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Panel-data models with large N and large T: An overview

2021 Stata Economics Virtual Symposium

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November 10, 2021

Motivation

- This talk will be an overview and not very technical.
- For most topics it is a touch-and-go rather than a deep discussion.
- Panel-Time Series regression became very popular in the past years.
- Growing body of literature on methods, for an overview see Smith and Fuertes (2012); Baltagi (2015); Sul (2019); Elhorst et al. (2021).
- Aim of this talk: Overview of the literature and methods and their applications in Stata.

Panel-Time Series??? I

- Panel-Time Series models are a mix of time series and panel data models with a large number of observations over time (T) and cross-section units (N):
- What is large?
- In *theory* it means that N and T grow with the same speed to infinity $(N, T) \xrightarrow{j} \infty$ with $T/N \rightarrow \kappa, \; 0 < \kappa < \infty$.
- In *practice* much harder.
  - Pesaran et al. (1999, p. 80): "When T is large enough that it is sensible to run separate regressions for each group..."
  - Smith and Fuertes (2012, p. 4): "Similar arguments hold for N being large if averaging across units is required for consistency or for central limit theorems to be valid."
  - In a nutshell: enough data to estimate the model in both dimensions.

Panel-Time Series??? II

- Topics when using panel time series models:
  - 'Classical' time series topics (Unit Roots, Stationarity, Cointegration etc.)
  - Dependence over time
  - Cross-Sectional Dependence
  - Slope Heterogeneity
  - Structural Breaks
- In short: panel-time series models combine the 'best' from panel data and time series!

Econometric Model - General Model

- Most general model: dynamic panel model with heterogeneous slopes and interactive fixed effects:

$$\begin{aligned} y_{i,t} &= \lambda_i y_{i,t-1} + \beta_i x_{i,t} + u_{i,t} \\ x_{i,t} &= \gamma_{x,1,i} f_{1,t} + \gamma_{x,2,i} f_{2,t} + \xi_{i,t} \\ u_{i,t} &= \gamma_{u,1,i} f_{1,t} + \gamma_{u,3,i} f_{3,t} + \epsilon_{i,t} \end{aligned}$$

- We observe $y_{i,t}$ and $x_{i,t}$, the common factors $(f_{l,t})$ and the loadings $(\gamma_{k,l,i})$ are unobserved.
- $\xi_{i,t}$ and $\epsilon_{i,t}$ are both IID white noise.
- Heterogeneous slopes for $\lambda_i \sim IID(\lambda, \sigma^2_\lambda)$ and $\beta_i \sim IID(\beta, \sigma^2_\beta)$
- Unit specific and time fixed effects can be nested in the interactive fixed effects.
- Potential dependence across units via the common factors $(f_{m,t}, m = 1, 2, 3)$.

The classics

Unit Roots, Stationary, Cointegration

- The 'classics' receive a lot of attention and there are plenty of packages in Stata
- Unit Roots:
  - `xtbunitroot` (Chen et al., 2021)
  - `xtunitroot`
  - `multipurt`, `pescadf`,....
- Granger Causality:
  - `xtgranger` (Xiao et al., 2021)
  - `xtgcause` (Lopez and Weber, 2017)
- Cointegration:
  - `xtwest` (Persyn and Westerlund, 2008)
  - `xtpedroni` (Neal, 2014)

Cross-Section Dependence (CSD) I

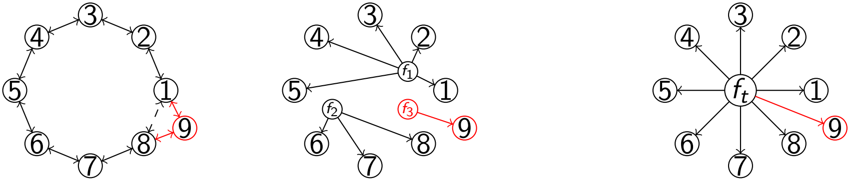
$$x_{i,t} = \gamma_{x,1,i} f_{1,t} + \gamma_{x,2,i} f_{2,t} + \xi_{i,t}$$
$$u_{i,t} = \gamma_{u,1,i} f_{1,t} + \gamma_{u,3,i} f_{3,t} + \epsilon_{i,t}$$

- Cross-section dependence occurs if the factor loadings are not equal to zero.
- It implies that all units are exposed to the same common factor (or shock).
- If it is not accounted for, then CSD potentially leads to:
  1. Omitted variable bias if $\gamma_{x,1,i} \neq 0$ and $\gamma_{u,1,i} \neq 0$
  2. Residuals can be correlated across units if $\gamma_{u,1,i} \neq 0$ and $\gamma_{u,3,i} \neq 0$
- If $\gamma_{x,1,i} = \gamma_{x,2,i} = 0$ then no first order problem for estimator.

