If the same dependent variable appears in more than one equation, however, `reg3` will create a unique equation name based on the dependent variable name. Because equation names must be used for cross-equation tests, you have more control in this situation if explicit names are placed on the equations.

**Example 3: Using the full syntax of reg3**

Klein’s (1950) model of the U.S. economy is often used to demonstrate system estimators. It contains several common features that will serve to demonstrate the full syntax of `reg3`. The Klein model is defined by the following seven relationships:

\[
\begin{align*}
  c &= \beta_0 + \beta_1 p + \beta_2 L.p + \beta_3 w + \epsilon_1 \\
  i &= \beta_4 + \beta_5 p + \beta_6 L.p + \beta_7 L.k + \epsilon_2 \\
  wp &= \beta_8 + \beta_9 y + \beta_{10} L.y + \beta_{11} yr + \epsilon_3 \\
  y &= c + i + g \\
  p &= y - t - wp \\
  k &= L.k + i \\
  w &= wg + wp
\end{align*}
\]

Here we have used Stata’s lag operator `L.` to represent variables that appear with a one-period lag in our model; see [U] 13.9 Time-series operators.

The variables in the model are listed below. Two sets of variable names are shown. The concise first name uses traditional economics mnemonics, whereas the second name provides more guidance for everyone else. The concise names serve to keep the specification of the model small (and quite understandable to economists).

<table>
<thead>
<tr>
<th>Short name</th>
<th>Long name</th>
<th>Variable definition</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>c</td>
<td>consump</td>
<td>Consumption</td>
<td>endogenous</td>
</tr>
<tr>
<td>p</td>
<td>profits</td>
<td>Private industry profits</td>
<td>endogenous</td>
</tr>
<tr>
<td>wp</td>
<td>wagepriv</td>
<td>Private wage bill</td>
<td>endogenous</td>
</tr>
<tr>
<td>wg</td>
<td>wagegovt</td>
<td>Government wage bill</td>
<td>exogenous</td>
</tr>
<tr>
<td>w</td>
<td>wagetot</td>
<td>Total wage bill</td>
<td>endogenous</td>
</tr>
<tr>
<td>i</td>
<td>invest</td>
<td>Investment</td>
<td>endogenous</td>
</tr>
<tr>
<td>k</td>
<td>capital</td>
<td>Capital stock</td>
<td>endogenous</td>
</tr>
<tr>
<td>y</td>
<td>totinc</td>
<td>Total income/demand</td>
<td>endogenous</td>
</tr>
<tr>
<td>g</td>
<td>govt</td>
<td>Government spending</td>
<td>exogenous</td>
</tr>
<tr>
<td>t</td>
<td>taxnetx</td>
<td>Indirect bus. taxes + net exports</td>
<td>exogenous</td>
</tr>
<tr>
<td>yr</td>
<td>year</td>
<td>Year—1931</td>
<td>exogenous</td>
</tr>
</tbody>
</table>
Equations (1)–(3) are behavioral and contain explicit disturbances ($\epsilon_1$, $\epsilon_2$, and $\epsilon_3$). The remaining equations are identities that specify additional variables in the system and their accounting relationships with the variables in the behavioral equations. Some variables are explicitly endogenous by appearing as dependent variables in (1)–(3). Others are implicitly endogenous as linear combinations that contain other endogenous variables (for example, $w$ and $p$). Still other variables are implicitly exogenous by appearing in the identities but not in the behavioral equations (for example, $wg$ and $g$).

Using the concise names, we can fit Klein’s model with the following command:

```
. use http://www.stata-press.com/data/r13/klein2
. reg3 (c p L.p w) (i p L.p L.k) (wp y L.y yr), endog(w p y) exog(t wg g)
```

