

ivregress — Single-equation instrumental-variables regression
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Syntax

```
ivregress estimator depvar [varlist1] (varlist2 = varlistIV) [if] [in] [weight]
    [, options]
```

<i>estimator</i>	Description
<code>2sls</code>	two-stage least squares (2SLS)
<code>liml</code>	limited-information maximum likelihood (LIML)
<code>gmm</code>	generalized method of moments (GMM)

<i>options</i>	Description
Model	
<code>noconstant</code>	suppress constant term
<code>hascons</code>	has user-supplied constant
GMM ¹	
<code>wmatrix(<i>wmtype</i>)</code>	<i>wmtype</i> may be <code>robust</code> , <code>cluster <i>clustvar</i></code> , <code>hac <i>kernel</i></code> , or <code>unadjusted</code>
<code>center</code>	center moments in weight matrix computation
<code>igmm</code>	use iterative instead of two-step GMM estimator
<code>eps(#)</code> ²	specify # for parameter convergence criterion; default is <code>eps(1e-6)</code>
<code>weps(#)</code> ²	specify # for weight matrix convergence criterion; default is <code>weps(1e-6)</code>
<code>optimization_options</code> ²	control the optimization process; seldom used
SE/Robust	
<code>vce(<i>vcetype</i>)</code>	<i>vcetype</i> may be <code>unadjusted</code> , <code>robust</code> , <code>cluster <i>clustvar</i></code> , <code>bootstrap</code> , <code>jackknife</code> , or <code>hac <i>kernel</i></code>
Reporting	
<code>level(#)</code>	set confidence level; default is <code>level(95)</code>
<code>first</code>	report first-stage regression
<code>small</code>	make degrees-of-freedom adjustments and report small-sample statistics
<code>noheader</code>	display only the coefficient table
<code>depname(<i>depname</i>)</code>	substitute dependent variable name
<code>eform(<i>string</i>)</code>	report exponentiated coefficients and use <i>string</i> to label them
<code>display_options</code>	control column formats, row spacing, line width, display of omitted variables and base and empty cells, and factor-variable labeling

<code>perfect</code>	do not check for collinearity between endogenous regressors and excluded instruments
<code>coeflegend</code>	display legend instead of statistics

¹These options may be specified only when `gmm` is specified.

²These options may be specified only when `igmm` is specified.

`varlist1`, `varlist2`, and `varlistiv` may contain factor variables; see [U] 11.4.3 Factor variables.

`depvar`, `varlist1`, `varlist2`, and `varlistiv` may contain time-series operators; see [U] 11.4.4 Time-series varlists.

`bootstrap`, `by`, `jackknife`, `rolling`, `statsby`, and `svy` are allowed; see [U] 11.1.10 Prefix commands.

Weights are not allowed with the `bootstrap` prefix; see [R] `bootstrap`.

`aweight`s are not allowed with the `jackknife` prefix; see [R] `jackknife`.

`hascons`, `vce()`, `noheader`, `depname()`, and `weights` are not allowed with the `svy` prefix; see [SVY] `svy`.

`aweight`s, `fweight`s, `iweight`s, and `pweight`s are allowed; see [U] 11.1.6 `weight`.

`perfect` and `coeflegend` do not appear in the dialog box.

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

Menu

Statistics > Endogenous covariates > Single-equation instrumental-variables regression

Description

`ivregress` fits a linear regression of `depvar` on `varlist1` and `varlist2`, using `varlistiv` (along with `varlist1`) as instruments for `varlist2`. `ivregress` supports estimation via two-stage least squares (2SLS), limited-information maximum likelihood (LIML), and generalized method of moments (GMM).

In the language of instrumental variables, `varlist1` and `varlistiv` are the exogenous variables, and `varlist2` are the endogenous variables.

Options

Model

`noconstant`; see [R] estimation options.

`hascons` indicates that a user-defined constant or its equivalent is specified among the independent variables.

GMM

`wmatrix(wmtype)` specifies the type of weighting matrix to be used in conjunction with the GMM estimator.

Specifying `wmatrix(robust)` requests a weighting matrix that is optimal when the error term is heteroskedastic. `wmatrix(robust)` is the default.

Specifying `wmatrix(cluster clustvar)` requests a weighting matrix that accounts for arbitrary correlation among observations within clusters identified by `clustvar`.

Specifying `wmatrix(hac kernel #)` requests a heteroskedasticity- and autocorrelation-consistent (HAC) weighting matrix using the specified kernel (see below) with `#` lags. The bandwidth of a kernel is equal to `# + 1`.

Specifying `wmatrix(hac kernel opt)` requests an HAC weighting matrix using the specified kernel, and the lag order is selected using Newey and West's (1994) optimal lag-selection algorithm.

Specifying `wmatrix(hac kernel)` requests an HAC weighting matrix using the specified kernel and $N - 2$ lags, where N is the sample size.

There are three kernels available for HAC weighting matrices, and you may request each one by using the name used by statisticians or the name perhaps more familiar to economists:

`bartlett` or `nwest` requests the Bartlett (Newey–West) kernel;

`parzen` or `gallant` requests the Parzen (Gallant 1987) kernel; and

`quadraticspectral` or `andrews` requests the quadratic spectral (Andrews 1991) kernel.

Specifying `wmatrix(unadjusted)` requests a weighting matrix that is suitable when the errors are homoskedastic. The GMM estimator with this weighting matrix is equivalent to the 2SLS estimator.

`center` requests that the sample moments be centered (demeaned) when computing GMM weight matrices. By default, centering is not done.

`igmm` requests that the iterative GMM estimator be used instead of the default two-step GMM estimator.

Convergence is declared when the relative change in the parameter vector from one iteration to the next is less than `eps()` or the relative change in the weight matrix is less than `weps()`.

`eps(#)` specifies the convergence criterion for successive parameter estimates when the iterative GMM estimator is used. The default is `eps(1e-6)`. Convergence is declared when the relative difference between successive parameter estimates is less than `eps()` and the relative difference between successive estimates of the weighting matrix is less than `weps()`.