Cross-Section Dependence (CSD) II

- Dependence is measured by constant α (Chudik et al., 2011)

$$\lim_{N\to\infty} N^{-\alpha} \sum_{i=1}^{N} |\gamma_{k,i,l}| = K < \infty$$



(Semi-) Weak CSD: $0 \leq \alpha < 0.5$

(Semi-) Strong CSD: $0.5 \leq \alpha \leq 1$

Weak and strong cross-sectional dependence with additional unit 9 as $N \to \infty$

- We can a) estimate the number of factors, b) estimate the exponent of cross-section dependence and c) test for weak cross-section dependence

Estimating number of factors and exponent of CSD

Estimating number of factors

- Either directly estimated (Onatski, 2010; Ahn and Horenstein, 2013; Gagliardini et al., 2019) or determined by information criteria (Bai and Ng, 2002).
- `xtnumfac`[1] (Reese and Ditzen, 2021) implements the methods above.

Estimating the exponent of cross-section dependence

- Bailey et al. (2016, 2019) propose an estimator for the exponent of CSD.
- Estimation only possible for $\alpha > 1/2$.
- In Stata implemented by `xtcse2` (Ditzen, 2021).

[1] available upon request/soon

Testing for weak cross-sectional dependence

...or a zoo of tests...

- Pesaran (2015, 2021) proposes a test for weak cross-section dependence, the CD-test:

  H_0 weak dependence vs. H_1 strong dependence
- Further developments: CDw (Juodis and Reese, 2021), CDw with power enhancement (Fan et al., 2015) and CD* (Pesaran and Xie, 2021)
- CDw, CDw+ and CD* should be applied to residuals, CD can be generally applied.
- In Stata there is a zoo of tests: `xtcsd` (De Hoyos and Sarafidis, 2006), `xtcd` (Eberhardt, 2011), `xtcdf` (Wursten, 2017) and `xtcd2` (Ditzen, 2018).
- The latest version of `xtcd2`[2] implements the CD, CDw, CDw+ and CD*.

[2] update available soon

Testing for slope homogeneity

$$y_{i,t} = \lambda_i y_{i,t-1} + \beta_i x_{i,t} + u_{i,t}$$

- With a large number of cross-sectional units, we are able to estimate coefficients for each unit, i.e. λ_i and β_i.
- Is this necessary? Pesaran and Yamagata (2008) and Blomquist and Westerlund (2013) develop test for slope homogeneity $\beta_i = \beta \forall i$.

  H_0 : slope homogeneity vs. H_1 : slope heterogeneity
- In Stata: `xthst` (Bersvendsen and Ditzen, 2021).

Structural Breaks

- We have a large number of observations over time, possible that coefficients break.
- Assume we have s breaks, then:

$$y_{i,t} = \alpha_i + \beta_i x_{i,t} + \delta_{l,i} z_{i,t} + u_{i,t}, \quad l = 1, ..., s$$

- Bai and Perron (1998, 2003) propose methods to estimate number of breaks and location in time series. Three tests:
  1. No breaks vs. s breaks
  2. No breaks vs. up to s breaks
  3. s breaks vs. $s+1$ breaks
- Karavias et al. (2021); Ditzen et al. (2021a) generalize the methods for panel time series models with cross-section dependence.
- In Stata: `xtbreak` (Ditzen et al., 2021b).

Estimation

...finally...

