

**ivpoisson** — Poisson model with continuous endogenous covariates

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## Description

`ivpoisson` estimates the parameters of a Poisson regression model in which some of the covariates are endogenous. The model is also known as an exponential conditional mean model in which some of the covariates are endogenous. The model may be specified using either additive or multiplicative error terms. The model is frequently used to model count outcomes and is also used to model nonnegative outcome variables.

## Quick start

Two-step GMM estimation of the Poisson regression of  $y_1$  on  $x$  and endogenous regressor  $y_2$  that is instrumented using  $z$

```
ivpoisson gmm y1 x (y2 = z)
```

Same as above, but specify multiplicative errors rather than additive

```
ivpoisson gmm y1 x (y2 = z), multiplicative
```

Use iterative GMM estimation

```
ivpoisson gmm y1 x (y2 = z), igmm
```

Specify a weight matrix that allows for correlation within clusters identified by `cvar`

```
ivpoisson gmm y1 x (y2 = z), wmatrix(cluster cvar)
```

Use the control-function estimator

```
ivpoisson cfunction y1 x (y2 = z)
```

## Menu

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## Syntax

*Generalized method of moments estimator*

```
ivpoisson gmm depvar [varlist1] [(varlist2 = varlistiv)] [if] [in] [weight]  
[ , reg_err_opt options]
```

*Control-function estimator*

```
ivpoisson cfunction depvar [varlist1] (varlist2 = varlistiv) [if] [in] [weight]  
[ , options]
```

*reg\_err\_opt*

Description

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Model

additive

add regression errors to the conditional mean term; the default

multiplicative

multiply regression errors by the conditional mean term

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<i>options</i>	Description
Model	
<u>noconstant</u>	suppress constant term
<u>exposure</u> ( <i>varname<sub>e</sub></i> )	include $\ln(\text{varname}_e)$ in model with coefficient constrained to 1
<u>offset</u> ( <i>varname<sub>o</sub></i> )	include <i>varname<sub>o</sub></i> in model with coefficient constrained to 1
* <u>twostep</u>	use two-step GMM estimator; the default for <code>ivpoisson gmm</code>
* <u>onestep</u>	use one-step GMM estimator; the default for <code>ivpoisson cfunction</code>
* <u>igmm</u>	use iterative GMM estimator
Weight matrix	
<u>wmatrix</u> ( <i>wmtype</i> )	specify weight matrix; <i>wmtype</i> may be <u>robust</u> , <u>cluster</u> <i>clustvar</i> , or <u>unadjusted</u>
<u>center</u>	center moments in weight-matrix computation
<u>winitial</u> ( <i>iwtype</i> [, <u>independent</u> ])	specify initial weight matrix; <i>iwtype</i> may be <u>unadjusted</u> , <u>identity</u> , or the name of a Stata matrix ( <u>independent</u> may not be specified with <code>ivpoisson gmm</code> )
SE/Robust	
<u>vce</u> ( <i>vcetype</i> )	<i>vcetype</i> may be <u>robust</u> , <u>cluster</u> <i>clustvar</i> , <u>bootstrap</u> , <u>jackknife</u> , or <u>unadjusted</u>
Reporting	
<u>level</u> (#)	set confidence level; default is <code>level(95)</code>
<u>irr</u>	report incidence-rate ratios
<u>display_options</u>	control columns and column formats, row spacing, line width, display of omitted variables and base and empty cells, and factor-variable labeling
Optimization	
<u>from</u> ( <i>initial_values</i> )	specify initial values for parameters
‡ <u>igmmiterate</u> (#)	specify maximum number of iterations for iterated GMM estimator
‡ <u>igmmeps</u> (#)	specify # for iterated GMM parameter convergence criterion; default is <code>igmmeps(1e-6)</code>
‡ <u>igmmweps</u> (#)	specify # for iterated GMM weight-matrix convergence criterion; default is <code>igmmweps(1e-6)</code>
<u>optimization_options</u>	control the optimization process; seldom used

\*You can specify at most one of these options.

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

*varlist<sub>1</sub>* and *varlist<sub>iv</sub>* may contain factor variables; see [U] 11.4.3 Factor variables.

*depvar*, *varlist<sub>1</sub>*, *varlist<sub>2</sub>*, and *varlist<sub>iv</sub>* may contain time-series operators; see [U] 11.4.4 Time-series varlists.

`bootstrap`, `by`, `collect`, `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`, `fweights`, `iweights`, and `pweights` are allowed; see [U] 11.1.6 weight.

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

## Options

### Model

`noconstant`, `exposure(varnamee)`, `offset(varnameo)`; see [R] [Estimation options](#).

