Estimating Impulse Response Functions in Stata

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Stata

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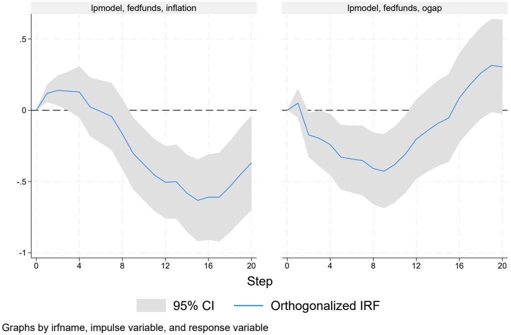
Outline

- Impulse response functions
- Impulse response functions in Stata
- The local projection estimator
- Instruments in impulse response estimation

Introduction

- Impulse response functions trace out the path of an outcome after an unexpected disturbance.
- Key object of interest in time–series econometrics.
- Teaser: one model's predictions of the paths of inflation and the output gap after a monetary policy shock:



The setting

- Collection of time–series variables driven by unobserved disturbances
  - Price and quantity driven by supply and demand shocks
  - Output, inflation, and interest rates driven by aggregate demand, aggregate supply, and monetary policy shocks
- Question: What effect does an unexpected, one-time increase in a disturbance have on the outcomes of interest?
- Policy questions:
  - How does inflation respond to an oil price increase?
  - How does GDP respond to an interest rate increase?
  - How does employment respond to a government spending increase?

Answering policy questions

- Answers are inherently dynamic: outcome variables might only respond to a disturbance after a lag.
- Effects one year or five years out might differ from effects on impact.
- Questions of causal inference at the forefront: how to disentangle causes from observed time series?
- Instruments and exogenous policy actions are only occasionally available.

An abstract definition

- Let y_t be an outcome of interest
- Let x_t be a disturbance
- We are interested in the time path of the variable in periods following a shock, relative to no shock:

$$IRF(h) = E[y_{t+h}|x_t = 1] - E[y_{t+h}|x_t = 0]$$

A model-centric definition

- Define and estimate a model for one or more outcomes $\mathbf{y}_t$ in terms of past values, observed exogenous variables, and unobserved disturbances.
- The simplest possible model:

$$y_t = \alpha y_{t-1} + e_t$$

- Then the impulse–response function after an unexpected 1-unit increase in e_t is: $1, \alpha, \alpha^2, \ldots$
- Further lags create more interesting short-run dynamics
- Eventually, the impulse–response function converges to 0

Impulse responses in multiple-equation models

- With a collection of variables, identification issues become crucial
- Two variables, one lag, two shocks:

$$y_{1t} = a_{11}y_{1,t-1} + a_{12}y_{2,t-1} + u_{1t}$$
$$y_{2t} = a_{21}y_{1,t-1} + a_{22}y_{2,t-1} + u_{2t}$$

- The residuals (u_{1t}, u_{2t}) may be correlated
- Wish to decompose into economically meaningful shocks

$$\begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix} = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \begin{pmatrix} e_{1t} \\ e_{2t} \end{pmatrix}$$

  where (e_{1t}, e_{2t}) are orthogonal
- Triangular decompositions
- More creative decompositions

Impulse responses in other models

- Autoregressive moving average models,

$$y_t = a_1 y_{t-1} + \cdots + a_p y_{t-p} + e_t + \psi_1 e_{t-1} + \cdots + \psi_q e_{t-q}$$

- Structural vector autoregression models,

$$\mathbf{y}_t = \mathbf{A}_1 \mathbf{y}_{t-1} + \cdots + \mathbf{A}_p \mathbf{y}_{t-p} + \mathbf{B}\mathbf{e}_t$$

- Vector error correction models,

$$\Delta \mathbf{y}_t = \boldsymbol{\Gamma} \mathbf{y}_{t-1} + \mathbf{A}_1 \Delta \mathbf{y}_{t-1} + \cdots + \mathbf{A}_p \Delta \mathbf{y}_{t-p} + \mathbf{u}_t$$

- DSGE models,

$$\begin{aligned} \mathbf{y}_t &= \mathbf{G}(\theta)\mathbf{x}_t \\ \mathbf{x}_{t+1} &= \mathbf{H}(\theta)\mathbf{x}_t + \mathbf{M}(\theta)\mathbf{e}_{t+1} \end{aligned}$$

Impulse responses as moving-average coefficients I

- Regardless of the model, we perform two steps: use the model to obtain moving-average coefficients, and have some method for disentangling residuals into structural shocks
- Consider a vector autoregression:

$$\mathbf{y}_t = \mathbf{A}_1 \mathbf{y}_{t-1} + \cdots + \mathbf{A}_p \mathbf{y}_{t-p} + \mathbf{u}_t$$

- Invert to write $\mathbf{y}_t$ as a function of current and past shocks

$$\mathbf{y}_t = \mathbf{u}_t + \mathbf{\Phi}_1 \mathbf{u}_{t-1} + \mathbf{\Phi}_2 \mathbf{u}_{t-2} + \dots$$