- Pesaran (2006); Chudik and Pesaran (2015) proposes to approximate the common factors using cross-section averages.

$$y_{i,t} = \alpha_i + \lambda_i y_{i,t-1} + \beta_i x_{i,t} + \sum_{l=0}^{p_T} \left(\psi_{l,x,i} \bar{x}_{t-l} + \psi_{l,y,i} \bar{y}_{t-l} \right) + \epsilon_{i,t}$$

where $p_T = \sqrt[3]{T}$ are the number of lags of the cross-section averages $\bar{x}_t = 1/N \sum_{i=1}^{N} x_{i,t}$ and $\bar{y}_t = 1/N \sum_{i=1}^{N} y_{i,t}$.

- We can use the pooled or mean group estimator.
- In a dynamic model the pooled estimator will be biased however!
- Long run relationships can be estimated using CS-ECM, CS-ARDL and CS-DL estimator.

Estimation

CCE-MG and CCE-P

Mean Group Estimator (Pesaran and Smith, 1995; Pesaran, 2006; Chudik and Pesaran, 2019)

- $\hat{\beta}_{MG} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_i$
- Variance estimator $V(\hat{\beta}_{MG}) = \frac{1}{N(N-1)}\sum_{i=1}^{N}\left(\hat{\beta}_i - \hat{\beta}_{MG}\right)^2$
- Note: Variance estimator is independent (!!) of residuals. It relies on the assumption that we consistently estimate the individual slope coefficients and that they are distributed around a common mean.

Pooled CCE Estimator (Pesaran, 2006)

- Estimate β_p directly with the condition $\beta_i = \beta_p$.
- Various variance estimators, such as $V(\hat{\beta}_p)_{np} = f(\hat{\beta}_i, \hat{\beta}_{MG}, \tilde{X}'\tilde{X})$ or $V(\hat{\beta}_p)_{hac} = f(\hat{\beta}_p, \tilde{X}'\tilde{X}, \hat{\epsilon}_{i,t})$.
- Depending on the estimator, we need to make sure that the residuals are cross-section dependence free!

Introduction

- We want to estimate a simple Solow-style growth model.
- Data: Penn World Tables with 93 countries over years 1960 - 2007
- Static model:

$$log\_rgdpo_{i,t} = \beta_{0,i} + \beta_{1,i} log\_hc_{i,t} \\ + \beta_{2,i} log\_ck_{i,t} + \beta_{3,i} log\_ngd_{i,t} + u_{i,t}$$

- Variables:
  - `log_rgdpo`: Real GDP per capita
  - `log_hc`: human capital
  - `log_ngd`: population growth rate
  - `log_ck`: capital stock

Testing for cross-section dependence

- First step we are using `xtcd2` to test for weak cross-section dependence.[3]

  H_0 : weak dependence, H_1: strong dependence

```
. xtcd2 log_rgdpo log_hc log_ck log_ngd, pesaran
Testing for weak cross-sectional dependence (CSD)
   H0: weak cross-section dependence
   H1: strong cross-section dependence
```

	CD
log_rgdpo	145.97 (0.000)
log_hc	427.70 (0.000)
log_ck	417.23 (0.000)
log_ngd	75.83 (0.000)

```
p-values in parenthesis.
References
  CD:        Pesaran (2015, 2021)
```

- We only use the CD test (Pesaran, 2015) as indicated by the option `pesaran`.
- We find strong cross-section dependence for all variables.

[3] Preliminary version, results might change!

Estimating the exponent and number of common factors I

- We use xtcse2

```
. xtcse2 log_rgdpo log_hc log_ck log_ngd, nocd
Cross-Sectional Dependence Exponent Estimation and Test
Panel Variable (i): id
Time Variable (t): year
Estimation of Cross-Sectional Exponent (alpha)
```

variable	alpha	Std. Err.	[95% Conf.	Interval]
log_rgdpo	.9554411	.0399948	.8770528	1.033829
log_hc	1.002321	.0544753	.8955511	1.10909
log_ck	1.002318	.0676462	.8697337	1.134902
log_ngd	.9790158	.133342	.7176703	1.240361

```
0.5 <= alpha < 1 implies strong cross-sectional dependence.
Variables are centered around zero.
```

- Again, test for cross-section dependence confirms earlier results, strong cross-section dependence found.