Three-stage least-squares regression

<table>
<thead>
<tr>
<th>Equation</th>
<th>Obs</th>
<th>Parms</th>
<th>RMSE</th>
<th>&quot;R-sq&quot;</th>
<th>chi2</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>c</td>
<td>21</td>
<td>3</td>
<td>.9443305</td>
<td>0.9801</td>
<td>864.59</td>
<td>0.0000</td>
</tr>
<tr>
<td>i</td>
<td>21</td>
<td>3</td>
<td>1.446736</td>
<td>0.8258</td>
<td>162.98</td>
<td>0.0000</td>
</tr>
<tr>
<td>wp</td>
<td>21</td>
<td>3</td>
<td>.7211282</td>
<td>0.9863</td>
<td>1594.75</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

| Coef.     | Std. Err. | z    | P>|z|   | [95% Conf. Interval] |
|-----------|-----------|------|-------|---------------------|
| c         |           |      |       |                     |
| p         | --.       | .1248904 | .1081291 | 1.16 | 0.248 | -.0870387 | .3368194 |
| L1.       | .1631439 | .1004382 | 1.62 | 0.104 | -.0337113 | .3599992 |
| w         | .790081 | .0379379 | 20.83 | 0.000 | .715724 | .8644379 |
| _cons     | 16.44079 | 1.304549 | 12.60 | 0.000 | 13.88392 | 18.99766 |
| i         |           |      |       |                     |
| p         | --.       | -.0130791 | .1618962 | -0.08 | 0.936 | -.3303898 | .3042316 |
| L1.       | .7557238 | .1529331 | 4.94 | 0.000 | .4559805 | 1.055467 |
| k         | L1.      | -.1948482 | .0325307 | -5.99 | 0.000 | -.2586072 | -.1310893 |
| _cons     | 28.17785 | 6.793768 | 4.15 | 0.000 | 14.86231 | 41.49339 |
| wp        |           |      |       |                     |
| y         | --.       | .4004919 | .0318134 | 12.59 | 0.000 | .3381388 | .462845 |
| L1.       | .181291 | .0341588 | 5.31 | 0.000 | .1143411 | .2482409 |
| yr        | .149674 | .0279352 | 5.36 | 0.000 | .094922 | .2044261 |
| _cons     | 1.797216 | 1.115854 | 1.61 | 0.107 | -.3898181 | 3.984251 |

Endogenous variables: c i wp w p y
Exogenous variables: L.p L.k L.y yr t wg g

We used the `exog()` option to identify $t$, $wg$, and $g$ as exogenous variables in the system. These variables must be identified because they are part of the system but appear directly in none of the behavioral equations. Without this option, `reg3` would not know they were part of the system and could be used as instrumental variables. The `endog()` option specifying $w$, $p$, and $y$ is also required. Without this information, `reg3` would be unaware that these variables are linear combinations that include endogenous variables. We did not include $k$ in the `endog()` option because only its lagged value appears in the behavioral equations.
Rather than listing additional endogenous and exogenous variables, we could specify the full list of exogenous variables in an \texttt{inst()} option,

\begin{verbatim}
  . reg3 (c p L.p w) (i p L.p L.k) (wp y L.y yr), inst(g t wg yr L.p L.k L.y)
\end{verbatim}
or equivalently,

\begin{verbatim}
  . global conseqn "(c p L.p w)"
  . global inveqn "(i p L.p L.k)"
  . global wageqn "(wp y L.y yr)"
  . global inlist "g t wg yr L.p L.k L.y"
  . reg3 $conseqn $inveqn $wageqn, inst($inlist)
\end{verbatim}

Macros and explicit equations can also be mixed in the specification

\begin{verbatim}
  . reg3 $conseqn (i p L.p L.k) $wageqn, endog(w p y) exog(t wg g)
\end{verbatim}
or

\begin{verbatim}
  . reg3 (c p L.p w) $inveqn (wp y L.y yr), endog(w p y) exog(t wg g)
\end{verbatim}

Placing the equation-binding parentheses in the global macros was also arbitrary. We could have used

\begin{verbatim}
  . global consump "c p L.p w"
  . global invest "i p L.p L.k"
  . global wagepriv "wp y L.y yr"
  . reg3 ($consump) ($invest) ($wagepriv), endog($enlist) exog($exlist) ireg3
\end{verbatim}

\texttt{reg3} is tolerant of all combinations, and these commands will produce identical output.