  The $\mathbf{\Phi}_i$ are the simple impulse–response coefficients
- Combine with a theory for how residuals map into shocks

$$\mathbf{u}_t = \mathbf{B}\mathbf{e}_t$$

Impulse responses as moving-average coefficients II

- Then we can write

$$\mathbf{y}_t = \mathbf{B}\mathbf{e}_t + \mathbf{\Phi}_1\mathbf{B}\mathbf{e}_{t-1} + \mathbf{\Phi}_2\mathbf{B}\mathbf{e}_{t-2} + \dots$$

  which are "structural" impulse–response functions
- Punchline: need to identify $(\mathbf{B}, \mathbf{\Phi}_i)$
- The $\mathbf{\Phi}_i$ can be consistently estimated (assuming correct specification) solely from the reduced form
- IRF identification problems are problems with the impact matrix $\mathbf{B}$

IRF identification as a simultaneous-equations problem

- Alternate way to think about the identification problem.
- A two-equation structural VAR is equivalent to

$$y_{1t} = b_{12} y_{2t} + \cdots + e_{1t}$$
$$y_{2t} = b_{21} y_{1t} + \cdots + e_{2t}$$

- No amount of information on (y_{1t}, y_{2t}) alone can identify both b_{12} and b_{21}
- Situation extrapolates to larger models with more equations.
- Structural models make assumptions on some of these coefficients (say, setting them equal to 0) to estimate the remaining ones.

Impulse response functions in Stata

The `irf` suite of commands

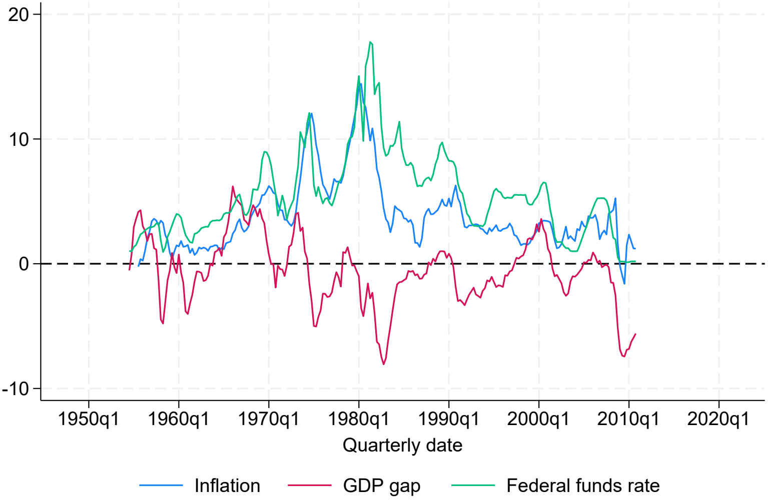
- Stata has a suite of commands to create, manage, graph, and tabulate impulse responses
  - `irf set`
  - `irf create`
  - `irf describe`
  - `irf table` and `irf graph`
- This suite is available after estimating many time-series models
  - `arima` and `arfima`
  - `var` and `svar`
  - `vec`
  - `dsge` and `dsgenl`
  - `lpirf`
- Bayesian IRFs are available as well after estimating
  - `bayes: var`
  - `bayes: dsge` and `bayes: dsgenl`

Data and questions

```
. use usmacro3

. describe

Contains data from dta/usmacro3.dta
 Observations:           312
    Variables:             5                 24 Jan 2024 15:48
--------------------------------------------------------------------------------
Variable      Storage   Display    Value
    name         type    format    label      Variable label
--------------------------------------------------------------------------------
date            float   %tq                   Quarterly date
fedfunds        double  %10.0g                Federal funds rate
inflation       float   %9.0g                 Inflation
ogap            float   %9.0g                 GDP gap
netoil          float   %9.0g                 Net oil price increase
--------------------------------------------------------------------------------
Sorted by: date
     Note: Dataset has changed since last saved.
```

Data and questions

```
. tsline inflation ogap fedfunds, yline(0) legend(rows(1))
```



Estimating a VAR

```
. quietly var inflation ogap fedfunds, lag(1/4)
. // (setup omitted)
. collect preview
```

	Inflation		GDP gap		Federal funds rate	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
L.inflation	1.15	(0.07)	-0.09	(0.09)	-0.08	(0.09)
L2.inflation	-0.22	(0.11)	0.12	(0.13)	0.32	(0.14)
L3.inflation	0.10	(0.11)	-0.19	(0.13)	-0.16	(0.14)
L4.inflation	-0.10	(0.07)	0.13	(0.08)	0.03	(0.09)
L.ogap	0.09	(0.06)	1.20	(0.07)	0.38	(0.07)
L2.ogap	-0.11	(0.08)	-0.10	(0.10)	-0.21	(0.11)
L3.ogap	0.01	(0.08)	-0.18	(0.10)	-0.10	(0.11)
L4.ogap	0.03	(0.06)	0.01	(0.07)	-0.02	(0.07)
L.fedfunds	0.21	(0.05)	0.11	(0.07)	1.14	(0.07)
L2.fedfunds	-0.16	(0.08)	-0.38	(0.10)	-0.52	(0.10)
L3.fedfunds	0.16	(0.08)	0.38	(0.10)	0.47	(0.10)
L4.fedfunds	-0.19	(0.05)	-0.13	(0.07)	-0.19	(0.07)
Intercept	0.20	(0.08)	0.16	(0.10)	0.16	(0.11)