`additive`, the default, specifies that the regression errors be added to the conditional mean term and have mean 0.

`multiplicative` specifies that the regression errors be multiplied by the conditional mean term and have mean 1.

`twostep`, `onestep`, and `igmm` specify which estimator is to be used.

`twostep` requests the two-step GMM estimator. `gmm` obtains parameter estimates based on the initial weight matrix, computes a new weight matrix based on those estimates, and then reestimates the parameters based on that weight matrix. `twostep` is the default for `ivpoisson gmm`.

`onestep` requests the one-step GMM estimator. The parameters are estimated based on an initial weight matrix, and no updating of the weight matrix is performed except when calculating the appropriate variance–covariance (VCE) matrix. `onestep` is the default for `ivpoisson cfunction`.

`igmm` requests the iterative GMM estimator. `gmm` obtains parameter estimates based on the initial weight matrix, computes a new weight matrix based on those estimates, reestimates the parameters based on that weight matrix, computes a new weight matrix, and so on, to convergence. Convergence is declared when the relative change in the parameter vector is less than `igmmeps()`, the relative change in the weight matrix is less than `igmmweps()`, or `igmmiterate()` iterations have been completed. Hall (2005, sec. 2.4 and 3.6) mentions that there may be gains to finite-sample efficiency from using the iterative estimator.

### Weight matrix

`wmatrix(wmtype)` specifies the type of weight matrix to be used in conjunction with the two-step and iterated GMM estimators.

Specifying `wmatrix(robust)` requests a weight matrix that is appropriate when the errors are independent but not necessarily identically distributed. `wmatrix(robust)` is the default.

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

Specifying `wmatrix(unadjusted)` requests a weight matrix that is suitable when the errors are homoskedastic.

`wmatrix()` cannot be specified if `onestep` is also specified.

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

`winitial(wmtype[, independent])` specifies the weight matrix to use to obtain the first-step parameter estimates.

Specifying `winitial(unadjusted)` requests a weighting matrix that assumes the error functions are independent and identically distributed. This matrix is of the form  $(\mathbf{Z}'\mathbf{Z})^{-1}$ , where  $\mathbf{Z}$  represents all the exogenous regressors and instrumental variables.

`winitial(identity)` requests that the identity matrix be used.

`winitial(matname)` requests that Stata matrix `matname` be used.

Including the independent suboption creates a weight matrix that assumes error functions are independent. Elements of the weight matrix corresponding to covariances between any two error functions are set equal to zero. This suboption only applies to `ivpoisson cfunction`.

`winitial(unadjusted)` is the default for `ivpoisson gmm`.

`winitial(unadjusted, independent)` is the default for `ivpoisson cfunction`.

#### SE/Robust

`vce(vcetype)` 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)` specifies that an unadjusted (nonrobust) VCE matrix be used; this, along with the `twostep` option, results in the “optimal two-step GMM” estimates often discussed in textbooks. `vce(unadjusted)` may not be set in `ivpoisson cfunction`.

The default `vcetype` is based on the `wmtype` specified in the `wmatrix()` option. If `wmatrix()` is specified but `vce()` is not, then `vcetype` is set equal to `wmtype`. To override this behavior in `ivpoisson gmm` and obtain an unadjusted (nonrobust) VCE matrix, specify `vce(unadjusted)`. The default `vcetype` for `ivpoisson cfunction` is `robust`.

Specifying `vce(bootstrap)` or `vce(jackknife)` results in standard errors based on the bootstrap or jackknife, respectively. See [R] [vce\\_option](#), [R] [bootstrap](#), and [R] [jackknife](#) for more information on these VCEs.

The syntax for `vcetypes` is identical to those for `wmatrix()`.

#### Reporting

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

`irr` reports estimated coefficients transformed to incidence-rate ratios, that is,  $e^{\beta_i}$  rather than  $\beta_i$ .

Standard errors and confidence intervals are similarly transformed. This option affects how results are displayed, not how they are estimated or stored. `irr` may be specified at estimation or when replaying previously estimated results. `irr` is not allowed with `additive`.

`display_options`: `noci`, `nopvalues`, `noomitted`, `vsquish`, `noemptycells`, `baselevels`, `allbaselevels`, `nofvlabel`, `fvwrap(#)`, `fvwrapon(style)`, `cformat(%fmt)`, `pformat(%fmt)`, `sformat(%fmt)`, and `nolstretch`; see [R] [Estimation options](#).