`weps(#)` specifies the convergence criterion for successive estimates of the weighting matrix when the iterative GMM estimator is used. The default is `weps(1e-6)`. Convergence is declared when the relative difference between successive parameter estimates is less than `eps()` and the relative difference between successive estimates of the weighting matrix is less than `weps()`.

optimization_options: `iterate(#)`, `[no]log`. `iterate()` specifies the maximum number of iterations to perform in conjunction with the iterative GMM estimator. The default is 16,000 or the number set using `set maxiter` (see [R] [maximize](#)). `log/nolog` specifies whether to show the iteration log. These options are seldom used.

SE/Robust

`vce(vctype)` specifies the type of standard error reported, which includes types that are robust to some kinds of misspecification (`robust`), that allow for intragroup correlation (`cluster clustvar`), and that use bootstrap or jackknife methods (`bootstrap`, `jackknife`); see [R] [vce_option](#).

`vce(unadjusted)`, the default for `2sls` and `liml`, specifies that an unadjusted (nonrobust) VCE matrix be used. The default for `gmm` is based on the `wmtype` specified in the `wmatrix()` option; see `wmatrix(wmtype)` above. If `wmatrix()` is specified with `gmm` but `vce()` is not, then `vctype` is set equal to `wmtype`. To override this behavior and obtain an unadjusted (nonrobust) VCE matrix, specify `vce(unadjusted)`.

`ivregress` also allows the following:

`vce(hac kernel [#|opt])` specifies that an HAC covariance matrix be used. The syntax used with `vce(hac kernel ...)` is identical to that used with `wmatrix(hac kernel ...)`; see `wmatrix(wmtype)` above.

Reporting

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

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

small requests that the degrees-of-freedom adjustment $N/(N - k)$ be made to the variance–covariance matrix of parameters and that small-sample F and t statistics be reported, where N is the sample size and k is the number of parameters estimated. By default, no degrees-of-freedom adjustment is made, and Wald and z statistics are reported. Even with this option, no degrees-of-freedom adjustment is made to the weighting matrix when the GMM estimator is used.

noheader suppresses the display of the summary statistics at the top of the output, displaying only the coefficient table.

depname(*depname*) is used only in programs and ado-files that use **ivregress** to fit models other than instrumental-variables regression. **depname**() may be specified only at estimation time. *depname* is recorded as the identity of the dependent variable, even though the estimates are calculated using *depvar*. This method affects the labeling of the output—not the results calculated—but could affect later calculations made by **predict**, where the residual would be calculated as deviations from *depname* rather than *depvar*. **depname**() is most typically used when *depvar* is a temporary variable (see [P] **macro**) used as a proxy for *depname*.

eform(*string*) is used only in programs and ado-files that use **ivregress** to fit models other than instrumental-variables regression. **eform**() specifies that the coefficient table be displayed in “exponentiated form”, as defined in [R] **maximize**, and that *string* be used to label the exponentiated coefficients in the table.

display_options: **noomitted**, **vsquish**, **noemptycells**, **baselevels**, **allbaselevels**, **nofvlabel**, **fvwrap(#)**, **fvwrapon(style)**, **cformat(%fint)**, **pformat(%fint)**, **sformat(%fint)**, and **no!stretch**; see [R] **estimation options**.

The following options are available with **ivregress** but are not shown in the dialog box:

perfect requests that **ivregress** not check for collinearity between the endogenous regressors and excluded instruments, allowing one to specify “perfect” instruments. This option cannot be used with the LIML estimator. This option may be required when using **ivregress** to implement other estimators.

coeflegend; see [R] **estimation options**.

Remarks and examples

[stata.com](http://www.stata.com)

ivregress performs instrumental-variables regression and weighted instrumental-variables regression. For a general discussion of instrumental variables, see [Baum \(2006\)](#), [Cameron and Trivedi \(2005; 2010, chap. 6\)](#) [Davidson and MacKinnon \(1993, 2004\)](#), [Greene \(2012, chap. 8\)](#), and [Wooldridge \(2010, 2013\)](#). See [Hall \(2005\)](#) for a lucid presentation of GMM estimation. [Angrist and Pischke \(2009, chap. 4\)](#) offer a casual yet thorough introduction to instrumental-variables estimators, including their use in estimating treatment effects. Some of the earliest work on simultaneous systems can be found in Cowles Commission monographs—[Koopmans and Marschak \(1950\)](#) and [Koopmans and Hood \(1953\)](#)—with the first developments of 2SLS appearing in [Theil \(1953\)](#) and [Basmann \(1957\)](#). However, [Stock and Watson \(2011, 422–424\)](#) present an example of the method of instrumental variables that was first published in 1928 by Philip Wright.

The syntax for **ivregress** assumes that you want to fit one equation from a system of equations or an equation for which you do not want to specify the functional form for the remaining equations of the system. To fit a full system of equations, using either 2SLS equation-by-equation or three-stage least squares, see [R] **reg3**. An advantage of **ivregress** is that you can fit one equation of a multiple-equation system without specifying the functional form of the remaining equations.

Formally, the model fit by `ivregress` is

$$y_i = \mathbf{y}_i\boldsymbol{\beta}_1 + \mathbf{x}_{1i}\boldsymbol{\beta}_2 + u_i \quad (1)$$

$$\mathbf{y}_i = \mathbf{x}_{1i}\boldsymbol{\Pi}_1 + \mathbf{x}_{2i}\boldsymbol{\Pi}_2 + \mathbf{v}_i \quad (2)$$

Here y_i is the dependent variable for the i th observation, \mathbf{y}_i represents the endogenous regressors (`varlist2` in the syntax diagram), \mathbf{x}_{1i} represents the included exogenous regressors (`varlist1` in the syntax diagram), and \mathbf{x}_{2i} represents the excluded exogenous regressors (`varlistiv` in the syntax diagram). \mathbf{x}_{1i} and \mathbf{x}_{2i} are collectively called the instruments. u_i and \mathbf{v}_i are zero-mean error terms, and the correlations between u_i and the elements of \mathbf{v}_i are presumably nonzero.

The rest of the discussion is presented under the following headings:

2SLS and LIML estimators

GMM estimator

2SLS and LIML estimators

The most common instrumental-variables estimator is 2SLS.