Switching to the full variable names, we can fit Klein’s model with the commands below. We will use global macros to store the lists of endogenous and exogenous variables. Again this is not necessary: these lists could have been typed directly on the command line. However, assigning the lists to local macros makes additional processing easier if alternative models are to be fit. We will also use the \texttt{ireg3} option to produce the iterated estimates.

\begin{verbatim}
  . use http://www.stata-press.com/data/r13/kleinfull
  . global conseqn "(consump profits L.profits wagetot)"
  . global inveqn "(invest profits L.profits L.capital)"
  . global wageqn "(wagepriv totinc L.totinc year)"
  . global enlist "wagetot profits totinc"
  . global exlist "taxnetx wagegovt govt"
  . reg3 $conseqn $inveqn $wageqn, endog($enlist) exog($exlist) ireg3
\end{verbatim}

Iteration 1: tolerance = 0.3712549
Iteration 2: tolerance = 0.1894712
Iteration 3: tolerance = 0.1076401
\dots
Iteration 24: tolerance = 7.049e-07

\begin{verbatim}
Three-stage least-squares regression, iterated
\end{verbatim}

\begin{verbatim}
\begin{tabular}{lrrrrr}
\hline
Equation & Obs & Parms & RMSE & "R-sq" & chi2 & P \\
\hline
consump & 21 & 3 & .9565088 & 0.9796 & 970.31 & 0.0000 \\
invest & 21 & 3 & 2.134327 & 0.6209 & 56.78 & 0.0000 \\
wagepriv & 21 & 3 & .7782334 & 0.9840 & 1312.19 & 0.0000 \\
\hline
\end{tabular}
\end{verbatim}
Example 4: Constraints with reg3

As a simple example of constraints, (1) above may be rewritten with both wages explicitly appearing (rather than as a variable containing the sum). Using the longer variable names, we have

\[
\text{consump} = \beta_0 + \beta_1 \text{profits} + \beta_2 \text{L.profits} + \beta_3 \text{wagepriv} + \beta_{12} \text{wagegovt} + \epsilon_1
\]

To retain the effect of the identity in (7), we need \(\beta_3 = \beta_{12}\) as a constraint on the system. We obtain this result by defining the constraint in the usual way and then specifying its use in reg3. Because reg3 is a system estimator, we will need to use the full equation syntax of constraint. The assumption that the following commands are entered after the model above has been estimated. We are simply changing the definition of the consumption equation (consump) and adding a constraint on two of its parameters. The rest of the model definition is carried forward.

\[
\text{endogenous variables: consump invest wagepriv wagetot profits totinc}
\]

\[
\text{exogenous variables: L.profits L.capital L.totinc year taxnetx wagegovt govt}
\]
Three-stage least-squares regression, iterated

<table>
<thead>
<tr>
<th>Equation</th>
<th>Obs</th>
<th>Parms</th>
<th>RMSE</th>
<th>&quot;R-sq&quot;</th>
<th>chi2</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>consump</td>
<td>21</td>
<td>3</td>
<td>.9565086</td>
<td>0.9796</td>
<td>970.31</td>
<td>0.0000</td>
</tr>
<tr>
<td>invest</td>
<td>21</td>
<td>3</td>
<td>2.134326</td>
<td>0.6209</td>
<td>56.78</td>
<td>0.0000</td>
</tr>
<tr>
<td>wagepriv</td>
<td>21</td>
<td>3</td>
<td>.7782334</td>
<td>0.9840</td>
<td>1312.19</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

(1) [consump]wagepriv - [consump]wagegovt = 0

|         | Coef.  | Std. Err. | z     | P>|z|   | [95% Conf. Interval] |
|---------|--------|-----------|-------|-------|---------------------|
| consump | profits|--.1645097|.0961978|1.71   |0.087   |-.0240346 .353054   |
|         | L1.    |.1765639  |.0901001|1.96   |0.050   |-.0000291 .3531568  |
|         | wagepriv| .7658012 |.0347599|22.03  |0.000  |.6976729 .8339294   |
|         | wagegovt| .7658012 |.0347599|22.03  |0.000  |.6976729 .8339294   |
|         | _cons  |16.55899  |1.224401|13.52  |0.000  |14.1592 18.95877    |