#### Optimization

`from(initial_values)` specifies the initial values to begin the estimation. You can specify a  $1 \times k$  matrix, where  $k$  is the number of parameters in the model, or you can specify a parameter name, its initial value, another parameter name, its initial value, and so on. For example, to initialize the coefficient for `male` to 1.23 and the constant `_cons` to 4.57, you would type

```
ivpoisson ..., from(male 1.23 _cons 4.57) ...
```

Initial values declared using this option override any that are declared within substitutable expressions. If you specify a parameter that does not appear in your model, `ivpoisson` exits with error code 480. If you specify a matrix, the values must be in the same order in which the parameters are declared in your model. `ivpoisson` ignores the row and column names of the matrix.

`igmmiterate(#)`, `igmmeps(#)`, and `igmmweps(#)` control the iterative process for the iterative GMM estimator for `ivpoisson`. These options can be specified only if you also specify `igmm`.

`igmmiterate(#)` specifies the maximum number of iterations to perform with the iterative GMM estimator. The default is the number set using `set maxiter`, which is 300 by default.

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

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

*optimization\_options*: `technique()`, `conv_maxiter()`, `conv_ptol()`, `conv_vtol()`, `conv_nrtol()`, and `tracelevel()`. `technique()` specifies the optimization technique to use; `gn` (the default), `nr`, `dfp`, and `bfgs` are allowed. `conv_maxiter()` specifies the maximum number of iterations; `conv_ptol()`, `conv_vtol()`, and `conv_nrtol()` specify the convergence criteria for the parameters, gradient, and scaled Hessian, respectively. `tracelevel()` allows you to obtain additional details during the iterative process. See [M-5] [optimize\(\)](#).

## Remarks and examples

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

`ivpoisson` estimates the parameters of a Poisson regression model in which some of the covariates are endogenous. A regressor is endogenous if it is related to the unobserved error term. The model is also known as an exponential conditional mean model in which some of the covariates are endogenous. The model may be specified using either additive or multiplicative error terms.

The model is frequently used to model count outcomes and is also used to model nonnegative outcome variables. Poisson regression is a special exponential conditional mean model. See [R] [poisson](#) for more information on Poisson regression.

The exponential conditional mean model has an error form representation in which the dependent variable  $y$  is a function of the exogenous covariates  $\mathbf{x}$ , endogenous covariates  $\mathbf{y}_2$ , and an error  $\epsilon$ . The covariates  $\mathbf{x}$  are independent of  $\epsilon$ , while  $\mathbf{y}_2$  are not.

`ivpoisson` allows  $\epsilon$  to enter either additively,

$$y_i = \exp(\mathbf{x}'_i\boldsymbol{\beta}_1 + \mathbf{y}'_{2,i}\boldsymbol{\beta}_2) + \epsilon_i$$

or multiplicatively,

$$y_i = \exp(\mathbf{x}'_i\boldsymbol{\beta}_1 + \mathbf{y}'_{2,i}\boldsymbol{\beta}_2)\epsilon_i$$

Mullahy (1997), Cameron and Trivedi (2013), Windmeijer and Santos Silva (1997), and Wooldridge (2010) discuss the generalized method of moments (GMM) estimators implemented in `ivpoisson`. GMM is frequently used in modern econometrics. Many econometric and statistical models can be expressed as conditions on the population moments. The parameter estimates produced by GMM estimators make the sample-moment conditions as true as possible given the data. See [R] [gmm](#) for further information on GMM estimation and how Stata performs it.

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

[GMM estimator for additive model](#)

[GMM estimator for multiplicative model](#)

[CF estimator for multiplicative model](#)

## GMM estimator for additive model

The GMM estimator uses additional variables, known as instruments and denoted by  $\mathbf{z}_i$ , to specify moment conditions that hold in the population. The GMM parameter estimates make the sample versions of these population-moment conditions as close to true as possible. The instrumental variables are assumed to be correlated with the endogenous covariates  $\mathbf{y}_{2,i}$  but independent of the errors  $\epsilon_i$ .