(with an assist from collect)

Computing IRFs

- `irf set` *filename* sets a destination file for IRF results. It can hold results from multiple models, facilitating model comparison.
- `irf create` *irfname* estimates IRFs using the most recently estimated time–series model and sends the results to the file specified in `irf set`.

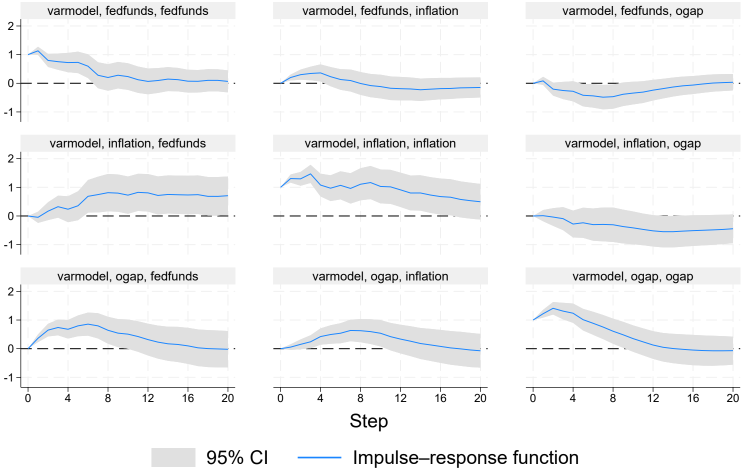
```
. quietly var inflation ogap fedfunds, lag(1/8)

. irf set modelirfs.irf, replace
(file modelirfs.irf created)
(file modelirfs.irf now active)

. irf create varmodel, step(20)
(file modelirfs.irf updated)
```

Graphing IRFs

- `irf graph` *irftype* graphs IRFs and related statistics
- Many models produce several kinds of IRFs: simple, orthogonalized, and/or structural; along with dynamic multipliers (responses to impulses to exogenous variables)
- We can look at the simple IRFs:

Graphing IRFs II

```
. irf graph irf, yline(0) xlabel(0(4)20)
```



Graphs by irfname, impulse variable, and response variable

Orthogonalized impulse responses I

- The simple IRFs shown above are responses to impulses to the VAR residuals, or forecast errors.
- They have statistical meaning, but not economic meaning because the VAR residuals are correlated.
- For economic interpretation, we need shocks that are orthogonal, so that it is meaningful to change one without changing the others.
- Consider again the VAR

$$\mathbf{y}_t = \mathbf{A}_1\mathbf{y}_{t-1} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{u}_t$$
$$\mathbf{u}_t = \mathbf{B}\mathbf{e}_t$$

- We can always calculate the covariance matrix of the VAR residuals $\mathbf{U}$

$$\boldsymbol{\Sigma}_{\mathbf{u}} = \frac{1}{T}\mathbf{U}'\mathbf{U}$$

Orthogonalized impulse responses II

- The covariance of VAR residuals is related to the impact matrix **B**

$$\mathbf{\Sigma_u} = \mathbf{B}\mathbf{B}'$$

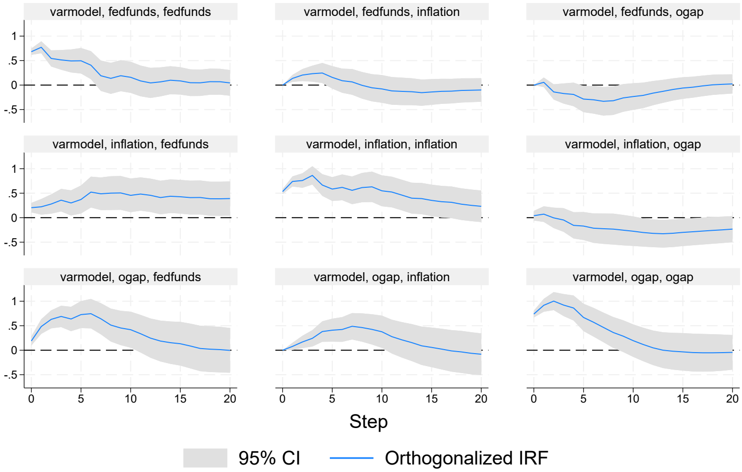
- $\mathbf{\Sigma_u}$ is symmetric, positive definite, with $k(k+1)/2$ unique elements
- **B** is, in principle, completely unrestricted with k^2 elements
- Orthongalization solves this identification problem by assuming **B** is lower-triangular.
- Orthogonalization produces statistically uncorrelated shocks by construction.
- Hence it is sensible to consider a disturbance to one shock, holding the ohters constant.
- But still no guarantee that these shocks are economically meaningful