► Example 1: 2SLS estimator

We have state data from the 1980 census on the median dollar value of owner-occupied housing (`hsgnval`) and the median monthly gross rent (`rent`). We want to model `rent` as a function of `hsgnval` and the percentage of the population living in urban areas (`pcturban`):

$$\text{rent}_i = \beta_0 + \beta_1 \text{hsgnval}_i + \beta_2 \text{pcturban}_i + u_i$$

where i indexes states and u_i is an error term.

Because random shocks that affect rental rates in a state probably also affect housing values, we treat `hsgnval` as endogenous. We believe that the correlation between `hsgnval` and u is not equal to zero. On the other hand, we have no reason to believe that the correlation between `pcturban` and u is nonzero, so we assume that `pcturban` is exogenous.

Because we are treating `hsgnval` as an endogenous regressor, we must have one or more additional variables available that are correlated with `hsgnval` but uncorrelated with u . Moreover, these excluded exogenous variables must not affect `rent` directly, because if they do then they should be included in the regression equation we specified above. In our dataset, we have a variable for family income (`faminc`) and for region of the country (`region`) that we believe are correlated with `hsgnval` but not the error term. Together, `pcturban`, `faminc`, and factor variables `2.region`, `3.region`, and `4.region` constitute our set of instruments.

To fit the equation in Stata, we specify the dependent variable and the list of included exogenous variables. In parentheses, we specify the endogenous regressors, an equal sign, and the excluded exogenous variables. Only the additional exogenous variables must be specified to the right of the equal sign; the exogenous variables that appear in the regression equation are automatically included as instruments.

Here we fit our model with the 2SLS estimator:

```
. use http://www.stata-press.com/data/r13/hsng
(1980 Census housing data)
. ivregress 2sls rent pcturban (hsngval = faminc i.region)
Instrumental variables (2SLS) regression                Number of obs =      50
                                                       Wald chi2(2)      =    90.76
                                                       Prob > chi2       =    0.0000
                                                       R-squared        =    0.5989
                                                       Root MSE        =    22.166
```

rent	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
hsngval	.0022398	.0003284	6.82	0.000	.0015961	.0028836
pcturban	.081516	.2987652	0.27	0.785	-.504053	.667085
_cons	120.7065	15.22839	7.93	0.000	90.85942	150.5536

```
Instrumented:  hsngval
Instruments:   pcturban faminc 2.region 3.region 4.region
```

As we would expect, states with higher housing values have higher rental rates. The proportion of a state's population that is urban does not have a significant effect on rents.

◀

□ Technical note

In a simultaneous-equations framework, we could write the model we just fit as

$$\begin{aligned} \text{hsngval}_i &= \pi_0 + \pi_1 \text{faminc}_i + \pi_2 \text{2.region}_i + \pi_3 \text{3.region}_i + \pi_4 \text{4.region}_i + v_i \\ \text{rent}_i &= \beta_0 + \beta_1 \text{hsngval}_i + \beta_2 \text{pcturban}_i + u_i \end{aligned}$$

which here happens to be recursive (triangular), because `hsngval` appears in the equation for `rent` but `rent` does not appear in the equation for `hsngval`. In general, however, systems of simultaneous equations are not recursive. Because this system is recursive, we could fit the two equations individually via OLS if we were willing to assume that u and v were independent. For a more detailed discussion of triangular systems, see [Kmenta \(1997, 719–720\)](#).

Historically, instrumental-variables estimation and systems of simultaneous equations were taught concurrently, and older textbooks describe instrumental-variables estimation solely in the context of simultaneous equations. However, in recent decades, the treatment of endogeneity and instrumental-variables estimation has taken on a much broader scope, while interest in the specification of complete systems of simultaneous equations has waned. Most recent textbooks, such as [Cameron and Trivedi \(2005\)](#), [Davidson and MacKinnon \(1993, 2004\)](#), and [Wooldridge \(2010, 2013\)](#), treat instrumental-variables estimation as an integral part of the modern economists' toolkit and introduce it long before shorter discussions on simultaneous equations.

□

In addition to the 2SLS member of the κ -class estimators, `ivregress` implements the LIML estimator. Both theoretical and Monte Carlo exercises indicate that the LIML estimator may yield less bias and confidence intervals with better coverage rates than the 2SLS estimator. See [Poi \(2006\)](#) and [Stock, Wright, and Yogo \(2002\)](#) (and the papers cited therein) for Monte Carlo evidence.

▷ Example 2: LIML estimator

Here we refit our model with the LIML estimator:

```
. ivregress liml rent pcturban (hsngval = faminc i.region)
Instrumental variables (LIML) regression          Number of obs =      50
                                                Wald chi2(2) =    75.71
                                                Prob > chi2 =   0.0000
                                                R-squared =    0.4901
                                                Root MSE =   24.992
```

rent	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
hsngval	.0026686	.0004173	6.39	0.000	.0018507 .0034865
pcturban	-.1827391	.3571132	-0.51	0.609	-.8826681 .5171899
_cons	117.6087	17.22625	6.83	0.000	83.84587 151.3715

```
Instrumented:  hsngval
Instruments:   pcturban faminc 2.region 3.region 4.region
```

These results are qualitatively similar to the 2SLS results, although the coefficient on `hsngval` is about 19% higher.

◀

GMM estimator

Since the celebrated paper of [Hansen \(1982\)](#), the GMM has been a popular method of estimation in economics and finance, and it lends itself well to instrumental-variables estimation. The basic principle is that we have some *moment* or *orthogonality* conditions of the form

$$E(\mathbf{z}_i u_i) = \mathbf{0} \quad (3)$$

From (1), we have $u_i = y_i - \mathbf{y}_i \beta_1 - \mathbf{x}_{1i} \beta_2$. What are the elements of the instrument vector \mathbf{z}_i ? By assumption, \mathbf{x}_{1i} is uncorrelated with u_i , as are the excluded exogenous variables \mathbf{x}_{2i} , and so we use $\mathbf{z}_i = [\mathbf{x}_{1i} \ \mathbf{x}_{2i}]$. The moment conditions are simply the mathematical representation of the assumption that the instruments are exogenous—that is, the instruments are orthogonal to (uncorrelated with) u_i .

