ivlpirf - Instrumental-variables local-projection impulse-response functions

Description Options Acknowledgments Quick start Remarks and examples References Menu Stored results Also see Syntax Methods and formulas

Description

ivlpirf uses instrumental variables (IV) to estimate impulse-response functions (IRFs) by local projections. Structural IRFs or cumulative structural IRFs for the response of one or more variables to an endogenous impulse variable may be estimated.

Quick start

IV local-projection IRFs for response variable y, endogenous impulse variable x, and instrument z
ivlpirf y, endogenous(x = z)

Same as above, but with 16 steps instead of the default 4

ivlpirf y, endogenous(x = z) step(16)

Same as above, but do not compute IRF for the endogenous impulse variable

ivlpirf y, endogenous(x = z) step(16) noendogirf

IV local-projection IRFs for response variables y1, y2, and y3 with endogenous impulse variable x and instruments z1 and z2

ivlpirf y1 y2 y3, endogenous(x = z1 z2)

Same as above, but request the cumulative impulse-response function instead of the default simple impulse-response function

ivlpirf y1 y2 y3, endogenous(x = z1 z2) cumulative

Menu

Statistics > Multivariate time series > Instrumental-variables local-projection IRFs

Syntax

ivlpirf depvarlist [if] [in], endogenous(depvarive = varlistive) [options]

*depvar*_{iv} is an endogenous impulse variable.

varlist_{iv} is a list of instruments.

options	Description		
Model			
* endogenous(<i>endospec</i>)	specify endogenous impulse variable and instruments		
lags(numlist)	include specified lags of dependent and endogenous impulse variables; default is lags(1 2)		
<u>st</u> ep(#)	set forecast horizon to # steps; default is step(4)		
$exog(varlist_{exo})$	include exogenous variables as controls		
noconstant	suppress constant terms in IV local projections		
noendogirf	suppress IRF for the endogenous impulse variable		
<u>cumul</u> ative	report cumulative IRFs		
SE/Robust			
vce(<i>vcetype</i>)	<i>vcetype</i> may be <u>r</u> obust, <u>cl</u> uster <i>clustvar</i> , conventional, or hac <i>hacspec</i>		
Reporting			
<u>l</u> evel(#)	set confidence level; default is level(95)		
display_options	control columns and column formats and row spacing		
<u>coefl</u> egend	display legend instead of statistics		

*endogenous() is required. The full specification is endogenous ($depvar_{iv} = varlist_{iv}$).

You must tsset your data before using ivlpirf; see [TS] tsset.

varlist_{iv} and varlist_{exo} may contain factor variables; see [U] 11.4.3 Factor variables.

depvarlist, depvariv, varlistiv, and varlistexo may contain time-series operators; see [U] 11.4.4 Time-series varlists.

by, collect, rolling, and statsby are allowed; see [U] 11.1.10 Prefix commands.

coeflegend does not appear in the dialog box.

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

Options

Model

endogenous (*depvar*_{iv} = *varlist*_{iv}) specifies the endogenous impulse variable *depvar*_{iv} and its instruments *varlist*_{iv}. endogenous () is required.

lags (*numlist*) specifies the lags of the dependent variables to be included in the model. The default is lags (1 2). Lags may be skipped; for example, lags (1 3) would include lags 1 and 3 but not lag 2.

step(#) specifies the step (forecast) horizon; the default is four periods.

exog(*varlist*_{exo}) specifies a list of exogenous variables to be included as controls in the IV local projections.

noconstant suppresses the constant terms in the IV local projections.

- noendogirf suppresses the computation and reporting of the IRF for the endogenous impulse variable. By default, this IRF is calculated.
- cumulative specifies that cumulative IRFs be calculated. The default is to calculate simple IRFs.