Orthogonalized IRFs in Stata

- Orthogonalization is such a common identification scheme that Stata does it automatically when creating IRFs after `var`.
- We can graph them with `irf graph oirf`

Orthogonalized IRFs

```
. irf graph oirf, yline(0)
```



Graphs by irfname, impulse variable, and response variable

Identification in structural VARs I

- Orthogonalization consisted of the model

$$\begin{aligned} \mathbf{y}_t &= \mathbf{A}_1\mathbf{y}_{t-1} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{u}_t \\ \mathbf{u}_t &= \mathbf{B}\mathbf{e}_t \\ \mathbf{B} & \quad \text{lower triangular} \end{aligned}$$

- Orthogonalization is equivalent to giving the shocks a recursive structure
- A general structural VAR with short-run restrictions takes the form

$$\begin{aligned} \mathbf{y}_t &= \mathbf{A}_1\mathbf{y}_{t-1} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{u}_t \\ \mathbf{A}\mathbf{u}_t &= \mathbf{B}\mathbf{e}_t \end{aligned}$$

where some terms in $(\mathbf{A}, \mathbf{B})$ are restricted on the basis of theory.

Structural VARs and structural IRFs I

- svar estimates structural VARs with short-run or long-run restrictions
- Stata's matrices are used to define constraints on the matrices $(\mathbf{A}, \mathbf{B})$
- Example: Orthogonalization sets $\mathbf{A} = \mathbf{I}$ and sets the upper-triangular portion of $\mathbf{B}$ to zero. The remaining parameters in $\mathbf{B}$ are estimated. Setting this up in Stata involves:

```
. matrix A  = I(3)
. matrix B = (., 0, 0 \ ., ., 0 \ ., ., .)
. matlist A

             |        c1         c2         c3
-------------+---------------------------------
          r1 |         1
          r2 |         0          1
          r3 |         0          0          1
. matlist B
             |        c1         c2         c3
-------------+---------------------------------
          r1 |         .          0          0
          r2 |         .          .          0
          r3 |         .          .          .
```

Structural VARs and structural IRFs II

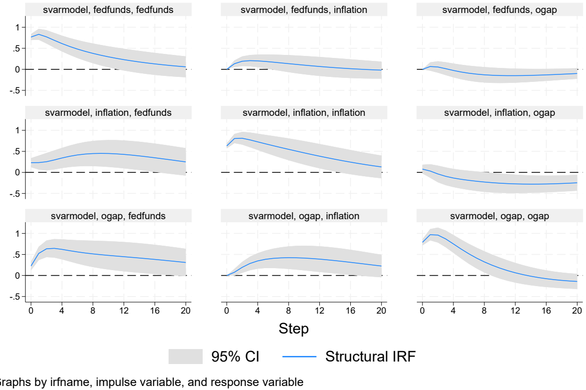
- Estimation:

```
. svar inflation ogap fedfunds, aeq(A) beq(B) nocnsreport nolog
Estimating short-run parameters

Structural vector autoregression

Sample: 1956q1 thru 2010q4                       Number of obs     =        220
Exactly identified model                         Log likelihood    =  -723.8898
```

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
/A						
1_1	1	(constrained)				
2_1	0	(constrained)				
3_1	0	(constrained)				
1_2	0	(constrained)				
2_2	1	(constrained)				
3_2	0	(constrained)				
1_3	0	(constrained)				
2_3	0	(constrained)				
3_3	1	(constrained)				
/B						
1_1	.6294081	.0300059	20.98	0.000	.5705977	.6882185
2_1	.0784342	.0532413	1.47	0.141	-.0259169	.1827853
3_1	.2313289	.0550465	4.20	0.000	.1234397	.3392181
1_2	0	(constrained)				
2_2	.7877468	.0375544	20.98	0.000	.7141416	.861352
3_2	.2260354	.052843	4.28	0.000	.122465	.3296057
1_3	0	(constrained)				
2_3	0	(constrained)				
3_3	.7673186	.0365805	20.98	0.000	.6956222	.839015

Structural VARs and structural IRFs III

```
. irf create svarmodel, step(20)
(file modelirfs.irf updated)
. irf graph sirf, irf(svarmodel) yline(0) xlabel(0(4)20)
```



Structural VARs with non-recursive constraints I

- The constraints in `svar` need not be recursive
- Setup:

```
. matrix A  = (., 0, 0 \ 0, . , 0 \ 0, 0, .)
. matrix B = (1, ., 0 \ 0, 1, . \ ., 0, 1)
. matlist A

             |        c1         c2         c3
-------------+---------------------------------
          r1 |         .
          r2 |         0          .
          r3 |         0          0          .
. matlist B

             |        c1         c2         c3
-------------+---------------------------------
          r1 |         1          .          0
          r2 |         0          1          .
          r3 |         .          0          1
```