If the number of elements in \mathbf{z}_i is just equal to the number of unknown parameters, then we can apply the analogy principle to (3) and solve

$$\frac{1}{N} \sum_i \mathbf{z}_i u_i = \frac{1}{N} \sum_i \mathbf{z}_i (y_i - \mathbf{y}_i \beta_1 - \mathbf{x}_{1i} \beta_2) = \mathbf{0} \quad (4)$$

This equation is known as the method of moments estimator. Here where the number of instruments equals the number of parameters, the method of moments estimator coincides with the 2SLS estimator, which also coincides with what has historically been called the indirect least-squares estimator ([Judge et al. 1985](#), 595).

The “generalized” in GMM addresses the case in which the number of instruments (columns of \mathbf{z}_i) exceeds the number of parameters to be estimated. Here there is no unique solution to the population moment conditions defined in (3), so we cannot use (4). Instead, we define the objective function

$$Q(\beta_1, \beta_2) = \left(\frac{1}{N} \sum_i \mathbf{z}_i u_i \right)' \mathbf{W} \left(\frac{1}{N} \sum_i \mathbf{z}_i u_i \right) \quad (5)$$

where \mathbf{W} is a positive-definite matrix with the same number of rows and columns as the number of columns of \mathbf{z}_i . \mathbf{W} is known as the weighting matrix, and we specify its structure with the `wmatrix()` option. The GMM estimator of (β_1, β_2) minimizes $Q(\beta_1, \beta_2)$; that is, the GMM estimator chooses β_1 and β_2 to make the moment conditions as close to zero as possible for a given \mathbf{W} . For a more general GMM estimator, see [R] `gmm`. `gmm` does not restrict you to fitting a single linear equation, though the syntax is more complex.

A well-known result is that if we define the matrix \mathbf{S}_0 to be the covariance of $\mathbf{z}_i u_i$ and set $\mathbf{W} = \mathbf{S}_0^{-1}$, then we obtain the optimal two-step GMM estimator, where by optimal estimator we mean the one that results in the smallest variance given the moment conditions defined in (3).

Suppose that the errors u_i are heteroskedastic but independent among observations. Then

$$\mathbf{S}_0 = E(\mathbf{z}_i u_i u_i \mathbf{z}_i') = E(u_i^2 \mathbf{z}_i \mathbf{z}_i')$$

and the sample analogue is

$$\widehat{\mathbf{S}} = \frac{1}{N} \sum_i \widehat{u}_i^2 \mathbf{z}_i \mathbf{z}_i' \quad (6)$$

To implement this estimator, we need estimates of the sample residuals \widehat{u}_i . `ivregress gmm` obtains the residuals by estimating β_1 and β_2 by 2SLS and then evaluates (6) and sets $\mathbf{W} = \widehat{\mathbf{S}}^{-1}$. Equation (6) is the same as the center term of the “sandwich” robust covariance matrix available from most Stata estimation commands through the `vce(robust)` option.

► Example 3: GMM estimator

Here we refit our model of rents by using the GMM estimator, allowing for heteroskedasticity in u_i :

```
. ivregress gmm rent pcturban (hsngval = faminc i.region), wmatrix(robust)
Instrumental variables (GMM) regression                                Number of obs =      50
                                                                    Wald chi2(2) =    112.09
                                                                    Prob > chi2 =    0.0000
                                                                    R-squared =     0.6616
                                                                    Root MSE =     20.358

GMM weight matrix: Robust
```

rent	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
hsngval	.0014643	.0004473	3.27	0.001	.0005877	.002341
pcturban	.7615482	.2895105	2.63	0.009	.1941181	1.328978
_cons	112.1227	10.80234	10.38	0.000	90.95052	133.2949

```
Instrumented:  hsngval
Instruments:   pcturban faminc 2.region 3.region 4.region
```

Because we requested that a heteroskedasticity-consistent weighting matrix be used during estimation but did not specify the `vce()` option, `ivregress` reported standard errors that are robust to heteroskedasticity. Had we specified `vce(unadjusted)`, we would have obtained standard errors that would be correct only if the weighting matrix \mathbf{W} does in fact converge to \mathbf{S}_0^{-1} .

□ Technical note

Many software packages that implement GMM estimation use the same heteroskedasticity-consistent weighting matrix we used in the [previous example](#) to obtain the optimal two-step estimates but do not use a heteroskedasticity-consistent VCE, even though they may label the standard errors as being “robust”. To replicate results obtained from other packages, you may have to use the `vce(unadjusted)` option. See [Methods and formulas](#) below for a discussion of robust covariance matrix estimation in the GMM framework. □

By changing our definition of \mathbf{S}_0 , we can obtain GMM estimators suitable for use with other types of data that violate the assumption that the errors are independent and identically distributed. For example, you may have a dataset that consists of multiple observations for each person in a sample. The observations that correspond to the same person are likely to be correlated, and the estimation technique should account for that lack of independence. Say that in your dataset, people are identified by the variable `personid` and you type

```
. ivregress gmm ..., wmatrix(cluster personid)
```

Here `ivregress` estimates \mathbf{S}_0 as

$$\hat{\mathbf{S}} = \frac{1}{N} \sum_{c \in C} \mathbf{q}_c \mathbf{q}_c'$$

where C denotes the set of clusters and

$$\mathbf{q}_c = \sum_{i \in c_j} \hat{u}_i \mathbf{z}_i$$

where c_j denotes the j th cluster. This weighting matrix accounts for the within-person correlation among observations, so the GMM estimator that uses this version of \mathbf{S}_0 will be more efficient than the estimator that ignores this correlation.