Under additive errors, the dependent variable  $y_i$  is determined by exogenous covariates  $\mathbf{x}_i$ , endogenous covariates  $\mathbf{y}_{2,i}$ , and zero-mean error  $\epsilon_i$  as

$$y_i = \exp(\mathbf{x}'_i\boldsymbol{\beta}_1 + \mathbf{y}'_{2,i}\boldsymbol{\beta}_2) + \epsilon_i$$

This leads to the following error function

$$u(y_i, \mathbf{x}_i, \mathbf{y}_{2,i}, \boldsymbol{\beta}_1, \boldsymbol{\beta}_2) = y_i - \exp(\mathbf{x}'_i\boldsymbol{\beta}_1 + \mathbf{y}'_{2,i}\boldsymbol{\beta}_2)$$

The population-moment conditions for GMM estimation are  $E\{\tilde{\mathbf{z}}_i u(y_i, \mathbf{x}_i, \mathbf{y}_{2,i}, \boldsymbol{\beta}_1, \boldsymbol{\beta}_2)\} = \mathbf{0}$ , where the vector  $\tilde{\mathbf{z}}_i$  is partitioned as  $(\mathbf{x}'_i, \mathbf{z}'_i)$ . The sample-moment conditions are formed by replacing the expectation with the corresponding sample mean. The GMM estimator solves a minimization problem to make the sample-moment conditions as close to zero as possible. Details on how estimation is performed are given in [Methods and formulas](#).

Now, we will demonstrate how `ivpoisson gmm` works in the additive error setting with an example.

### ► Example 1: `ivpoisson gmm` with additive errors

This example uses simulated data based on the following story. A news website randomly samples 500 young adults in a major city. The website wants to model the number of times the sampled individuals visit its website (`visits`) based on their overall time spent on the Internet (`time`) and the number of times they receive an ad for the website through email or viewing another website (`ad`). The website also suspects the gender of the individual may matter, so an exogenous dummy variable, `female`, is included in the model.

We suspect time spent on the Internet is correlated with unobserved factors that additively affect the number of times an individual visits the website. So we treat `time` as an endogenous regressor. Two instruments are used for this variable. The time spent on the phone (`phone`) is one instrument. The other instrument is the time spent interacting with friends and family that live out of town (`frfam`).

We model the number of visits the website receives using an exponential conditional mean model with additive errors and use `ivpoisson gmm` to estimate the parameters of the regression in the output below. To allow for heteroskedasticity of the errors, we use robust standard errors, which is the default; see [Obtaining standard errors](#) in [R] `gmm` for a discussion of why robust standard errors is the default.

```
. use https://www.stata-press.com/data/r18/website
(Visits to website)
. ivpoisson gmm visits ad female (time = phone frfam)

Step 1
Iteration 0: GMM criterion Q(b) = .33829416
Iteration 1: GMM criterion Q(b) = .00362656
Iteration 2: GMM criterion Q(b) = .00131886
Iteration 3: GMM criterion Q(b) = .00131876

Step 2
Iteration 0: GMM criterion Q(b) = .00027102
Iteration 1: GMM criterion Q(b) = .00025811
Iteration 2: GMM criterion Q(b) = .00025811
```





In the output below, we estimate the parameters of the regression with `ivpoisson gmm`. To allow for heteroskedasticity of the errors, we use robust standard errors, which is the default.

```
. use https://www.stata-press.com/data/r18/trip
(Household trips)
. ivpoisson gmm trips cbd ptn worker weekend (tcost = pt), multiplicative

Step 1
Iteration 0: GMM criterion Q(b) = .04949852
Iteration 1: GMM criterion Q(b) = .00011194
Iteration 2: GMM criterion Q(b) = 1.563e-08
Iteration 3: GMM criterion Q(b) = 3.685e-16

Step 2
Iteration 0: GMM criterion Q(b) = 2.287e-16
Iteration 1: GMM criterion Q(b) = 1.275e-31

note: model is exactly identified.

Exponential mean model with endogenous regressors
Number of parameters = 6                Number of obs = 5,000
Number of moments = 6
Initial weight matrix: Unadjusted
GMM weight matrix: Robust
```

trips	Robust				
	Coefficient	std. err.	z	P> z	[95% conf. interval]
tcost	.0352185	.0098182	3.59	0.000	.0159752 .0544617
cbd	-.008398	.0020172	-4.16	0.000	-.0123517 -.0044444
ptn	-.0113146	.0021819	-5.19	0.000	-.015591 -.0070383
worker	.6623018	.0519909	12.74	0.000	.5604015 .764202
weekend	.3009323	.0362682	8.30	0.000	.2298479 .3720167
_cons	.2654423	.1550127	1.71	0.087	-.0383769 .5692616

Endogenous: tcost

Exogenous: cbd ptn worker weekend pt

We find that all coefficients are significant. At fixed values of the other covariates, we see that additional mileage from the central business district and public transit nodes reduces the expected number of trips taken. Individuals who live farther away from the central business district may still be out of the house the same amount of time, but they will take fewer trips because the transit time has increased. The situation is similar for those who live farther from public transit.