Structural VARs with non-recursive constraints II

- Estimation:

```
. svar inflation ogap fedfunds, aeq(A) beq(B) nocnsreport nolog
Estimating short-run parameters

Structural vector autoregression

Sample: 1956q1 thru 2010q4                        Number of obs     =        220
Exactly identified model                          Log likelihood    =  -723.8898

------------------------------------------------------------------------------
             | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
/A           |
         1_1 |   5.456983   1.311046     4.16   0.000      2.88738    8.026585
         2_1 |          0  (constrained)
         3_1 |          0  (constrained)
         1_2 |          0  (constrained)
         2_2 |   12.19719   8.362181     1.46   0.145    -4.192381    28.58676
         3_2 |          0  (constrained)
         1_3 |          0  (constrained)
         2_3 |          0  (constrained)
         3_3 |   4.013121   .8971846     4.47   0.000     2.254671     5.77157
-------------+----------------------------------------------------------------
/B           |
         1_1 |          1  (constrained)
         2_1 |          0  (constrained)
         3_1 |   3.188577   .7303245     4.37   0.000     1.757167    4.619987
         1_2 |   3.285871   .8124037     4.04   0.000      1.69359    4.878153
         2_2 |          1  (constrained)
         3_2 |          0  (constrained)
         1_3 |          0  (constrained)
         2_3 |   9.603887   6.606896     1.45   0.146    -3.345392    22.55317
         3_3 |          1  (constrained)
------------------------------------------------------------------------------
```

Recap

- We've seen how to set up and estimate IRFs in Stata
- We've seen a few methods for identifying the impact matrix **B**
- Next: the local projection estimator

The local projection estimator

Local projections

- In a VAR, we estimate the $(\mathbf{A}_1, \ldots, \mathbf{A}_p)$ lag coefficients, then invert them to obtain the $(\mathbf{\Phi}_1, \mathbf{\Phi}_2, \ldots,)$ moving-average coefficients.
- Local projections (Jorda 2005) estimate the MA coefficients directly.
- Moving-average coefficients computed on the basis of "long" regressions

$$\mathbf{y}_{t+h} = \mathbf{\Phi}_{h+1}\mathbf{y}_{t-1} + \mathbf{u}_{t+h}$$

- Popularly combined with exogenous variables:

$$y_{t+h} = \beta_h x_t + controls + u_{t+h}$$

with x_t an observed or constructed, exogenous impulse of interest.

LP in the context of VAR

- Both VAR and LP produce estimates of the moving average coefficients
- LPs provide a simpler and more convenient way to impose cross-equation restrictions and perform tests directly on the moving average coefficients
- But identification of structural IRFs still requires an estimate of the impact matrix, which LPs do not necessarily help with.
- . . . hence the rising popularity of constructed exogenous regressors in VAR/LP studies.

LP estimation

- LPs estimate the h moving average coefficients directly.
- Most LPs also include lags of the dependent variable as controls.
- With p lags and h impulse–response horizons, we lose $p + h$ observations: p in the beginning of the sample and h at the end.
- Hence small-sample issues are magnified relative to a VAR.
- Stata estimates the full set of IRFs, at all horizons for all variables, jointly.
- This allows easy tests of coefficients across horizons and across variables

LP estimation with lpirf

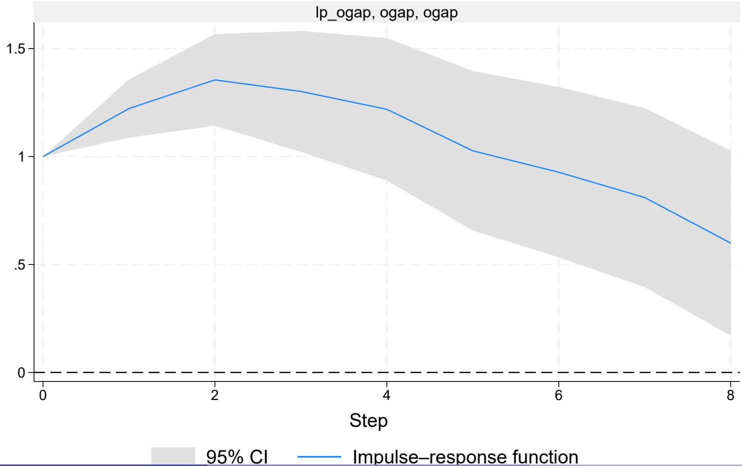
```
. lpirf ogap, lags(1/4)
Local-projection impulse-responses
Sample: 1955q3 thru 2009q1                        Number of obs       = 215
                                                  Number of impulses  =   1
                                                  Number of responses =   1
                                                  Number of controls  =   3
```