Estimating the exponent and number of common factors II

- Next we estimate the number of factors using `xtnumfac` (only for the dependent variable)

```
. xtnumfac log_rgdpo
Information criteria for number of common factors in log_rgdpo
                                   N  =        93
                                   T  =        48
```

IC	# factors	IC	# factors
PC_{p1}	8	IC_{p1}	8
PC_{p2}	8	IC_{p2}	8
PC_{p3}	8	IC_{p3}	8
ER	1	GR	1
GOL	1	ED	4

```
8 factors maximally considered.
PC_{p1},...,IC_{p3} from Bai and Ng (2002)
ER, GR from Ahn and Horenstein (2013)
ED from Onatski (2010)
GOL from Gagliardini, Ossola, Scaillet (2019)
```

- Evidence for common factors, but results differ.
- Ignore GOL as it is only for residuals.
- Advantage of the CCE estimator, no detailed knowledge of number of factors required.

Testing for slope homogeneity

- `xthst` implements tests for slope homogeneity:

  H_0 homogeneous slopes vs. H_1 heterogeneous slopes

- We control for cross-section dependence using the `cr()` option:

```
. xthst log_rgdpo log_hc log_ck log_ngd, ///
> cr(log_rgdpo log_hc log_ck log_ngd) hac
Testing for slope heterogeneity
(Blomquist, Westerlund. 2013. Economic Letters)
H0: slope coefficients are homogenous
-------------------------------------
         Delta          p-value
         45.915           0.000
 adj.    48.842           0.000
-------------------------------------
HAC Kernel: bartlett
with average bandwith 3
Variables partialled out: constant
Cross Sectional Averaged Variables: log_rgdpo log_hc log_ck log_ngd
```

- We find that the slopes are heterogenous.

Number of breaks

- xtbreak implements estimators for number of and location of breaks.
- As before, we control for strong cross-section dependence using the csd option:

```
. xtbreak log_rgdpo log_hc log_ck log_ngd, csd vce(hac)
Sequential test for multiple breaks at unknown breakpoints
(Ditzen, Karavias & Westerlund. 2021)
```

	Test Statistic	Bai & Perron Critical Values: 1% Critical Value	5% Critical Value	10% Critical Value
F(1|0)	0.08	18.26	13.98	12.08
F(2|1)	5.21	19.77	15.72	13.91
F(3|2)	1.66	20.75	16.83	14.96
F(4|3)	0.62	21.98	17.61	15.68
F(5|4)	0.63	22.46	18.14	16.35
Detected number of breaks:		.	.	.

```
The detected number of breaks indicates the highest number of
 breaks for which the null hypothesis is rejected.
No breaks found, cannot estimate breakpoints.
```

- We find no evidence for structural breaks.
- Note: assumption that slope coefficients are homogenous!

Estimation

- We established we have a) cross-section dependence, b) heterogeneous slopes, and c) no breaks.
- Hence, we need an estimator which accounts for a) and b): the CCE-MG estimator and estimate the following equation:

$$\begin{aligned} log\_rgdpo_{i,t} &= \beta_{0,i} + \beta_{1,i} log\_hc_{i,t} + \beta_{2,i} log\_ck_{i,t} \\ &+ \beta_{3,i} log\_ngd_{i,t} + \gamma_i \bar{z}_t + \epsilon_{i,t} \end{aligned}$$

- where $\bar{z}_t$ is a vector with the cross-section averages of the dependent and independent variables.
- The CCE-MG estimator will be used and remaining cross-section dependence in the residuals is tested after.
- The analysis will be done using `xtdcce2`.[4]

[4] update available soon

Static MG

```
. xtdcce2 log_rgdpo log_hc log_ck log_ngd, fast2 nocross
(Dynamic) Common Correlated Effects Estimator - Mean Group (xtdcce2fast)

Panel Variable (i): id                              Number of obs      =       4371
Time Variable (t): year                             Number of groups   =         93

Degrees of freedom per group:                       Obs per group (T) =         47
 without cross-sectional averages    = 43
 with cross-sectional averages       = 43
Number of                                           R-squared (mg)     =       0.92
 cross-sectional lags                none           CD Statistic       =      31.22
 variables in mean group regression = 372              p-value         =     0.0000
 variables partialled out            = 0
--------------------------------------------------------------------------------
   log_rgdpo |      Coef.   Std. Err.       z    P>|z|      [95% Conf. Interval]
-------------+------------------------------------------------------------------
 Mean Group: |
      log_hc | -.1585699    .2677876    -0.59    0.554     -.683424    .3662842
      log_ck |  .3685834    .0416629     8.85    0.000     .2869257    .4502412
     log_ngd |   .318421    .1599968     1.99    0.047     .0048329     .632009
       _cons |  4.900441    .5768085     8.50    0.000     3.769917    6.030965
--------------------------------------------------------------------------------
Mean Group Variables: log_hc log_ck log_ngd _cons
```