To interpret the other parameters, we will look at the partial effects of their respective independent variables. The partial effects of a change in an independent variable on the modeled conditional expectation function vary over the data because the model is nonlinear. However, under the multiplicative error model, the ratio of the new value to the old value after a discrete change in an independent variable is constant over the data.

Let  $\mathbf{w} = (\mathbf{x}', \mathbf{y}_2')$ . If we add 1 to the  $j$ th independent variable in  $\mathbf{w}$ , the functional form of the model implies that

$$\frac{E(y|\mathbf{w}, w_j + 1, \epsilon)}{E(y|\mathbf{w}, w_j, \epsilon)} = \frac{E(y|w_1, \dots, w_j + 1, \dots, w_k, \epsilon)}{E(y|w_1, \dots, w_j, \dots, w_k, \epsilon)} = e^{\beta_j}$$

When  $y$  is a count variable, this normalized effect is called the incidence-rate ratio (IRR) for a one-unit change in  $w_j$ .

More generally, the IRR for a  $\Delta w_j$  change in  $w_j$  is  $e^{\beta_j \Delta w_j}$  under a multiplicative-error exponential conditional mean model. We can calculate incidence-rate ratios for different changes in the covariates by using `lincom`; see [R] [lincom](#).

Here we replay the `ivpoisson` results by typing the command name and we specify the `irr` option to get the incidence-rate ratios. Each significance test for a coefficient equaling zero becomes a test for the incidence-rate ratio equaling one.

```
. ivpoisson, irr
Exponential mean model with endogenous regressors
Number of parameters = 6           Number of obs = 5,000
Number of moments = 6
Initial weight matrix: Unadjusted
GMM weight matrix: Robust
```

trips	IRR	Robust std. err.	z	P> z	[95% conf. interval]	
tcost	1.035846	.0101701	3.59	0.000	1.016103	1.055972
cbd	.9916371	.0020003	-4.16	0.000	.9877243	.9955655
ptn	.9887491	.0021573	-5.19	0.000	.9845299	.9929864
worker	1.939251	.1008234	12.74	0.000	1.751376	2.14728
weekend	1.351118	.0490026	8.30	0.000	1.258409	1.450657
_cons	1.304008	.2021377	1.71	0.087	.9623501	1.766962

Note: **\_cons** estimates baseline incidence rate.

Endogenous: tcost

Exogenous: cbd ptn worker weekend pt

Holding other covariates and the error constant, the expected number of trips made from houses with a full-time worker is nearly twice that of those houses without a full-time worker. Similarly, the expected number of trips made during a weekend day is close to 35% higher than the expected number of trips made on other days. For each additional dollar of weekly transportation cost, the expected number of household trips is increased by approximately 3.6%.

◀

## CF estimator for multiplicative model

Control-function (CF) estimators can be used to account for endogenous covariates. As [Wooldridge \(2010, sec. 18.5\)](#) describes, CF estimators assume a certain structural relationship between the endogenous covariates and the exogenous covariates and use functions of first-stage parameter estimates to control for the endogeneity in the second stage.

Wooldridge (2010, sec. 18.5) notes that the VCE of the second-stage estimator must be adjusted to account for estimates from the first stage. `ivpoisson cfunction` solves this problem by stacking the moment conditions that define each stage and applying a single GMM estimator. See Newey (1984) and Wooldridge (2010, sec. 14.2) for a description of this technique. No adjustment to the VCE is necessary because there is only one stage.

The CF estimator augments the original multiplicative model with an estimated term that controls for the endogeneity of  $\mathbf{y}_{2,i}$ . When  $\mathbf{y}_{2,i}$  is exogenous, the coefficient on this control term is zero. Let  $\mathbf{z}$  be instrumental variables, and the vector  $\tilde{\mathbf{z}}_i$  be  $(\mathbf{x}'_i, \mathbf{z}'_i)$ .

The augmented model is

$$y_i = \exp(\mathbf{x}'_i\boldsymbol{\beta}_1 + \mathbf{y}'_{2,i}\boldsymbol{\beta}_2 + \mathbf{v}'_i\boldsymbol{\rho} + c_i)$$

where

$$\mathbf{y}_{2,i} = \mathbf{B}\tilde{\mathbf{z}}'_i + \mathbf{v}_i$$

The term  $\mathbf{v}'_i\boldsymbol{\rho}$  controls for the endogeneity of  $\mathbf{y}_{2,i}$ , and we normalize  $E\{\exp(c_i)\} = 1$ . The coefficient vector  $\boldsymbol{\rho}$  measures the strength of the endogeneity of  $\mathbf{y}_{2,i}$ ;  $\mathbf{y}_{2,i}$  is exogenous when  $\boldsymbol{\rho} = \mathbf{0}$ .