	IRF coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
ogap						
F1.	1.222087	.0685199	17.84	0.000	1.087791	1.356384
F2.	1.354971	.1081866	12.52	0.000	1.142929	1.567013
F3.	1.301492	.1425385	9.13	0.000	1.022122	1.580863
F4.	1.218761	.1682287	7.24	0.000	.8890384	1.548483
F5.	1.026617	.1881264	5.46	0.000	.6578963	1.395338
F6.	.9274278	.2011277	4.61	0.000	.5332248	1.321631
F7.	.8099336	.2112339	3.83	0.000	.3959227	1.223944
F8.	.5991371	.2186316	2.74	0.006	.1706271	1.027647

```
Impulses:  ogap
Responses: ogap
Controls:  L2.ogap L3.ogap L4.ogap
```

LP IRF graphs

```
. irf create lp_ogap
(file modelirfs.irf updated)
. irf graph irf, irf(lp_ogap) yline(0)
```



LPs and VARs: further comparisons

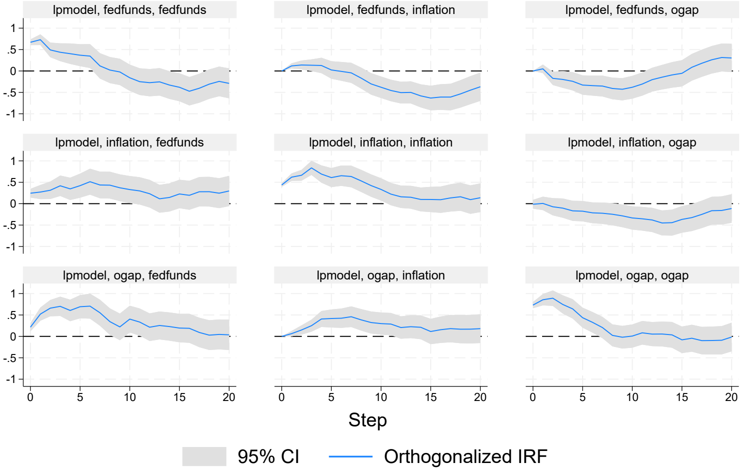
- LPs and VARs both estimate moving-average coefficients
- LPs and VARs both require additional identifying assumptions to make causal statements about their IRFs
- In principle, any identification strategy used in a VAR can also be used in an LP
- Stata implements orthogonalized IRFs for LPs

IRF comparison I

- We can estimate LP IRFs for the same model specification as in the VAR before, graphing the orthogonalized IRFs

```
. quietly lpirf inflation ogap fedfunds, lags(1/8) step(20)

. irf create lpmodel
(file modelirfs.irf updated)

. irf graph oirf, irf(lpmodel) yline(0)
```

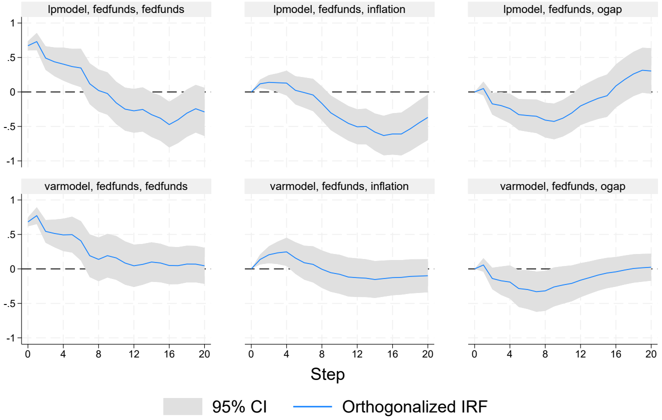
IRF comparison II



Graphs by irfname, impulse variable, and response variable

IRF comparison III

```
. irf graph oirf, irf(varmodel lpmodel) impulse(fedfunds)
```

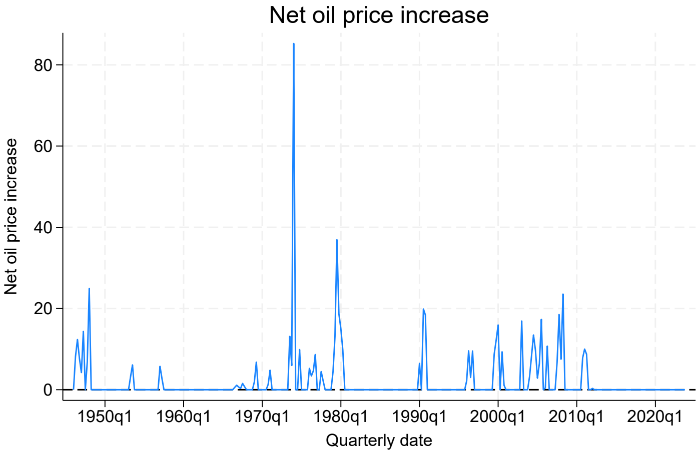


Graphs by irfname, impulse variable, and response variable

LPs with exogenous variables I

- `lpirf` allows for exogenous variables and computes dynamic multipliers for them.
- Convention: dynamic multipliers computed for any $t-$dated variable in the set of controls.
- The dataset I have been using has a constructed measure of oil price shocks, the *net oil price increase* (Hamilton 1996, 2003)
- The net oil price increase is the difference between the price of oil in period t and its maximum in the previous $t - \ell$ quarters.
- Captures persistent movements in the price of oil.