- We use the option `fast2` which uses a speed optimized version of `xtdcce`.
- No cross-sectional averages added, a lot of cross-section dependence left in the model.
- Likely that the remaining CSD is correlated with the CSD in the variables.
- Next step: add cross-section averages.

Static CCE-MG

```
. xtdcce2 log_rgdpo log_hc log_ck log_ngd, fast2 ///
> cr(log_rgdpo log_hc log_ck log_ngd)
(Dynamic) Common Correlated Effects Estimator - Mean Group (xtdcce2fast)
Panel Variable (i): id                            Number of obs      =      4371
Time Variable (t): year                           Number of groups   =        93
Degrees of freedom per group:                     Obs per group (T)  =        47
 without cross-sectional averages    = 43
 with cross-sectional averages       = 39
Number of                                         R-squared (mg)     =      0.96
 cross-sectional lags                = 0          CD Statistic       =      0.29
 variables in mean group regression = 372            p-value         =    0.7754
 variables partialled out            = 372
-------------------------------------------------------------------------------
   log_rgdpo|     Coef.   Std. Err.      z     P>|z|     [95% Conf. Interval]
-------------------------------------------------------------------------------
 Mean Group:|
      log_hc| -.6393411   .3986611   -1.60    0.109    -1.420702   .1420203
      log_ck|  .2714685   .0535893    5.07    0.000     .1664354   .3765017
     log_ngd| -.0349364   .1418044   -0.25    0.805    -.312868    .2429953
       _cons| -2.315308   1.330156   -1.74    0.082    -4.922366   .2917494
-------------------------------------------------------------------------------
Mean Group Variables: log_hc log_ck log_ngd _cons
Cross Sectional Averaged Variables: log_rgdpo log_hc log_ck log_ngd
```

- Cross-section dependence is well taken out of the model.
- Only physical capital is significant.
- Comparing the model to a pooled model possible but does not improve results.

Static CCE-MG

Testing for CSD

- Re-run the tests for weak cross-section dependence[5]

```
. xtcd2
Residuals calculated using  predict, residuals from xtdcce2.
Testing for weak cross-sectional dependence (CSD)
   H0: weak cross-section dependence
   H1: strong cross-section dependence
```

	CD	CDw	CDw+	CD*
residuals	0.29	-0.82	5550.32	-1.32
	(0.775)	(0.415)	(0.000)	(0.188)

```
p-values in parenthesis.
References
  CD:        Pesaran (2015, 2021)
  CDw:       Juodis, Reese (2021)
  CDw+:      CDw with power enhancement from Fan et. al. (2015)
  CD*:       Pesaran, Xie (2021) with 4 PC(s)
```

[5] Preliminary version, results might change!

Dynamic Models

- It is more standard to estimate a dynamic model:

$$log\_rgdpo_{i,t} = \beta_{0,i} + \lambda_i log\_rgdpo_{i,t-1} + \beta_{1,i} log\_hc_{i,t} + \beta_{2,i} log\_ck_{i,t} + \beta_{3,i} log\_ngd_{i,t} + \sum_{l=1}^{p_T} \gamma_{i,l} \bar{z}_{t-l} + \epsilon_{i,t}$$

- To account for the dynamics, we add $p_T = \sqrt[3]{T}$ lags of the cross-section averages (Chudik and Pesaran, 2015).
- Some notes:
  - Interpretation of the CD test requires care.
  - CCE Pooled would be biased.