▷ Example 4: GMM estimator with clustering

We have data from the National Longitudinal Survey on young women’s wages as reported in a series of interviews from 1968 through 1988, and we want to fit a model of wages as a function of each woman’s age and age squared, job tenure, birth year, and level of education. We believe that random shocks that affect a woman’s wage also affect her job tenure, so we treat tenure as endogenous. As additional instruments, we use her union status, number of weeks worked in the past year, and a dummy indicating whether she lives in a metropolitan area. Because we have several observations for each woman (corresponding to interviews done over several years), we want to control for clustering on each person.

```

. use http://www.stata-press.com/data/r13/nlswork
(National Longitudinal Survey. Young Women 14-26 years of age in 1968)
. ivregress gmm ln_wage age c.age#c.age birth_yr grade
> (tenure = union wks_work msp), wmatrix(cluster idcode)
Instrumental variables (GMM) regression                Number of obs =   18625
                                                       Wald chi2(5)   = 1807.17
                                                       Prob > chi2    = 0.0000
                                                       R-squared     =      .
GMM weight matrix: Cluster (idcode)                 Root MSE     =  .46951
                                                       (Std. Err. adjusted for 4110 clusters in idcode)

```

ln_wage	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
tenure	.099221	.0037764	26.27	0.000	.0918194	.1066227
age	.0171146	.0066895	2.56	0.011	.0040034	.0302259
c.age#c.age	-.0005191	.0001111	-4.68	0.000	-.0007366	-.0003016
birth_yr	-.0085994	.0021932	-3.92	0.000	-.012898	-.0043008
grade	.071574	.0029938	23.91	0.000	.0657062	.0774417
_cons	.8575071	.1616274	5.31	0.000	.5407231	1.174291

```

Instrumented:  tenure
Instruments:   age c.age#c.age birth_yr grade union wks_work msp

```

Both job tenure and years of schooling have significant positive effects on wages.

4

Time-series data are often plagued by serial correlation. In these cases, we can construct a weighting matrix to account for the fact that the error in period t is probably correlated with the errors in periods $t - 1$, $t - 2$, etc. An HAC weighting matrix can be used to account for both serial correlation and potential heteroskedasticity.

To request an HAC weighting matrix, you specify the `wmatrix(hac kernel [#|opt])` option. *kernel* specifies which of three kernels to use: `bartlett`, `parzen`, or `quadraticspectral`. *kernel* determines the amount of weight given to lagged values when computing the HAC matrix, and `#` denotes the maximum number of lags to use. Many texts refer to the bandwidth of the kernel instead of the number of lags; the bandwidth is equal to the number of lags plus one. If neither `opt` nor `#` is specified, then $N - 2$ lags are used, where N is the sample size.

If you specify `wmatrix(hac kernel opt)`, then `ivregress` uses Newey and West's (1994) algorithm for automatically selecting the number of lags to use. Although the authors' Monte Carlo simulations do show that the procedure may result in size distortions of hypothesis tests, the procedure is still useful when little other information is available to help choose the number of lags.

For more on GMM estimation, see Baum (2006); Baum, Schaffer, and Stillman (2003, 2007); Cameron and Trivedi (2005); Davidson and MacKinnon (1993, 2004); Hayashi (2000); or Wooldridge (2010). See Newey and West (1987) and Wang and Wu (2012) for an introduction to HAC covariance matrix estimation.

Stored results

`ivregress` stores the following in `e()`:

Scalars

<code>e(N)</code>	number of observations
<code>e(mss)</code>	model sum of squares
<code>e(df_m)</code>	model degrees of freedom
<code>e(rss)</code>	residual sum of squares
<code>e(df_r)</code>	residual degrees of freedom
<code>e(r2)</code>	R^2
<code>e(r2_a)</code>	adjusted R^2
<code>e(F)</code>	F statistic
<code>e(rmse)</code>	root mean squared error
<code>e(N_clust)</code>	number of clusters
<code>e(chi2)</code>	χ^2
<code>e(kappa)</code>	κ used in LIML estimator
<code>e(J)</code>	value of GMM objective function
<code>e(wlagopt)</code>	lags used in HAC weight matrix (if Newey–West algorithm used)
<code>e(vcelagopt)</code>	lags used in HAC VCE matrix (if Newey–West algorithm used)
<code>e(rank)</code>	rank of <code>e(V)</code>
<code>e(iterations)</code>	number of GMM iterations (0 if not applicable)

Macros

<code>e(cmd)</code>	<code>ivregress</code>
<code>e(cmdline)</code>	command as typed
<code>e(depvar)</code>	name of dependent variable
<code>e(instd)</code>	instrumented variable
<code>e(insts)</code>	instruments
<code>e(constant)</code>	<code>noconstant</code> or <code>hasconstant</code> if specified
<code>e(wtype)</code>	weight type
<code>e(wexp)</code>	weight expression
<code>e(title)</code>	title in estimation output
<code>e(clustvar)</code>	name of cluster variable
<code>e(hac_kernel)</code>	HAC kernel
<code>e(hac_lag)</code>	HAC lag
<code>e(vce)</code>	<code>vcetype</code> specified in <code>vce()</code>
<code>e(vcetype)</code>	title used to label Std. Err.
<code>e(estimator)</code>	<code>2sls</code> , <code>liml</code> , or <code>gmm</code>
<code>e(exogr)</code>	exogenous regressors
<code>e(wmatrix)</code>	<code>wmtype</code> specified in <code>wmatrix()</code>
<code>e(moments)</code>	<code>centered</code> if <code>center</code> specified
<code>e(small)</code>	<code>small</code> if small-sample statistics
<code>e(depname)</code>	<code>depname</code> if <code>depname(<i>depname</i>)</code> specified; otherwise same as <code>e(depvar)</code>
<code>e(properties)</code>	<code>b V</code>
<code>e(estat_cmd)</code>	program used to implement <code>estat</code>
<code>e(predict)</code>	program used to implement <code>predict</code>
<code>e(footnote)</code>	program used to implement footnote display
<code>e(marginsok)</code>	predictions allowed by <code>margins</code>
<code>e(marginsnotok)</code>	predictions disallowed by <code>margins</code>
<code>e(asbalanced)</code>	factor variables <code>fvset</code> as <code>asbalanced</code>
<code>e(asobserved)</code>	factor variables <code>fvset</code> as <code>asobserved</code>

Matrices

<code>e(b)</code>	coefficient vector
<code>e(Cns)</code>	constraints matrix
<code>e(W)</code>	weight matrix used to compute GMM estimates
<code>e(S)</code>	moment covariance matrix used to compute GMM variance–covariance matrix
<code>e(V)</code>	variance–covariance matrix of the estimators
<code>e(V_modelbased)</code>	model-based variance

Functions

<code>e(sample)</code>	marks estimation sample
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Methods and formulas

Methods and formulas are presented under the following headings:

Notation
2SLS and LIML estimators
GMM estimator

Notation

Items printed in lowercase and italicized (for example, x) are scalars. Items printed in lowercase and boldfaced (for example, \mathbf{x}) are vectors. Items printed in uppercase and boldfaced (for example, \mathbf{X}) are matrices.

