Instrumental-variable estimation of large-T panel-data models with common factors

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```
ssc install xtivdfreg
net install xtivdfreg, from(http://www.kripfganz.de/stata/)
```

Common factors in panel data models

- Consider the following (dynamic) panel data model:

$$y_{it} = \alpha y_{i,t-1} + \beta' \mathbf{x}_{it} + u_{it}$$

- A popular approach to account for omitted variables, unobserved heterogeneity, and cross-sectional dependence is to assume a common-factor structure for the regression errors:

$$u_{it} = \gamma'_{y,i} \mathbf{f}_{y,t} + \varepsilon_{it}$$

  - Factors $\mathbf{f}_{y,t}$ are a compact way of summarizing the unobserved variation over time that is common for all units (countries, firms, individuals, ...).
  - The corresponding factor loadings $\gamma_{y,i}$ allow for heterogeneous effects on the units' outcome.
  - Unit-fixed effects and time-fixed effects are special cases.

Common factors in panel data models

- A common approach to estimating common-factor models is the Pesaran (2006) common correlated effects (CCE) estimator:
  - Unobserved common factors are projected out by observed cross-sectional averages.
  - Stata implementation: `xtdcce2` (Ditzen, 2018).
- An alternative is the iterative principal components (IPC) approach of Bai (2009):
  - Principal components are factored out from the error term using nonlinear optimization techniques.
  - Stata implementation: `regife` (Gomez, 2015).
- These approaches suffer from potential shortcomings such as incidental-parameters bias (and size distortions due to ineffective bias correction), the necessity of additional assumptions, computational complexity, and limited flexibility.

Common factors in panel data models

- The unobserved factors are typically allowed to be correlated with the observed explanatory variables, which may themselves be driven by common factors:

$$\mathbf{x}_{it} = \mathbf{\Gamma}'_{x,i}\mathbf{f}_{x,t} + \mathbf{v}_{it}$$

- Norkute, Sarafidis, Yamagata, and Cui (2021) and Cui, Norkute, Sarafidis, and Yamagata (2021) developed a new two-stage instrumental variables (IV) approach.
  - In the first stage, principal components analysis (PCA) is used to project out common factors from exogenous covariates (and their lags). The defactored covariates are valid instruments.
  - In the second stage, PCA is applied to extract factors from the first-stage residuals and to defactor the entire model. The same instruments as in the first stage remain valid.

Common factors in panel data models

- This IV approach is implemented in our new `xtivdfreg` package. It offers a lot of flexibility and is computationally simple due to a linear objective function.
  - External instruments can be incorporated.
  - The covariates and the error term can be driven by different factors.
  - A model with heterogeneous slopes can be estimated using a mean-group estimator.
  - (High-dimensional) fixed effects can be partialled out prior to the estimation; `xtivdfreg` utilizes `reghdfe` (Correia, 2016).
  - Unbalanced panel data set are supported.

Determinants of banks' capital adequacy ratios

```
. xtivdfreg L(0/1).CAR size ROA liquidity, absorb(id t) iv(size ROA liquidity, lags(2)) factmax(3)

Defactored instrumental variables estimation

Group variable: id                             Number of obs          =     16200
Time variable: t                               Number of groups       =       300

Number of instruments  =       9               Obs per group      min =        54
Number of factors in X =       1                                  avg =        54
Number of factors in u =       1                                  max =        54

Second-stage estimator (model with homogeneous slope coefficients)
------------------------------------------------------------------------------
             |               Robust
         CAR | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
         CAR |
         L1. |   .3732316   .0315035    11.85   0.000     .3114859    .4349773
             |
        size |  -2.025311   .1770844   -11.44   0.000     -2.37239   -1.678232
         ROA |   .1999087   .0295306     6.77   0.000     .1420297    .2577877
   liquidity |   1.998128   .4538704     4.40   0.000     1.108559    2.887698
       _cons |   29.99368    4.12824     7.27   0.000     21.90248    38.08488
-------------+----------------------------------------------------------------
     sigma_f |  2.0800886   (std. dev. of factor error component)
     sigma_e |   1.115956   (std. dev. of idiosyncratic error component)
         rho |  .77650224   (fraction of variance due to factors)
------------------------------------------------------------------------------
Hansen test of the overidentifying restrictions         chi2(5)     =   7.3151
H0: overidentifying restrictions are valid              Prob > chi2 =   0.1982
```

Determinants of banks' capital adequacy ratios

```
. xtivdfreg L(0/1).CAR size ROA liquidity, absorb(id t) iv(size ROA liquidity, lags(2)) factmax(0)
(output partially omitted)