SE/Robust

- vce(vcetype) specifies the type of standard error reported, which includes types that are robust to some kinds of misspecification (robust) and that allow for intragroup correlation (cluster clustvar); see [R] vce_option.
 - vce(conventional) uses the unadjusted variance estimator from generalized method of moments (GMM); see [R] gmm.
 - vce(hac *hacspec*) requests a heteroskedasticity- and autocorrelation-consistent (HAC) variancecovariance matrix. The full syntax of *hacspec* is one of the following:
 - vce (hac kernel [#]) requests a HAC variance–covariance matrix using the specified kernel (see below) with optional # lags. The bandwidth of a kernel is equal to # + 1. If # is not specified, a kernel with N 2 lags is used, where N is the sample size.
 - vce (hac *kernel* opt [#]) requests a HAC variance–covariance matrix using the specified kernel (see below), and the lag order is selected using Newey and West's (1994) optimal lag-selection algorithm. # is an optional tuning parameter that affects the lag order selected; see the discussion in Methods and formulas in [R] **ivregress**.

kernel may be one of the following:

bartlett or <u>nw</u>est requests the Bartlett (Newey-West) kernel.

parzen or gallant requests the Parzen (Gallant 1987) kernel.

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

Reporting

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

display_options: noci, nopvalues, vsquish, cformat(%*fmt*), pformat(%*fmt*), sformat(%*fmt*), and nolstretch; see [R] Estimation options.

The following option is available with ivlpirf but is not shown in the dialog box:

coeflegend; see [R] Estimation options.

Remarks and examples

The local-projection method traces out the dynamic effect of an impulse variable on a response variable by using the sequence of projections

$$y_{t+h} = \beta_h x_t + \mathbf{w}' \mathbf{\gamma} + e_{t+h}$$

where y_{t+h} is the response variable at horizon h, x_t is the impulse variable, β_h is the impulse–response coefficient, variables in **w** are controls with coefficients γ , and e_{t+h} is an error term. All variables are measured over time t. The collection of coefficients $(\beta_0, \beta_1, \ldots, \beta_H)$ traces out the response of y_t to an impulse in x_t . This is the local-projection estimator of the IRF. In many contexts, x_t is endogenous, rendering a causal interpretation of the IRF impossible. However, if an instrument z_t is available, then x_t may be instrumented with z_t , and the resulting IV local projections can be interpreted as a causal IRF.

Jordà and Taylor (Forthcoming) provide an overview of the local-projection estimator, including the IV local-projection estimator used by ivlpirf, as well as applications of local projections to areas of applied economics.

Example 1: IV local projections

We use data on U.S. industrial production growth (ip_growth), inflation rate (inflation), and the interest rate (fedfunds) to estimate the effects of an interest rate increase on economic activity and prices. At horizon h, we model the response of industrial production growth to change in interest rate as

$$ip_growth_{t+h} = \beta_h \Delta fedfunds_t + \mathbf{w'} \mathbf{\gamma} + e_{t+h}$$

where w are controls, such as lags of ip_growth and change in fedfunds. We are concerned that the change in fedfunds is endogenous. We have available an instrument, money_inst, that captures monetary shocks. It is correlated with change in fedfunds but uncorrelated with any nonmonetary shocks. We use this variable as an instrument for change in fedfunds. In our ivlpirf command, we specify d.fedfunds, the first difference of fedfunds, as the endogenous impulse variable and the money_inst instrument in the endogenous() option.

```
. use https://www.stata-press.com/data/r19/usmacro3
(Federal Reserve Economic Data - St. Louis Fed, 2023-09-01)
. ivlpirf ip_growth, endogenous(d.fedfunds = money_inst)
Step 1:
Iteration 0: GMM criterion Q(b) = .22620934
Iteration 1: GMM criterion Q(b) = 4.665e-33
Iteration 2: GMM criterion Q(b) = 4.747e-34
Step 2:
Iteration 0: GMM criterion Q(b) = 2.524e-34
Iteration 1: GMM criterion Q(b) = 2.524e-34
Number of obs = 468
( 1) [D.fedfunds]D.fedfunds = 1
```