| invest | profits|---.3565311|.2601567|-1.37  |0.171   |-.8664288 .1533666  |
|         | L1.   |1.011298  |.2487744|4.07   |0.000  |.5237096 1.498887   |
|         | capital| -.2601999|.0508694|-5.12  |0.000  |-.359902 -.1604977  |
|         | _cons  |42.89626  |10.59386|4.05   |0.000  |22.13269 63.65984   |

| wagepriv | totinc|--.3747792|.0311027|12.05  |0.000  |.313819 .4357394   |
|          | L1.   |.1936506  |.0324018|5.98   |0.000  |.1301443 .257157   |
|          | year  |.1679262  |.0289291|5.80   |0.000  |.1112263 .2246261  |
|          | _cons |2.624766  |1.195559|2.20   |0.028  |.281512 4.968019   |

Endogenous variables: consump invest wagepriv wagetot profits totinc
Exogenous variables: L.profits wagegovt L.capital L.totinc year taxnetx
govt

As expected, none of the parameter or standard error estimates has changed from the previous estimates (before the seventh significant digit). We have simply decomposed the total wage variable into its two parts and constrained the coefficients on these parts. The warning about additional endogenous variables was just reg3’s way of letting us know that we had specified some information that was irrelevant to the estimation of the system. We had left the wagetot variable in our endog macro. It does not mean anything to the system to specify wagetot as endogenous because it is no longer in the system. That’s fine with reg3 and fine for our current purposes.

We can also impose constraints across the equations. For example, the admittedly meaningless constraint of requiring profits to have the same effect in both the consumption and investment equations could be imposed. Retaining the constraint on the wage coefficients, we would estimate this constrained system.
. constraint define 2 [consump]profits = [invest]profits
. reg3 $conseqn $inveqn $wageqn, endog($enlist) exog($exlist) constr(1 2) ireg3
note: additional endogenous variables not in the system have no effect
and are ignored: wagetot
Iteration 1: tolerance = .1427927
Iteration 2: tolerance = .032539
Iteration 3: tolerance = .00307811
Iteration 4: tolerance = .00016903
Iteration 5: tolerance = .00003409
Iteration 6: tolerance = 7.763e-06
Iteration 7: tolerance = 9.240e-07
Three-stage least-squares regression, iterated

<table>
<thead>
<tr>
<th>Equation</th>
<th>Obs</th>
<th>Parms</th>
<th>RMSE</th>
<th>&quot;R-sq&quot;</th>
<th>chi2</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>consump</td>
<td>21</td>
<td>3</td>
<td>.9504669</td>
<td>0.9798</td>
<td>1019.54</td>
<td>0.0000</td>
</tr>
<tr>
<td>invest</td>
<td>21</td>
<td>3</td>
<td>1.247066</td>
<td>0.8706</td>
<td>144.57</td>
<td>0.0000</td>
</tr>
<tr>
<td>wagepriv</td>
<td>21</td>
<td>3</td>
<td>0.7225276</td>
<td>0.9862</td>
<td>1537.45</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

(1) [consump]wagepriv - [consump]wagegovt = 0
(2) [consump]profits - [invest]profits = 0

| Coef.  | Std. Err. | z     | P>|z|   | [95% Conf. Interval] |
|--------|-----------|------|-------|----------------------|
| consump profits
| --.   | .1075413 | .0957767 | 1.12 | 0.262   | -.08017777 .2952602 |
| L1.   | .1712756 | .0912613 | 1.88 | 0.061   | -.0075932 .3501444 |
| wagepriv
| .798484 | .0340876 | 23.42 | 0.000   | .7316734 .8652946 |
| wagegovt
| .798484 | .0340876 | 23.42 | 0.000   | .7316734 .8652946 |
| _cons  | 16.2521 | 1.212157 | 13.41 | 0.000   | 13.87631 18.62788 |

| invest profits
| --.   | .1075413 | .0957767 | 1.12 | 0.262   | -.08017777 .2952602 |
| L1.   | .6443378 | .1058682 | 6.09 | 0.000   | .43684 .8518356 |
| capital L1. |
| -1.766669 | .0261889 | -6.75 | 0.000 | -2.279962 -1.253375 |
| _cons  | 24.31931 | 5.284325 | 4.60 | 0.000 | 13.96222 34.6764 |

| wagepriv totinc
| --.   | .4014106 | .0300552 | 13.36 | 0.000 | .3425035 .4603177 |
| L1.   | .1775359 | .0321583 | 5.52 | 0.000 | .1145068 .240565 |
| year  |
| .1549211 | .0282291 | 5.49 | 0.000 | .099593 .2102492 |
| _cons  | 1.959788 | 1.14467 | 1.71 | 0.087 | -0.2837242 4.203299 |