Number of instruments   =        9             Obs per group     min =        54
Number of factors in X =        0                               avg =        54
Number of factors in u =        0                               max =        54

Second-stage estimator (model with homogeneous slope coefficients)
------------------------------------------------------------------------------
             |               Robust
         CAR | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
         CAR |
         L1. |    .291951   .1070032     2.73   0.006     .0822287    .5016734
             |
        size |   -.388992   .0839478    -4.63   0.000    -.5535267   -.2244572
         ROA |   .2213907   .0687908     3.22   0.001     .0865632    .3562183
   liquidity |  -.1206136    .376421    -0.32   0.749    -.8583851     .617158
       _cons |   12.55552   3.501715     3.59   0.000     5.692282    19.41875
-------------+----------------------------------------------------------------
     sigma_f |          0   (std. dev. of factor error component)
     sigma_e |  2.0686632   (std. dev. of idiosyncratic error component)
         rho |          0   (fraction of variance due to factors)
------------------------------------------------------------------------------
Hansen test of the overidentifying restrictions        chi2(5)     =   19.1115
H0: overidentifying restrictions are valid             Prob > chi2 =    0.0018

. ivreghdfe CAR size ROA liquidity (L.CAR = L(0/2).(size ROA liquidity)), gmm2s absorb(id t) cluster(id)
(output omitted)
```

Determinants of banks' capital adequacy ratios

```
. xtivdfreg l(0/1).CAR size ROA liquidity, absorb(id t) iv(size ROA liquidity, lags(2)) factmax(3) mg

Defactored instrumental variables estimation

Group variable: id                              Number of obs        =     16200
Time variable: t                                Number of groups     =       300

Number of instruments   =       9               Obs per group     min =        54
Number of factors in X =        1                                 avg =        54
                                                                  max =        54

Mean-group estimator (model with heterogeneous slope coefficients)
------------------------------------------------------------------------------
             |               Robust
         CAR | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
         CAR |
         L1. |   .3751735   .0172599    21.74   0.000     .3413447    .4090022
             |
        size |  -2.178075   .1683235   -12.94   0.000    -2.507983   -1.848167
         ROA |   .2142237   .0375084     5.71   0.000     .1407086    .2877388
   liquidity |   1.456521   .2479702     5.87   0.000     .9705085    1.942534
       _cons |   31.90236   2.083698    15.31   0.000     27.81838    35.98633
------------------------------------------------------------------------------
```

Determinants of banks' capital adequacy ratios

```
. xtivdfreg l(0/1).CAR size ROA liquidity, absorb(id t) iv(size ROA, lags(2) factmax(3))
> iv(liquidity, lags(0) factmax(0) nodoubledefact) mg

Defactored instrumental variables estimation

Group variable: id                          Number of obs         =     16200
Time variable: t                            Number of groups      =       300

Number of instruments  =        7           Obs per group     min =        54
Number of factors in X =        *                             avg =        54
                                                              max =        54

Mean-group estimator (model with heterogeneous slope coefficients)
------------------------------------------------------------------------------
             |               Robust
         CAR |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         CAR |
         L1. |   .3768387   .0215774    17.46   0.000     .3345478    .4191297
             |
        size |  -2.199214   .1688277   -13.03   0.000    -2.530111   -1.868318
         ROA |   .2229961   .0394674     5.65   0.000     .1456415    .3003508
   liquidity |   1.473673   .2578282     5.72   0.000     .9683387    1.979007
       _cons |   32.13583   2.098844    15.31   0.000     28.02217    36.24949
------------------------------------------------------------------------------
* Number of factors in stage 1:
    1 -> size ROA
    0 -> liquidity
    1 -> size ROA (doubledefact)
```

Summary

- The new `xtivdfreg` command enables flexible IV estimation of large-N, large-T panel data models with a multifactor error structure. It can accomodate
  - static and dynamic models,
  - homogeneous and heterogeneous slopes,
  - high-dimensional fixed effects,
  - unbalanced panel data,
  - external instruments,
  - and flexible assumptions about the factor structure of the exogenous covariates.
- For further technical details and examples, see the help file and our article in the *Stata Journal 21* (3).

```
ssc install xtivdfreg
net install xtivdfreg, from(http://www.kripfganz.de/stata/)

help xtivdfreg
```

References

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- Cui, G., M. Norkuté, V. Sarafidis, and T. Yamagata (2021). Two-stage instrumental variable estimation of linear panel data models with interactive effects. *Econometrics Journal*: forthcoming.
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