The model is

$$\mathbf{y} = \mathbf{Y}\beta_1 + \mathbf{X}_1\beta_2 + \mathbf{u} = \mathbf{X}\beta + \mathbf{u}$$

$$\mathbf{Y} = \mathbf{X}_1\Pi_1 + \mathbf{X}_2\Pi_2 + \mathbf{v} = \mathbf{Z}\Pi + \mathbf{V}$$

where \mathbf{y} is an $N \times 1$ vector of the left-hand-side variable; N is the sample size; \mathbf{Y} is an $N \times p$ matrix of p endogenous regressors; \mathbf{X}_1 is an $N \times k_1$ matrix of k_1 included exogenous regressors; \mathbf{X}_2 is an $N \times k_2$ matrix of k_2 excluded exogenous variables, $\mathbf{X} = [\mathbf{Y} \ \mathbf{X}_1]$, $\mathbf{Z} = [\mathbf{X}_1 \ \mathbf{X}_2]$; \mathbf{u} is an $N \times 1$ vector of errors; \mathbf{V} is an $N \times p$ matrix of errors; $\beta = [\beta_1 \ \beta_2]$ is a $k = (p + k_1) \times 1$ vector of parameters; and Π is a $(k_1 + k_2) \times p$ vector of parameters. If a constant term is included in the model, then one column of \mathbf{X}_1 contains all ones.

Let \mathbf{v} be a column vector of weights specified by the user. If no weights are specified, $\mathbf{v} = \mathbf{1}$. Let \mathbf{w} be a column vector of normalized weights. If no weights are specified or if the user specified `fweights` or `iweights`, $\mathbf{w} = \mathbf{v}$; otherwise, $\mathbf{w} = \{\mathbf{v}/(\mathbf{1}'\mathbf{v})\}(\mathbf{1}'\mathbf{1})$. Let \mathbf{D} denote the $N \times N$ matrix with \mathbf{w} on the main diagonal and zeros elsewhere. If no weights are specified, \mathbf{D} is the identity matrix.

The weighted number of observations n is defined as $\mathbf{1}'\mathbf{w}$. For `iweights`, this is truncated to an integer. The *sum of the weights* is $\mathbf{1}'\mathbf{v}$. Define $c = 1$ if there is a constant in the regression and zero otherwise.

The order condition for identification requires that $k_2 \geq p$: the number of excluded exogenous variables must be at least as great as the number of endogenous regressors.

In the following formulas, if weights are specified, $\mathbf{X}'_1\mathbf{X}_1$, $\mathbf{X}'\mathbf{X}$, $\mathbf{X}'\mathbf{y}$, $\mathbf{y}'\mathbf{y}$, $\mathbf{Z}'\mathbf{Z}$, $\mathbf{Z}'\mathbf{X}$, and $\mathbf{Z}'\mathbf{y}$ are replaced with $\mathbf{X}'_1\mathbf{D}\mathbf{X}_1$, $\mathbf{X}'\mathbf{D}\mathbf{X}$, $\mathbf{X}'\mathbf{D}\mathbf{y}$, $\mathbf{y}'\mathbf{D}\mathbf{y}$, $\mathbf{Z}'\mathbf{D}\mathbf{Z}$, $\mathbf{Z}'\mathbf{D}\mathbf{X}$, and $\mathbf{Z}'\mathbf{D}\mathbf{y}$, respectively. We suppress the \mathbf{D} below to simplify the notation.

2SLS and LIML estimators

Define the κ -class estimator of β as

$$\mathbf{b} = \{\mathbf{X}'(\mathbf{I} - \kappa\mathbf{M}_Z)\mathbf{X}\}^{-1}\mathbf{X}'(\mathbf{I} - \kappa\mathbf{M}_Z)\mathbf{y}$$

where $\mathbf{M}_Z = \mathbf{I} - \mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}'$. The 2SLS estimator results from setting $\kappa = 1$. The LIML estimator results from selecting κ to be the minimum eigenvalue of $(\mathbf{Y}'\mathbf{M}_Z\mathbf{Y})^{-1/2}\mathbf{Y}'\mathbf{M}_{\mathbf{X}_1}\mathbf{Y}(\mathbf{Y}'\mathbf{M}_Z\mathbf{Y})^{-1/2}$, where $\mathbf{M}_{\mathbf{X}_1} = \mathbf{I} - \mathbf{X}_1(\mathbf{X}'_1\mathbf{X}_1)^{-1}\mathbf{X}'_1$.

The total sum of squares (TSS) equals $\mathbf{y}'\mathbf{y}$ if there is no intercept and $\mathbf{y}'\mathbf{y} - \{(\mathbf{1}'\mathbf{y})^2/n\}$ otherwise. The degrees of freedom is $n - c$. The error sum of squares (ESS) is defined as $\mathbf{y}'\mathbf{y} - 2\mathbf{b}\mathbf{X}'\mathbf{y} + \mathbf{b}'\mathbf{X}'\mathbf{X}\mathbf{b}$. The model sum of squares (MSS) equals TSS - ESS. The degrees of freedom is $k - c$.

The mean squared error, s^2 , is defined as $ESS/(n - k)$ if `small` is specified and ESS/n otherwise. The root mean squared error is s , its square root.

If $c = 1$ and `small` is not specified, a Wald statistic, W , of the joint significance of the $k - 1$ parameters of β except the constant term is calculated; $W \sim \chi^2(k - 1)$. If $c = 1$ and `small` is specified, then an F statistic is calculated as $F = W/(k - 1)$; $F \sim F(k - 1, n - k)$.