Endogenous variables: consump invest wagepriv wagetot profits totinc
Exogenous variables: L.profits wagegovt L.capital L.totinc year taxnetx
govt
Identification in a system of simultaneous equations involves the notion that there is enough information to estimate the parameters of the model given the specified functional form. Under-identification usually manifests itself as one matrix in the 3SLS computations. The most commonly violated order condition for 2SLS or 3SLS involves the number of endogenous and exogenous variables. There must be at least as many noncollinear exogenous variables in the remaining system as there are endogenous right-hand-side variables in an equation. This condition must hold for each structural equation in the system.

Put as a set of rules the following:
1. Count the number of right-hand-side endogenous variables in an equation and call this \( m_i \).
2. Count the number of exogenous variables in the same equation and call this \( k_i \).
3. Count the total number of exogenous variables in all the structural equations plus any additional variables specified in an \texttt{exog()} or \texttt{inst()} option and call this \( K \).
4. If \( m_i > (K - k_i) \) for any structural equation \((i)\), then the system is underidentified and cannot be estimated by 3SLS.

We are also possibly in trouble if any of the exogenous variables are linearly dependent. We must have \( m_i \) linearly independent variables among the exogenous variables represented by \((K - k_i)\).

The complete conditions for identification involve rank-order conditions on several matrices. For a full treatment, see Theil (1971) or Greene (2012, 331–334).

Henri Theil (1924–2000) was born in Amsterdam and awarded a PhD in 1951 by the University of Amsterdam. He researched and taught econometric theory, statistics, microeconomics, macroeconomic modeling, and economic forecasting, and policy at (now) Erasmus University Rotterdam, the University of Chicago, and the University of Florida. Theil’s many specific contributions include work on 2SLS and 3SLS, inequality and concentration, and consumer demand.

Stored results

\texttt{reg3} stores the following in \texttt{e()}:

Scalars

- \texttt{e(N)}  number of observations
- \texttt{e(k)}  number of parameters
- \texttt{e(k_eq)}  number of equations in \texttt{e(b)}
- \texttt{e(mss_#)}  model sum of squares for equation \#
- \texttt{e(df_m#)}  model degrees of freedom for equation \#
- \texttt{e(rss_#)}  residual sum of squares for equation \#
- \texttt{e(df_r)}  residual degrees of freedom (small)
- \texttt{e(r2_#)}  \( R^2 \) for equation \#
- \texttt{e(F_#)}  \( F \) statistic for equation \# (small)
- \texttt{e(rmse_#)}  root mean squared error for equation \#
- \texttt{e(dfk2_adj)}  divisor used with VCE when \texttt{dfk2} specified
- \texttt{e(ll)}  log likelihood
- \texttt{e(chi2_#)}  \( \chi^2 \) for equation \#
- \texttt{e(p_#)}  significance for equation \#
- \texttt{e(cons_#)}  1 when equation \# has a constant, 0 otherwise
- \texttt{e(rank)}  rank of \texttt{e(V)}
- \texttt{e(ic)}  number of iterations
The most concise way to represent a system of equations for 3SLS requires thinking of the individual equations and their associated data as being stacked. \texttt{reg3} does not expect the data in this format, but it is a convenient shorthand. The system could then be formulated as

\[
\begin{bmatrix}
  y_1 \\
  y_2 \\
  \vdots \\
  y_M
\end{bmatrix} =
\begin{bmatrix}
  Z_1 & 0 & \cdots & 0 \\
  0 & Z_2 & \cdots & 0 \\
  \vdots & \vdots & \ddots & \vdots \\
  0 & 0 & \cdots & Z_M
\end{bmatrix}
\begin{bmatrix}
  \beta_1 \\
  \beta_2 \\
  \vdots \\
  \beta_M
\end{bmatrix} +
\begin{bmatrix}
  \epsilon_1 \\
  \epsilon_2 \\
  \vdots \\
  \epsilon_M
\end{bmatrix}
\]

In full matrix notation, this is just

\[
y = ZB + \epsilon
\]

The \( Z \) elements in these matrices represent both the endogenous and the exogenous right-hand-side variables in the equations.