IRF coefficient	Robust std. err.	z	P> z	[95% conf	interval]
.3902078	.2381631	1.64	0.101	0765833	.8569989
.3610046	.3089668	1.17	0.243	2445592	.9665685
.1629727	.2189905	0.74	0.457	2662408	.5921862
0997817	.1333441	-0.75	0.454	3611313	.1615678
1677662	.1170584	-1.43	0.152	3971965	.061664
1	(constraine	d)			
1.476712	.5963349	2.48	0.013	.3079167	2.645506
.3870066	.3807016	1.02	0.309	3591549	1.133168
1729338	.2029923	-0.85	0.394	5707913	.2249238
3460389	.1569646	-2.20	0.027	6536839	0383939
	IRF coefficient .3902078 .3610046 .1629727 0997817 1677662 1 1.476712 .3870066 1729338 3460389	IRF Robust std. err. .3902078 .2381631 .3610046 .3089668 .1629727 .2189905 0997817 .1333441 1677662 .1170584 1 (constraine 1.476712 .5963349 .3870066 .3807016 1729338 .2029923 3460389 .1569646	IRF Robust z .coefficient std. err. z .3902078 .2381631 1.64 .3610046 .3089668 1.17 .1629727 .2189905 0.74 0997817 .1333441 -0.75 1677662 .1170584 -1.43 1 (constrained) 1.476712 .3870066 .3807016 1.02 1729338 .2029923 -0.85 3460389 .1569646 -2.20	IRF coefficient Robust std. err. z P> z .3902078 .2381631 1.64 0.101 .3610046 .3089668 1.17 0.243 .1629727 .218905 0.74 0.457 0997817 .1333441 -0.75 0.454 1677662 .1170584 -1.43 0.152 1 (constrained) 1.476712 .5963349 2.48 0.013 .3870066 .3807016 1.02 0.309 1729338 .2029923 -0.85 0.394 3460389 .1569646 -2.20 0.027 0.027	$\begin{array}{c cccc} IRF & Robust \\ coefficient & std. err. & z & P> z & [95\% \ conf. \\ \hline \\ .3902078 & .2381631 & 1.64 & 0.101 &0765833 \\ .3610046 & .3089668 & 1.17 & 0.243 &2445592 \\ .1629727 & .218905 & 0.74 & 0.457 &2662408 \\0997817 & .1333441 & -0.75 & 0.454 &3611313 \\1677662 & .1170584 & -1.43 & 0.152 &3971965 \\ \hline \\ 1.476712 & .5963349 & 2.48 & 0.013 & .3079167 \\ .3870066 & .3807016 & 1.02 & 0.309 &3591549 \\1729338 & .2029923 & -0.85 & 0.394 &5707913 \\3460389 & .1569646 & -2.20 & 0.027 &6536839 \\ \end{array}$

Note: Structural impulse-response functions are reported. Impulse: D.fedfunds Responses: ip_growth D.fedfunds Instrument: money_inst Controls: L.ip_growth L2.ip_growth LD.fedfunds L2D.fedfunds

The header of our ivlpirf output indicates that our model was fit using 468 observations of monthly data for January 1969 through December 2007.

The coefficient table displays the local-projection IRF coefficients. These coefficients are organized by response and step (horizon, in units of the time scale of the data). The ip_growth block of coefficients displays the response of industrial production growth to a shock to change in interest rates. The IRF coefficient of 0.39 labeled –. is the estimated instantaneous response to a shock to change in interest rate. The coefficient of 0.36 labeled F1. is the estimated response one month after the shock. The shocks labeled F2. and F3. are similarly the estimated responses after 2 and 3 months, respectively. The confidence intervals for these IRF coefficients all include 0; we don't find evidence of industrial production growth having a response to the shock in the first three months.

The fedfunds block of coefficients displays the response of change in fedfunds (D.fedfunds) to the shock in interest rate. The change interest rate itself rises by 1 unit in the impact period by construction, as we can see by the constrained value of 1 for the IRF coefficient. The scale of the data determines the units for interpreting the IRF coefficients. Because fedfunds is measured in percentage points, d.fedfunds is a percentage point change. The value 1 indicates a shock that raises the interest rate by 1%. Subsequent responses indicate a further change in the interest rate in the same direction, by 1.48%, in the first month after the shock. In the second period after the shock, there is further change in the interest rate in the same direction, by 0.39%. In subsequent periods, the interest rate changes in the reverse direction, by -0.17% in the third period after a shock and finally by -0.35% in the fourth period.