The R -squared is defined as $R^2 = 1 - ESS/TSS$.

The adjusted R -squared is $R_a^2 = 1 - (1 - R^2)(n - c)/(n - k)$.

If `robust` is not specified, then $\text{Var}(\mathbf{b}) = s^2 \{\mathbf{X}'(\mathbf{I} - \kappa \mathbf{M}_{\mathbf{Z}})\mathbf{X}\}^{-1}$. For a discussion of robust variance estimates in regression and regression with instrumental variables, see [Methods and formulas in \[R\] regress](#). If `small` is not specified, then $k = 0$ in the formulas given there.

This command also supports estimation with survey data. For details on VCEs with survey data, see [\[SVY\] variance estimation](#).

GMM estimator

We obtain an initial consistent estimate of β by using the 2SLS estimator; see above. Using this estimate of β , we compute the weighting matrix \mathbf{W} and calculate the GMM estimator

$$\mathbf{b}_{\text{GMM}} = \{\mathbf{X}'\mathbf{Z}\mathbf{W}\mathbf{Z}'\mathbf{X}\}^{-1}\mathbf{X}'\mathbf{Z}\mathbf{W}\mathbf{Z}'\mathbf{y}$$

The variance of \mathbf{b}_{GMM} is

$$\text{Var}(\mathbf{b}_{\text{GMM}}) = n\{\mathbf{X}'\mathbf{Z}\mathbf{W}\mathbf{Z}'\mathbf{X}\}^{-1}\mathbf{X}'\mathbf{Z}\widehat{\mathbf{S}}\mathbf{W}\mathbf{Z}'\mathbf{X}\{\mathbf{X}'\mathbf{Z}\mathbf{W}\mathbf{Z}'\mathbf{X}\}^{-1}$$

$\text{Var}(\mathbf{b}_{\text{GMM}})$ is of the sandwich form **DMD**; see [\[P\] _robust](#). If the user specifies the `small` option, `ivregress` implements a small-sample adjustment by multiplying the VCE by $N/(N - k)$.

If `vce(unadjusted)` is specified, then we set $\widehat{\mathbf{S}} = \mathbf{W}^{-1}$ and the VCE reduces to the “optimal” GMM variance estimator

$$\text{Var}(\beta_{\text{GMM}}) = n\{\mathbf{X}'\mathbf{Z}\mathbf{W}\mathbf{Z}'\mathbf{X}\}^{-1}$$

However, if \mathbf{W}^{-1} is not a good estimator of $E(\mathbf{z}_i u_i u_i \mathbf{z}_i')$, then the optimal GMM estimator is inefficient, and inference based on the optimal variance estimator could be misleading.

\mathbf{W} is calculated using the residuals from the initial 2SLS estimates, whereas \mathbf{S} is estimated using the residuals based on \mathbf{b}_{GMM} . The `wmatrix()` option affects the form of \mathbf{W} , whereas the `vce()` option affects the form of \mathbf{S} . Except for different residuals being used, the formulas for \mathbf{W}^{-1} and \mathbf{S} are identical, so we focus on estimating \mathbf{W}^{-1} .

If `wmatrix(unadjusted)` is specified, then

$$\mathbf{W}^{-1} = \frac{s^2}{n} \sum_i \mathbf{z}_i \mathbf{z}_i'$$

where $s^2 = \sum_i u_i^2/n$. This weight matrix is appropriate if the errors are homoskedastic.

If `wmatrix(robust)` is specified, then

$$\mathbf{W}^{-1} = \frac{1}{n} \sum_i u_i^2 \mathbf{z}_i \mathbf{z}_i'$$

which is appropriate if the errors are heteroskedastic.

If `wmatrix(cluster clustvar)` is specified, then

$$\mathbf{W}^{-1} = \frac{1}{n} \sum_c \mathbf{q}_c \mathbf{q}_c'$$

where c indexes clusters,

$$\mathbf{q}_c = \sum_{i \in c_j} u_i \mathbf{z}_i$$

and c_j denotes the j th cluster.

If `wmatrix(hac kernel [#])` is specified, then

$$\mathbf{W}^{-1} = \frac{1}{n} \sum_i u_i^2 \mathbf{z}_i \mathbf{z}_i' + \frac{1}{n} \sum_{l=1}^{l=n-1} \sum_{i=l+1}^{i=n} K(l, m) u_i u_{i-l} (\mathbf{z}_i \mathbf{z}_{i-l}' + \mathbf{z}_{i-l} \mathbf{z}_i')$$

where $m = \#$ if $\#$ is specified and $m = n - 2$ otherwise. Define $z = l/(m + 1)$. If *kernel* is `nwest`, then

$$K(l, m) = \begin{cases} 1 - z & 0 \leq z \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

If *kernel* is `gallant`, then

$$K(l, m) = \begin{cases} 1 - 6z^2 + 6z^3 & 0 \leq z \leq 0.5 \\ 2(1 - z)^3 & 0.5 < z \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

If *kernel* is `quadraticspectral`, then

$$K(l, m) = \begin{cases} 1 & z = 0 \\ 3 \{ \sin(\theta)/\theta - \cos(\theta) \} / \theta^2 & \text{otherwise} \end{cases}$$

where $\theta = 6\pi z/5$.

If `wmatrix(hac kernel opt)` is specified, then `ivregress` uses Newey and West's (1994) automatic lag-selection algorithm, which proceeds as follows. Define \mathbf{h} to be a $(k_1 + k_2) \times 1$ vector containing ones in all rows except for the row corresponding to the constant term (if present); that row contains a zero. Define

$$\begin{aligned} f_i &= (u_i \mathbf{z}_i) \mathbf{h} \\ \hat{\sigma}_j &= \frac{1}{n} \sum_{i=j+1}^n f_i f_{i-j} \quad j = 0, \dots, m^* \\ \hat{s}^{(q)} &= 2 \sum_{j=1}^{m^*} \hat{\sigma}_j j^q \\ \hat{s}^{(0)} &= \hat{\sigma}_0 + 2 \sum_{j=1}^{m^*} \hat{\sigma}_j \\ \hat{\gamma} &= c_\gamma \left\{ \left(\frac{\hat{s}^{(q)}}{\hat{s}^{(0)}} \right)^2 \right\}^{1/2q+1} \\ m &= \hat{\gamma} n^{1/(2q+1)} \end{aligned}$$

where q , m^* , and c_γ depend on the kernel specified:

Kernel	q	m^*	c_γ
Bartlett	1	$\text{int} \{20(T/100)^{2/9}\}$	1.1447
Parzen	2	$\text{int} \{20(T/100)^{4/25}\}$	2.6614
Quadratic spectral	2	$\text{int} \{20(T/100)^{2/25}\}$	1.3221

where $\text{int}(x)$ denotes the integer obtained by truncating x toward zero. For the Bartlett and Parzen kernels, the optimal lag is $\min\{\text{int}(m), m^*\}$. For the quadratic spectral, the optimal lag is $\min\{m, m^*\}$.