LPs with exogenous variables II



LPs with exogenous variables III

- I estimate LPs for the effect of a net oil price increase on outcome variables, modelling the net oil price increase as exogenous.
- For outcomes inflation, output gap, and interest rate, run

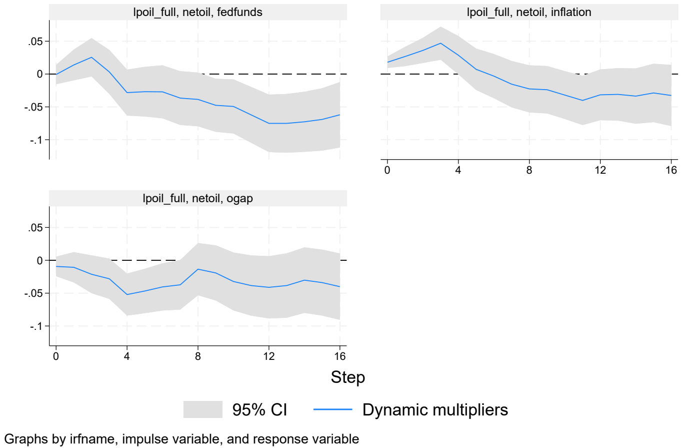
$$y_{t+h} = \beta_h netoil_t + \mathbf{z}'\gamma + u_{t+h}$$

where controls **z** include the first 8 lags of all outcome variables and of the net oil price increase

```
. quietly lpirf inflation ogap fedfunds, exog(L(0/8).netoil) ///
>         lags(1/8) step(17)

. irf create lpoil_full
(file modelirfs.irf updated)

. irf graph dm, irf(lpoil_full) impulse(netoil) yline(0) xlabel(0(4)16)
```

- The resulting impulse responses for a 1% net oil price increase are:

LPs with exogenous variables IV



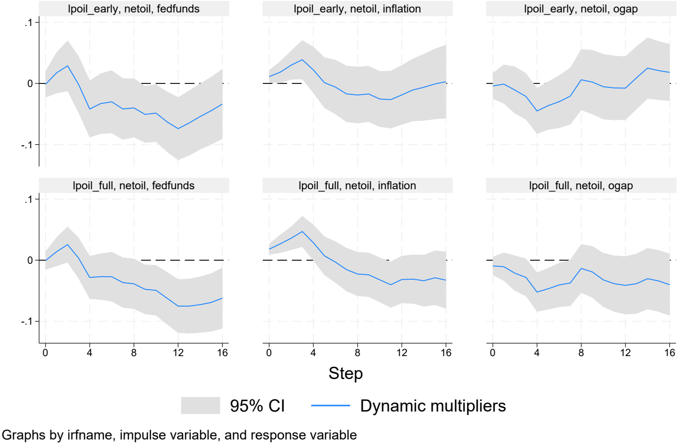
LPs with exogenous variables V

- For comparison, recompute the LPs for the sample through 1985q4,

```
. quietly lpirf inflation ogap fedfunds if tin(, 1985q4), ///
>         exog(L(0/8).netoil) lags(1/8) step(17)

. irf create lpoil_early
(file modelirfs.irf updated)

. irf graph dm, irf(lpoil_full lpoil_early) impulse(netoil) ///
>         yline(0) xlabel(0(4)16)
```

- Comparing the resulting IRFs:

LPs with exogenous variables VI



Summary

- Local projections provide an alternate method for constructing impulse response functions
- LP-IRFs are computed directly, simultaneously, jointly, allowing for easier tests of coefficients
- LPs do not solve identification problems, but can be combined with identification strategies
- Being a regression-based method, clear parallels with and extensions to other regression-based methods

Instruments in impulse response estimation

Instruments in micro

- Consider estimating a coefficient in a regression

$$y_t = \beta x_t + e_t$$

- When $cov(x_t, e_t) \neq 0$ we say x_t is endogenous and we know OLS estimation is inconsistent
- Solution: bring in an instrument z_t with the properties

$$cov(z_t, x_t) \neq 0 \qquad \text{(relevance)}$$
$$cov(z_t, e_t) = 0 \qquad \text{(exclusion)}$$

- Macroeconometrics has a notion of an instrument as well

Instruments in macro I

- Macro systems are driven by unobserved shocks
- An instrument is an observed variable the researcher believes to satisfy

$$cov(z_t, e_{1t}) \neq 0 \qquad \text{(relevance)}$$
$$cov(z_t, e_{jt}) = 0 \qquad \forall j \neq 1 \qquad \text{(exclusion)}$$

(Stock and Watson 2012; Gertler and Karadi 2015; many others)