Also assume that there will be correlation between the disturbances of the equations so that

\[
E(\epsilon\epsilon') = \Sigma
\]

where the disturbances are further assumed to have an expected value of 0; \( E(\epsilon) = 0 \).

The first stage of 3SLS regression requires developing instrumented values for the endogenous variables in the system. These values can be derived as the predictions from a linear regression of each endogenous regressor on all exogenous variables in the system or, more succinctly, as the projection of each regressor through the projection matrix of all exogenous variables onto the regressors. Designating the set of all exogenous variables as \( X \) results in
\[ \hat{z}_i = X(X'X)^{-1}X'z_i \quad \text{for each } i \]

Taken collectively, these \( \hat{Z} \) contain the instrumented values for all the regressors. They take on the actual values for the exogenous variables and first-stage predictions for the endogenous variables. Given these instrumented variables, a generalized least squares (GLS) or Aitken (1935) estimator can be formed for the parameters of the system

\[ \hat{B} = \left( \hat{Z}'(\Sigma^{-1} \otimes I)\hat{Z} \right)^{-1} \hat{Z}'(\Sigma^{-1} \otimes I)y \]

All that remains is to obtain a consistent estimator for \( \Sigma \). This estimate can be formed from the residuals of 2SLS estimates of each equation in the system. Alternately, and identically, the residuals can be computed from the estimates formed by taking \( \Sigma \) to be an identity matrix. This maintains the full system of coefficients and allows constraints to be applied when the residuals are computed.

If we take \( E \) to be the matrix of residuals from these estimates, a consistent estimate of \( \Sigma \) is

\[ \hat{\Sigma} = \frac{E'E}{n} \]

where \( n \) is the number of observations in the sample. An alternative divisor for this estimate can be obtained with the \texttt{dfk} option as outlined under options.

With the estimate of \( \hat{\Sigma} \) placed into the GLS estimating equation,

\[ \hat{B} = \left( \hat{Z}'(\hat{\Sigma}^{-1} \otimes I)\hat{Z} \right)^{-1} \hat{Z}'(\hat{\Sigma}^{-1} \otimes I)y \]

is the 3SLS estimates of the system parameters.

The asymptotic variance–covariance matrix of the estimator is just the standard formulation for a GLS estimator

\[ V_{\hat{B}} = \left( \hat{Z}'(\hat{\Sigma}^{-1} \otimes I)\hat{Z} \right)^{-1} \]

Iterated 3SLS estimates can be obtained by computing the residuals from the three-stage parameter estimates, using these to formulate a new \( \hat{\Sigma} \), and recomputing the parameter estimates. This process is repeated until the estimates \( \hat{B} \) converge—if they converge. Convergence is not guaranteed. When estimating a system by SURE, these iterated estimates will be the maximum likelihood estimates for the system. The iterated solution can also be used to produce estimates that are invariant to choice of system and restriction parameterization for many linear systems under full 3SLS.

The exposition above follows the parallel developments in Greene (2012) and Davidson and MacKinnon (1993).

References


**Also see**

[R] *reg3 postestimation* — Postestimation tools for *reg3*

[R] *ivregress* — Single-equation instrumental-variables regression

[R] *nlsur* — Estimation of nonlinear systems of equations

[R] *regress* — Linear regression

[R] *sureg* — Zellner’s seemingly unrelated regression

[MV] *mvreg* — Multivariate regression

[SEM] *example 7* — Nonrecursive structural model

[SEM] *intro 5* — Tour of models

[TS] *forecast* — Econometric model forecasting

[U] 20 Estimation and postestimation commands