Below the coefficient table, a note points out that the reported IRFs are structural IRFs; these provide a causal interpretation. We also see which variables are treated as the impulse, responses, instruments, and controls. Notice that, by default, two lags of each response (including the endogenous impulse variable) are treated as controls, but you may specify other controls. The lags() option modifies which lags of responses are to be used as controls, and the exog() option specifies additional exogenous variables to use as controls.

4

Example 2: Cumulative local projections

Consider again the model in example 1. This time, we compute cumulative IV local-projection IRFs. When the response is measured in growth rates, the cumulative IRF can be interpreted as the path of the level of the response variable, not the path of the growth rate, after an impulse. We are interested in the response of industrial production, so we use the cumulative option to compute the cumulative IRF for ip_growth.

```
. ivlpirf ip_growth, endogenous(d.fedfunds = money_inst) cumulative
Step 1:
Iteration 0: GMM criterion Q(b) = 1.814879
Iteration 1: GMM criterion Q(b) = 1.430e-32
Iteration 2: GMM criterion Q(b) = 4.570e-33
Step 2:
Iteration 0: GMM criterion Q(b) = 1.678e-32
Iteration 1: GMM criterion Q(b) = 1.678e-32
note: model is exactly identified.
Instrumental-variables local-projection impulse responses
Sample: 1969m1 thru 2007m12 Number of obs = 468
```

```
( 1) [D.fedfunds]D.fedfunds = 1
```

	CIRF coefficient	Robust std. err.	Z	P> z	[95% conf.	interval]
ip growth						
	.3902078	.2381631	1.64	0.101	0765833	.8569989
F1.	.7512125	.5259427	1.43	0.153	2796163	1.782041
F2.	.9141852	.7075975	1.29	0.196	4726805	2.301051
F3.	.8144034	.7943301	1.03	0.305	7424551	2.371262
F4.	.6466372	.7752842	0.83	0.404	872892	2.166166
fedfunds						
D1.	1	(constraine	d)			
FD.	2.476712	.5963349	4.15	0.000	1.307917	3.645506
F2D.	2.863718	.8591673	3.33	0.001	1.179781	4.547655
F3D.	2.690784	.93778	2.87	0.004	.8527694	4.528799
F4D.	2.344745	.8878207	2.64	0.008	.6046488	4.084842

Note: Cumulative structural impulse-response functions are reported. Impulse: D.fedfunds Responses: ip_growth D.fedfunds Instrument: money_inst Controls: L.ip growth L2.ip growth LD.fedfunds L2D.fedfunds The cumulative response of industrial production growth on impact is the same as the simple response we obtained in example 1. The cumulative response in step 1, one month after impact, is the sum of the simple response on impact and the simple response in step 1 that were reported in example 1. This pattern continues.

These cumulative IRF coefficients now represent the response of industrial production rather than the response of industrial production growth. Thus, after one month, estimated response of industrial production to the shock is 0.75. After two months, the estimated response is 0.91. This estimated response then decreases in the next two periods.

Instead of showing the output in a table, we can graph the IRFs using irf graph. This time, we compute 36 steps of responses, corresponding to three years, by using the step(36) option. As controls, we include 12 lags (one year) of the ip_growth and d.fedfunds variables.

```
. ivlpirf ip_growth, endogenous(d.fedfunds = money_inst)
> cumulative step(36) lag(1/12)
  (output omitted)
. irf set ivlpirf.irf, replace
(file ivlpirf.irf created)
(file ivlpirf.irf now active)
. irf create model1
(file ivlpirf.irf updated)
. irf graph csirf, impulse(D.fedfunds) yline(0) xlabel(0(12)36)
```

When we request cumulative IRFs in the ivlpirf command, we also need to request the cumulative IRFs, or more specifically cumulative structural IRFss, in the irf graph command. To do so, we specify the csirf statistic.



The graphs above display the cumulative IV local-projection IRF coefficients. Because both d.fedfunds and ip_growth are growth rates, both cumulative responses can be interpreted in levels of the variables. The left-hand panel shows the response of interest rate, and the right-hand panel shows the response of industrial production. On the left, we see that the interest rate rises after a shock to change in interest rate, with the response peaking a few periods after the shock but falling thereafter. On the right, we see that industrial production shows little movement on impact but then declines with a delay after the shock, reaching a trough about 24 periods (2 years) after the shock but then recovering slightly in the third year after the shock.