- An instrument thus satisfies

$$z_t = \gamma e_{1,t} + w_t$$

where $\gamma \neq 0$ ensures relevance, there is no feedback from other shocks, and w_t allows the instrument to be noisy

Instruments in macro II

- Consider a VAR augmented with an instrument:

$$
\begin{aligned}
\mathbf{y}_t &= \mathbf{A}(\ell)\mathbf{y}_{t-1} + \mathbf{u}_t \\
\mathbf{u}_t &= \mathbf{B}\mathbf{e}_t \\
z_t &= \gamma e_{1,t} + w_t
\end{aligned}
$$

Then we can write

$$
\begin{pmatrix} \mathbf{y}_t \\ z_t \end{pmatrix} = \begin{pmatrix} \mathbf{A}_y(\ell) & \mathbf{0} \\ \mathbf{A}_{zy}(\ell) & \mathbf{A}_z(\ell) \end{pmatrix} \begin{pmatrix} \mathbf{y}_{t-1} \\ z_{t-1} \end{pmatrix} + \begin{pmatrix} \mathbf{B}_1 & \mathbf{B}_2 & \mathbf{0} \\ \gamma & \mathbf{0} & \sigma_w \end{pmatrix} \begin{pmatrix} e_{1t} \\ \mathbf{e}_{jt} \\ w_t \end{pmatrix}
$$

- Thus, an SVAR-IV is just a large SVAR (Angelini and Fanelli 2019)
- $\mathbf{B}_1$ contains impact effects for the shock being instrumented
- $\mathbf{B}_2$ contains columns of impact effects for shocks without instruments
- The $\mathbf{0}$ blocks are implied by the propreties of the instrument

SVAR-IV estimation of oil shock IRFs I

- We estimate a VAR in inflation, the output gap, and interest rates, using net oil price shocks as an instrument for “inflation shocks”
- Setup:

```
. matrix A = I(4)
. matrix B1 = (.,0,0,0 \ .,.,0,0 \.,.,.,0 \ .,.,.,.)
. matrix B2 = (.,.,0,0 \ .,.,.,0 \ .,.,.,0 \ .,0,0,.)
. matlist B2

             |        c1         c2         c3         c4
-------------+--------------------------------------------
          r1 |         .          .          0          0
          r2 |         .          .          .          0
          r3 |         .          .          .          0
          r4 |         .          0          0          .
```

- Estimation:

SVAR-IV estimation of oil shock IRFs II

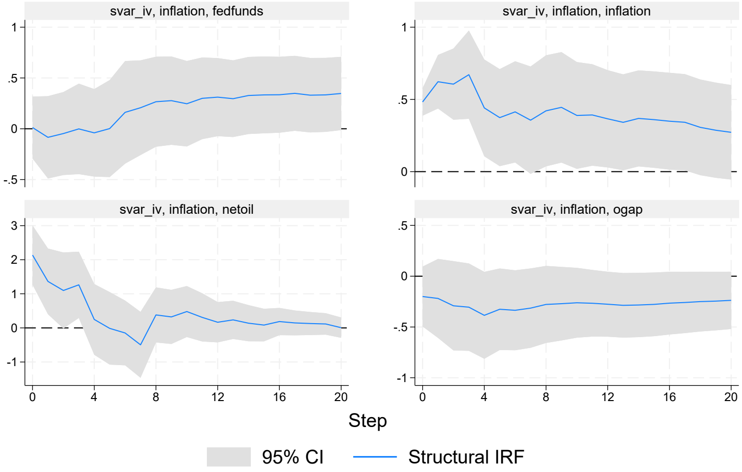
```
. // (constraint setup omitted)
. // get starting values using orthogonalized B matrix
. quietly svar inflation ogap fedfunds netoil, aeq(A) beq(B1)  ///
>         lags(1/8) varconstraint(1/12)

.
. // estimation using the instrument-implied B matrix
. matrix b = e(b)

. quietly svar inflation ogap fedfunds netoil, aeq(A) beq(B2)  ///
>         lags(1/8) from(b) noidencheck varconstraint(1/12)

.
. // parameter estimates; column 1 is identified
. matlist e(B)
```

	inflation	ogap	fedfunds	netoil
inflation	.4824677	.1998924	0	0
ogap	-.2000096	.614898	-.3432701	0
fedfunds	.0123024	.5273174	.505104	0
netoil	2.137743	0	0	6.310632

- Graphs:

```
. irf graph sirf, irf(svar_iv) impulse(inflation) ///
>         yline(0) xlabel(0(4)20) byopts(yrescale)
```

SVAR-IV estimation of oil shock IRFs III



Graphs by irfname, impulse variable, and response variable

Summary

- Instruments aid in solving the IRF identification problem.
- SVAR-IVs can be specified as large SVAR models with particular restrictions imposed by the nature of the instruments.
- Thus some SVAR-IVs can be estimated using existing `svar` tools.
- I showed SVAR-IV estimation of the effects of net oil price shocks.
- Extensions possible combining IV and LP, as well.

Thank you!