If `center` is specified, when computing weighting matrices `ivregress` replaces the term $u_i z_i$ in the formulas above with $u_i z_i - \bar{u} \bar{z}$, where $\bar{u} \bar{z} = \sum_i u_i z_i / N$.

References

- Andrews, D. W. K. 1991. Heteroskedasticity and autocorrelation consistent covariance matrix estimation. *Econometrica* 59: 817–858.
- Angrist, J. D., and J.-S. Pischke. 2009. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press.
- Basman, R. L. 1957. A generalized classical method of linear estimation of coefficients in a structural equation. *Econometrica* 25: 77–83.
- Bauldry, S. 2014. `mivfind`: A command for identifying model-implied instrumental variables for structural equation models in Stata. *Stata Journal* 14: 60–75.
- Baum, C. F. 2006. *An Introduction to Modern Econometrics Using Stata*. College Station, TX: Stata Press.
- Baum, C. F., M. E. Schaffer, and S. Stillman. 2003. Instrumental variables and GMM: Estimation and testing. *Stata Journal* 3: 1–31.
- . 2007. Enhanced routines for instrumental variables/generalized method of moments estimation and testing. *Stata Journal* 7: 465–506.
- Cameron, A. C., and P. K. Trivedi. 2005. *Microeconometrics: Methods and Applications*. New York: Cambridge University Press.
- . 2010. *Microeconometrics Using Stata*. Rev. ed. College Station, TX: Stata Press.
- Davidson, R., and J. G. MacKinnon. 1993. *Estimation and Inference in Econometrics*. New York: Oxford University Press.
- . 2004. *Econometric Theory and Methods*. New York: Oxford University Press.
- Desbordes, R., and V. Verardi. 2012. A robust instrumental-variables estimator. *Stata Journal* 12: 169–181.
- Finlay, K., and L. M. Magnusson. 2009. Implementing weak-instrument robust tests for a general class of instrumental-variables models. *Stata Journal* 9: 398–421.
- Gallant, A. R. 1987. *Nonlinear Statistical Models*. New York: Wiley.
- Greene, W. H. 2012. *Econometric Analysis*. 7th ed. Upper Saddle River, NJ: Prentice Hall.
- Hall, A. R. 2005. *Generalized Method of Moments*. Oxford: Oxford University Press.
- Hansen, L. P. 1982. Large sample properties of generalized method of moments estimators. *Econometrica* 50: 1029–1054.
- Hayashi, F. 2000. *Econometrics*. Princeton, NJ: Princeton University Press.
- Judge, G. G., W. E. Griffiths, R. C. Hill, H. Lütkepohl, and T.-C. Lee. 1985. *The Theory and Practice of Econometrics*. 2nd ed. New York: Wiley.
- Kmenta, J. 1997. *Elements of Econometrics*. 2nd ed. Ann Arbor: University of Michigan Press.
- Koopmans, T. C., and W. C. Hood. 1953. *Studies in Econometric Method*. New York: Wiley.

- Koopmans, T. C., and J. Marschak. 1950. *Statistical Inference in Dynamic Economic Models*. New York: Wiley.
- Newey, W. K., and K. D. West. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55: 703–708.
- . 1994. Automatic lag selection in covariance matrix estimation. *Review of Economic Studies* 61: 631–653.
- Nichols, A. 2007. Causal inference with observational data. *Stata Journal* 7: 507–541.
- Palmer, T. M., V. Didelez, R. R. Ramsahai, and N. A. Sheehan. 2011. Nonparametric bounds for the causal effect in a binary instrumental-variable model. *Stata Journal* 11: 345–367.
- Poi, B. P. 2006. Jackknife instrumental variables estimation in Stata. *Stata Journal* 6: 364–376.
- Stock, J. H., and M. W. Watson. 2011. *Introduction to Econometrics*. 3rd ed. Boston: Addison–Wesley.
- Stock, J. H., J. H. Wright, and M. Yogo. 2002. A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business and Economic Statistics* 20: 518–529.
- Theil, H. 1953. *Repeated Least Squares Applied to Complete Equation Systems*. Mimeograph from the Central Planning Bureau, The Hague.
- Wang, Q., and N. Wu. 2012. Long-run covariance and its applications in cointegration regression. *Stata Journal* 12: 515–542.
- Wooldridge, J. M. 2010. *Econometric Analysis of Cross Section and Panel Data*. 2nd ed. Cambridge, MA: MIT Press.
- . 2013. *Introductory Econometrics: A Modern Approach*. 5th ed. Mason, OH: South-Western.
- Wright, P. G. 1928. *The Tariff on Animal and Vegetable Oils*. New York: Macmillan.

Also see

- [R] **ivregress postestimation** — Postestimation tools for ivregress
- [R] **gmm** — Generalized method of moments estimation
- [R] **ivprobit** — Probit model with continuous endogenous regressors
- [R] **ivtobit** — Tobit model with continuous endogenous regressors
- [R] **reg3** — Three-stage estimation for systems of simultaneous equations
- [R] **regress** — Linear regression
- [SEM] **intro 5** — Tour of models
- [SVY] **svy estimation** — Estimation commands for survey data
- [TS] **forecast** — Econometric model forecasting
- [XT] **xtivreg** — Instrumental variables and two-stage least squares for panel-data models
- [U] **20 Estimation and postestimation commands**