Example 3: Simultaneous responses

We can compute multiple responses at once for the same endogenous impulse. We now add the inflation rate as a response variable and trace out the responses of inflation and industrial production growth. We thus have two local projections,

```
\texttt{ip_growth}_{t+h} = \beta_h \Delta \texttt{fedfunds}_t + \mathbf{w}' \mathbf{\gamma} + e_{t+h}
```

and

 $inflation_{t+h} = \beta_h \Delta fedfunds_t + \mathbf{w'} \mathbf{\gamma} + e_{t+h}$

which we estimate simultaneously for all horizons.

```
. ivlpirf ip_growth inflation, endogenous(d.fedfunds = money_inst) cumulative
Step 1:
Iteration 0: GMM criterion Q(b) = 1.8287366
Iteration 1: GMM criterion Q(b) = 1.543e-32
Iteration 2: GMM criterion Q(b) = 5.190e-33
Step 2:
Iteration 0: GMM criterion Q(b) = 1.982e-32
Iteration 1: GMM criterion Q(b) = 1.982e-32
note: model is exactly identified.
Instrumental-variables local-projection impulse responses
Sample: 1969m1 thru 2007m12
Number of obs = 468
```

```
( 1) [D.fedfunds]D.fedfunds = 1
```

	CIRF coefficient	Robust std. err.	Z	P> z	[95% conf.	interval]
ip_growth						
	.3767377	.2067382	1.82	0.068	0284617	.7819371
F1.	.725611	.4473294	1.62	0.105	1511386	1.60236
F2.	.8729816	.5831643	1.50	0.134	2699994	2.015963
F3.	.7572531	.6219763	1.22	0.223	4617981	1.976304
F4.	.5751773	.567312	1.01	0.311	5367338	1.687088
inflation						
	.0725715	.0391172	1.86	0.064	0040968	.1492398
F1.	.1381907	.0682327	2.03	0.043	.0044571	.2719243
F2.	.2424316	.0933341	2.60	0.009	.0595001	.425363
F3.	.4166317	.1646479	2.53	0.011	.0939278	.7393355
F4.	. 505858	.2142514	2.36	0.018	.085933	.925783
fedfunds						
D1.	1	(constrained	1)			
FD.	2.481322	.5854004	4.24	0.000	1.333959	3.628686
F2D.	2.867292	.8518579	3.37	0.001	1.197681	4.536903
F3D.	2.696978	.9320981	2.89	0.004	.8700996	4.523857
F4D.	2.354742	.8938336	2.63	0.008	.6028599	4.106623
Note: Cumulat Impulse: D Responses: i Instrument: m	ive structural .fedfunds p_growth infla oney_inst	. impulse-res	sponse fu unds	unctions	are reported.	

Controls: L.ip_growth L2.ip_growth L.inflation L2.inflation LD.fedfunds L2D.fedfunds

There are three blocks in the output table, one each for the responses of industrial production growth, inflation rate, and the change in interest rate itself. By default, two lags of each response variable are included in the controls for each equation.

As before, we compute and graph three years of the cumulative impulse responses:



The interest rate rises initially, then falls slowly (top-left panel). Industrial production declines, reaching a trough two years after the shock (bottom panel). New is the cumulative response of inflation rate (that is, the price level) in the top-right panel. Prices do not move much in the first two years after the shock but then finally show a slight decline in the third year.