`ivpoisson cfunction` estimates  $\boldsymbol{\beta}_1$  and  $\boldsymbol{\beta}_2$  and the auxiliary parameters  $\boldsymbol{\rho}$  and  $\mathbf{B}$  by GMM; see *Methods and formulas* for details.

### ► Example 3: Control-function estimator

We return to the [previous example](#), where we estimated the parameters of an exponential conditional mean model for the number of trips taken by a household in a 24-hour period. We will estimate the parameters of the regression with the CF estimator method and compare our results with those obtained with the GMM estimator in [example 2](#).

In the output below, we estimate the parameters of the regression with the `ivpoisson cfunction` command.

```

. ivpoisson cfunction trips cbd ptn worker weekend (tcost = pt)
Step 1
Iteration 0: GMM criterion Q(b) = .00056156
Iteration 1: GMM criterion Q(b) = 2.366e-07
Iteration 2: GMM criterion Q(b) = 5.552e-14
Iteration 3: GMM criterion Q(b) = 9.760e-27
note: model is exactly identified.
Exponential mean model with endogenous regressors
Number of parameters = 13                Number of obs =      5,000
Number of moments   = 13
Initial weight matrix: Unadjusted
GMM weight matrix:   Robust

```

		Robust				
	trips	Coefficient	std. err.	z	P> z	[95% conf. interval]
<b>trips</b>						
	cbd	-.0082567	.0020005	-4.13	0.000	-.0121777 -.0043357
	ptn	-.0113719	.0021625	-5.26	0.000	-.0156102 -.0071335
	worker	.6903044	.0521642	13.23	0.000	.5880645 .7925444
	weekend	.2978149	.0356474	8.35	0.000	.2279472 .3676825
	tcost	.0320718	.0092738	3.46	0.001	.0138955 .0502481
	_cons	.2145986	.1359327	1.58	0.114	-.0518246 .4810218
<b>tcost</b>						
	cbd	.0165466	.0043693	3.79	0.000	.0079829 .0251102
	ptn	-.040652	.0045946	-8.85	0.000	-.0496573 -.0316467
	worker	1.550985	.0996496	15.56	0.000	1.355675 1.746294
	weekend	.0423009	.0779101	0.54	0.587	-.1104002 .1950019
	pt	.7739176	.0150072	51.57	0.000	.7445041 .8033312
	_cons	12.13934	.1123471	108.05	0.000	11.91915 12.35954
	/c_tcost	.1599984	.0111752	14.32	0.000	.1380954 .1819014

Endogenous: tcost

Exogenous: cbd ptn worker weekend pt

The output table presents results for the estimated coefficients in each of three equations. First, in the `trips` equation, we see the results for the estimated coefficients in the equation for the dependent variable `trips`. Second, in the `tcost` equation, we see the estimated coefficients in the regression of `tcost` on the instrumental and exogenous variables. Third, the `/c_tcost` ancillary parameter corresponds to the estimate of  $\rho$ , the coefficient on the residual variable included to control for the endogeneity of `tcost`.

We find that all coefficients are significant in the exponential conditional mean equation, `trips`. The coefficient estimates in the `trips` equation are similar to the estimates obtained by the GMM estimator in [example 2](#). That the estimated coefficient on the `tcost` control variable is significantly different from zero suggests that `tcost` is endogenous.

## Stored results

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

### Scalars

<code>e(N)</code>	number of observations
<code>e(k)</code>	number of parameters
<code>e(k_eq)</code>	number of equations
<code>e(k_aux)</code>	number of auxiliary parameters
<code>e(k_dv)</code>	number of dependent variables
<code>e(Q)</code>	criterion function
<code>e(J)</code>	Hansen $J$ $\chi^2$ statistic
<code>e(J_df)</code>	$J$ statistic degrees of freedom
<code>e(N_clust)</code>	number of clusters
<code>e(rank)</code>	rank of <code>e(V)</code>
<code>e(ic)</code>	number of iterations used by iterative GMM estimator
<code>e(converged)</code>	1 if converged, 0 otherwise