Dynamic CCE-MG

```
. xtdcce2 log_rgdpo L.log_rgdpo log_hc log_ck log_ngd, fast2 ///
> cr(log_rgdpo log_hc log_ck log_ngd) cr_lags(3)
(Dynamic) Common Correlated Effects Estimator - Mean Group (xtdcce2fast)

Panel Variable (i): id                          Number of obs      =       4092
Time Variable (t): year                         Number of groups   =         93

Degrees of freedom per group:                   Obs per group (T)  =         44
 without cross-sectional averages    = 39
 with cross-sectional averages       = 23
Number of                                       R-squared (mg)     =       0.98
 cross-sectional lags                = 3        CD Statistic       =       1.40
 variables in mean group regression = 465          p-value         =     0.1601
 variables partialled out            = 1488
------------------------------------------------------------------------------
   log_rgdpo |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 Mean Group:
 L.log_rgdpo |   .3864255   .0311066    12.42   0.000     .3254577    .4473934
      log_hc |  -1.286829   .3900789    -3.30   0.001     -2.05137   -.5222887
      log_ck |   .2098063     .04939     4.25   0.000     .1130036    .3066089
     log_ngd |   .0052778   .1006462     0.05   0.958    -.1919851    .2025408
       _cons |  -2.174129   1.786946    -1.22   0.224    -5.676478    1.328221
------------------------------------------------------------------------------
Mean Group Variables: L.log_rgdpo log_hc log_ck log_ngd _cons
Cross Sectional Averaged Variables: log_rgdpo log_hc log_ck log_ngd
```

- Human and physical capital are now significant.
- Note the number of variables in the mean group regression and being partialled out.
- Value of CD-test statistic still low.
- We can estimate the long run relationships using the CS-ARDL estimator.

Dynamic CCE - CS-ARDL

```
. xtdcce2 log_rgdpo , fast2 cr(log_rgdpo log_hc log_ck log_ngd) cr_lags(3) ///
> lr(L.log_rgdpo log_hc log_ck log_ngd) lr_options(ardl)
(Dynamic) Common Correlated Effects Estimator - Mean Group (xtdcce2fast)
Panel Variable (i): id                          Number of obs     =       4092
Time Variable (t): year                         Number of groups  =         93
Degrees of freedom per group:                   Obs per group (T) =         44
 without cross-sectional averages    = 39
 with cross-sectional averages       = 23
Number of                                       R-squared (mg)    =       0.98
 cross-sectional lags                = 3        CD Statistic      =       1.40
 variables in mean group regression = 465          p-value        =     0.1601
 variables partialled out            = 1488
------------------------------------------------------------------------------
     log_rgdpo |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+--------------------------------------------------------------
 Short Run Est.|
---------------+--------------------------------------------------------------
 ...
---------------+--------------------------------------------------------------
 Adjust. Term  |
---------------+--------------------------------------------------------------
   Mean Group: |
   lr_log_rgdpo| -.6135745   .0311066  -19.72   0.000    -.6745423   -.5526066
---------------+--------------------------------------------------------------
 Long Run Est. |
---------------+--------------------------------------------------------------
   Mean Group: |
      lr_log_hc| -1.854644   .7475237   -2.48   0.013    -3.319763   -.3895246
      lr_log_ck|  .0895815   .2191939    0.41   0.683    -.3400306    .5191935
     lr_log_ngd| -.3731947   .3800709   -0.98   0.326     -1.11812    .3717306
------------------------------------------------------------------------------
Mean Group Variables: L.log_rgdpo log_hc log_ck log_ngd _cons
Cross Sectional Averaged Variables: log_rgdpo log_hc log_ck log_ngd
Long Run Variables: L.log_rgdpo log_hc log_ck log_ngd
Cointegration variable(s): lr_log_rgdpo
```

- The long run estimates are $\beta_{LR,i} = (\sum_{l=1}^{L_x} \beta_{l,i})/(1 - \sum_{l=1}^{L_y} \alpha_{l,i})$ and we can apply the MG estimator to $\beta_{LR,i}$.
- Adjustment is -0.614.
- CD test statistic still very low.

Conclusion

or take aways

- Panel-Time series models offer a lot of flexibility and insights into data.
- They require large N and large T.
- Account for cross-section dependence appropriately, there is some caution needed when using dynamic models.
- Cross-section dependence is a first order problem for estimators, using CSD robust standard errors does not help!
- Do you assume heterogeneous slopes or not?
- The road ahead:
  - Spatial Temporal Error correction models (Bhattacharjee et al., 2021)
  - Endogeneity (see next talk)
  - Lag selection
  - Correlation between common factors in exogenous variables (x) and error (u)

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