Stored results

ivlpirf stores the following in e():

Scalars	
e(N)	number of observations
e(N_gaps)	number of gaps in sample
e(k)	number of parameters
e(k_impulses)	number of impulse variables
e(k_responses)	number of response variables
e(k_controls)	number of control variables
e(k_instruments)	number of instruments
e(tmin)	minimum time in sample
e(tmax)	maximum time in sample
e(step)	maximum step
e(N_clust)	number of clusters
e(cumul)	1 if option cumulative was specified; otherwise 0
e(rank)	rank of e(V)
Macros	
e(cmd)	ivlpirf
e(cmdline)	command as typed
e(depvar)	names of dependent variables
e(responses)	names of response variables
e(impulse)	name of endogenous impulse variable
e(instruments)	names of instruments
e(controls)	names of control variables
e(exog)	names of exogenous variables
e(title)	title in estimation output
e(tsfmt)	format for the time variable
e(tvar)	time variable
e(tmins)	formatted minimum time
e(tmaxs)	formatted maximum time
e(lags)	lags used in controls
e(cons)	noconstant, if option specified
e(clustvar)	name of cluster variable
e(vce)	vcetype specified in vce()
e(vcetype)	title used to label Std. err.
e(properties)	b V
e(estat_cmd)	program used to implement estat
e(predict)	program used to implement predict
Matrices	
e(b)	coefficient vector
e(V)	variance-covariance matrix of the estimators
e(Cns)	constraints matrix
Functions	
e(sample)	marks estimation sample
- (Jamp 10)	

In addition to the above, the following is stored in r():

Matrices

r(table) 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

ivlpirf estimates local-projection IRFs by GMM. Coefficients for all responses at all horizons are computed simultaneously. Data are available for response variable y_t , endogenous impulse variable x_t , and instrument z_t , all measured over time indexed by t = 1, 2, ..., T. The local projection for response y_t to an impulse x_t at horizon h is

$$y_{t+h} = \beta_h x_t + \mathbf{w}' \mathbf{\gamma} + e_{t+h}$$

where β_h is the coefficient of interest, **w** is a vector of controls, and γ are coefficients on the controls. We have available an instrument z_t that is correlated with x_t and uncorrelated with e_t at all leads and lags. Note that this lead-lag exogeneity of the instrument is stronger than the usual requirement of lag exogeneity. To focus on the impulse–response coefficients, first partial out controls from the impulse variable, the response variable, and the instruments. These partialed-out variables are denoted y_t^{\perp} , x_t^{\perp} , and z_t^{\perp} , respectively. For the response variable y_t^{\perp} , at horizon h the moment condition is

$$E\{z_t^{\perp}(y_{t+h}^{\perp} - x_t^{\perp}\beta_h)\} = 0$$

All response coefficients for all variables are estimated simultaneously. This leads to a GMM problem,

$$\min_{\boldsymbol{\beta}} \left\{ \frac{1}{T} \sum \mathbf{z}_{t}^{\perp} (\mathbf{y}_{H}^{\perp} - x_{t}^{\perp} \boldsymbol{\beta}) \right\}^{\prime} \mathbf{W} \left\{ \frac{1}{T} \sum \mathbf{z}_{t}^{\perp} (\mathbf{y}_{H}^{\perp} - x_{t}^{\perp} \boldsymbol{\beta}) \right\}$$

where \mathbf{y}_H is the $(H + 1) \times 1$ vector of responses at all desired horizons $(y_t, y_{t+1}, \dots, y_{t+H})$, $\boldsymbol{\beta}$ is the $(H + 1) \times 1$ vector of IRF coefficients, \mathbf{z} is a vector of instruments, and \mathbf{W} is a weight matrix. When there is more than one response variable, the vector \mathbf{y}_H is extended to include all horizons of all response variables, and $\boldsymbol{\beta}$ becomes the $(H + 1)k \times 1$ vector of IRF coefficients for k response variables at all horizons $0, 1, \dots, H$. For more details of GMM estimation, see [R] ivregress and [R] gmm.

Cumulative responses are calculated by summing simple responses.

Acknowledgments

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References

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- Newey, W. K., and K. D. West. 1994. Automatic lag selection in covariance matrix estimation. Review of Economic Studies 61: 631–653. https://doi.org/10.2307/2297912.

Also see

- [TS] ivlpirf postestimation Postestimation tools for ivlpirf
- [TS] lpirf Local-projection impulse-response functions
- [TS] tsset Declare data to be time-series data
- [TS] var ivsvar Instrumental-variables structural vector autoregressive models
- [R] gmm Generalized method of moments estimation
- [R] ivregress Single-equation instrumental-variables regression
- [U] 20 Estimation and postestimation commands

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