### Macros

<code>e(cmd)</code>	<code>ivpoisson</code>
<code>e(cmdline)</code>	command as typed
<code>e(depvar)</code>	dependent variable of regression
<code>e(endog)</code>	names of endogenous variables
<code>e(exog)</code>	names of exogenous variables
<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(offset1)</code>	offset variable for first equation
<code>e(winit)</code>	initial weight matrix used
<code>e(winitname)</code>	name of user-supplied initial weight matrix
<code>e(estimator)</code>	<code>gmm</code> or <code>cfunction</code>
<code>e(additive)</code>	additive if additive errors specified
<code>e(multiplicative)</code>	multiplicative if multiplicative errors specified
<code>e(gmmestimator)</code>	<code>onestep</code> , <code>twostep</code> , or <code>igmm</code>
<code>e(wmatrix)</code>	<code>wmtype</code> specified in <code>wmatrix()</code>
<code>e(vce)</code>	<code>vcetype</code> specified in <code>vce()</code>
<code>e(vcetype)</code>	title used to label Std. err.
<code>e(technique)</code>	optimization technique
<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(V)</code>	variance-covariance matrix
<code>e(init)</code>	initial values of the estimators
<code>e(Wuser)</code>	user-supplied initial weight matrix
<code>e(W)</code>	weight matrix used for final round of estimation
<code>e(S)</code>	moment covariance matrix used in robust VCE computations
<code>e(V_modelbased)</code>	model-based variance

### Functions

<code>e(sample)</code>	marks estimation sample
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In addition to the above, the following is stored in `r()`:

Matrices	
<code>r(table)</code>	matrix containing the coefficients with their standard errors, test statistics, $p$ -values, and confidence intervals

Note that results stored in `r()` are updated when the command is replayed and will be replaced when any `r-class` command is run after the estimation command.

## Methods and formulas

The estimators in `ivpoisson` are GMM estimators that can be expressed in terms of error functions and the instruments that are used to form the moment conditions. When offsets  $o_j^\beta$  are used in the outcome variable equation, the following formulas apply with  $\mathbf{x}'_j\beta_1$  changed to  $\mathbf{x}'_j\beta_1 + o_j^\beta$ .

The error functions for the GMM estimators are given in the text.

Here we provide some details about the form of the error function used by the CF estimator.

Recall that the multiplicative model is

$$y_i = \exp(\mathbf{x}'_i\beta_1 + \mathbf{y}'_{2,i}\beta_2)\epsilon_i$$

We parameterize the endogenous variables in the form

$$\mathbf{y}_{2,i} = \mathbf{B}\tilde{\mathbf{z}}'_i + \mathbf{v}_i$$

This allows us to decompose  $\epsilon_i$  as

$$\epsilon_i = \exp(\mathbf{v}'_i\rho + c_i)$$

Given this setup, we obtain the following conditional mean:

$$E(y|\mathbf{x}_i, \mathbf{z}_i, \mathbf{y}_{2,i}, \mathbf{v}_i) = \exp(\mathbf{x}'_i\beta_1 + \mathbf{y}'_{2,i}\beta_2 + \mathbf{v}'_i\rho)$$

We estimate  $\mathbf{v}_i$  as the residuals of the linear regression of  $\mathbf{y}_{2,i}$  on  $\tilde{\mathbf{z}}_i$ . The estimates of  $\mathbf{v}_i$  are used as additional covariates in the exponential conditional mean model for  $y$  to estimate  $\beta_1$ ,  $\beta_2$ , and  $\rho$ . In essence, the estimates of  $\mathbf{v}_i$  control for the endogeneity.

The error functions for the endogenous covariates are defined as

$$\mathbf{u}_{en,i}(\mathbf{y}_{2,i}, \tilde{\mathbf{z}}_i, \mathbf{B}) = \mathbf{y}_{2,i} - \mathbf{B}\tilde{\mathbf{z}}'_i$$

Now, we define the error function for the dependent variable as

$$u_y(y_i, \mathbf{x}_i, \mathbf{y}_{2,i}, \mathbf{u}_{en,i}, \beta_1, \beta_2, \rho) = y_i / \exp(\mathbf{x}'_i\beta_1 + \mathbf{y}'_{2,i}\beta_2 + \mathbf{u}'_{en,i}\rho) - 1$$

$\mathbf{u}_{en,i}$  will be vector valued if we have multiple endogenous covariates  $\mathbf{y}_{2,i}$ . Call the dimension of  $\mathbf{y}_{2,i}$   $g$ .  $\mathbf{u}_{en,i}$  and  $u_{y,i}$  define  $g + 1$  separate error functions. We will use variables  $\tilde{\mathbf{z}}_i$  to instrument each error function in  $\mathbf{u}_{en,i}$ . So for error function  $j = 1, \dots, g$ , we have the error function  $u_{en,i,j}$  and the population-moment conditions  $E(\tilde{\mathbf{z}}_i u_{en,i,j}) = \mathbf{0}$ .

We calculate  $\widehat{\mathbf{v}}_{oi}$  previous to estimation as the residuals of the linear regression of  $\mathbf{y}_{2,i}$  on  $\widetilde{\mathbf{z}}_i$ . We use variables  $\mathbf{x}_i$ ,  $\mathbf{y}_{2,i}$ , and  $\widehat{\mathbf{v}}_{oi}$  to instrument the error function  $u_y$ . This leads to the population-moment conditions  $E \left\{ (\mathbf{x}'_i, \mathbf{y}'_{2,i}, \widehat{\mathbf{v}}'_{oi}) u_{y,i} \right\} = \mathbf{0}$

Details of GMM estimation can be found in *Methods and formulas* of [R] **gmm**. Determination of the weight matrix  $\mathbf{W}_N$  is discussed there.

Under the GMM estimation, the GMM estimators  $\widehat{\beta}_1$  and  $\widehat{\beta}_2$  are the values of  $\beta_1$  and  $\beta_2$  that minimize

$$Q(\beta_1, \beta_2) = \left\{ \frac{1}{N} \sum_i \widetilde{\mathbf{z}}_i u_i(y_i, \mathbf{x}_i, \mathbf{y}_{2,i}, \beta_1, \beta_2) \right\}' \mathbf{W}_N \left\{ \frac{1}{N} \sum_i \widetilde{\mathbf{z}}_i u_i(y_i, \mathbf{x}_i, \mathbf{y}_{2,i}, \beta_1, \beta_2) \right\} \quad (1)$$

for  $q \times q$  weight matrix  $\mathbf{W}_N$ , where  $q$  is the dimension of  $\widetilde{\mathbf{z}}_i$ . The error functions  $u_i$  were defined in the text.

In the CF method, we have multiple error functions as defined above. We can stack the moment conditions and write them more compactly as  $\mathbf{Z}'_i \mathbf{u}_i(\mathbf{B}, \beta_1, \beta_2, \rho)$ , where

$$\mathbf{Z}_i = \begin{bmatrix} \mathbf{x}'_i & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{y}'_{2,i} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \widetilde{\mathbf{z}}_i & \cdots & \mathbf{0} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \widetilde{\mathbf{z}}_i \end{bmatrix}$$

and

$$\mathbf{u}_i(\mathbf{B}, \beta_1, \beta_2, \rho) = \begin{bmatrix} u_y(y_i, \mathbf{x}_i, \mathbf{y}_{2,i}, \mathbf{u}_{en,i}, \beta_1, \beta_2, \rho) \\ \mathbf{u}_{en}(\mathbf{y}_{2,i}, \widetilde{\mathbf{z}}_i, \mathbf{B}) \end{bmatrix}$$

The matrix  $\mathbf{Z}_i$  has  $g + 1$  rows and  $k + gz$  columns, where  $k$  is the number of covariates for  $y_i$  and  $z$  is the number of exogenous covariates in  $\widetilde{\mathbf{z}}_i$ .

The GMM estimators  $\widehat{\mathbf{B}}$ ,  $\widehat{\beta}_1$ ,  $\widehat{\beta}_2$ , and  $\widehat{\rho}$  are the values of  $\mathbf{B}$ ,  $\beta_1$ ,  $\beta_2$ , and  $\rho$  that minimize

$$Q(\mathbf{B}, \beta_1, \beta_2, \rho) = \left\{ N^{-1} \sum_{i=1}^N \mathbf{Z}'_i \mathbf{u}_i(\mathbf{B}, \beta_1, \beta_2, \rho) \right\}' \mathbf{W}_N \left\{ N^{-1} \sum_{i=1}^N \mathbf{Z}'_i \mathbf{u}_i(\mathbf{B}, \beta_1, \beta_2, \rho) \right\} \quad (2)$$

for  $(k + gz) \times (k + gz)$  weight matrix  $\mathbf{W}_N$ .

By default, `ivpoisson` minimizes (1) and (2) using the Gauss–Newton method. See Hayashi (2000, 498) for a derivation. This technique is typically faster than quasi-Newton methods and does not require second-order derivatives.

## References

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## Also see

- [R] **ivpoisson postestimation** — Postestimation tools for ivpoisson
- [R] **gmm** — Generalized method of moments estimation
- [R] **ivprobit** — Probit model with continuous endogenous covariates
- [R] **ivregress** — Single-equation instrumental-variables regression
- [R] **ivtobit** — Tobit model with continuous endogenous covariates
- [R] **nl** — Nonlinear least-squares estimation
- [R] **nlsur** — Estimation of nonlinear systems of equations
- [R] **poisson** — Poisson regression
- [R] **regress** — Linear regression
- [U] **20 Estimation and postestimation commands**

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