

## **4: Long-Run Relationships (ARDL)**

**GECO 6281 Advanced Econometrics 1 (Lab)**

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Fall 2019

# Auto-Regressive Distributed Lag Models

- ▶ Model the relationship between variables in a single-equation setup
- ▶ Error Correction Representation is equivalent to co-integration of non-stationary variables
- ▶ EC representation is used to test for a long-run cointegrating relationship
- ▶ This allows for testing without knowing if the co-integrating variables are  $I(0)$  or  $I(1)$  themselves
- ▶ Examples: Wages and Labor Productivity, Foreign Direct Investment and Capital Intensity

## Engle-Granger (1987) Test for long-run relationships

Assume  $(y_t, x_t)'$  is a vector of I(1) variables

First Step: Run levels OLS  $y_t = \alpha_1 + x_t' \beta + v_t$

Test if  $v_t$  is stationary (e.g. Adjusted Dickey Fuller or KPSS test)

Second Step: Estimate an error correction model and include lagged residuals  $\hat{v}_{t-1}$  (if they are stationary):

$$\Delta y_t = \alpha_2 + \gamma \hat{v}_{t-1} + \sum_i^{p-1} \phi_{yi} \Delta y_{t-i} + \sum_j^{p-1} \phi_{xj} \Delta x_{t-j} + u_t$$

Test whether  $-1 \leq \gamma < 0$ .

## Engle-Granger (1987): Downsides

variables must be  $I(1)$  and tested beforehand.

In short panels, first-step OLS estimates may be biased because of omitted short-run dynamics (no  $x_t$  as covariate), which influences the second step.

Standard significance testing in the first step is not available because asymptotic distribution of  $\hat{\beta}$  is non-normal.

## Engle-Granger (1987): Application

```
use usa.dta, clear
gen date = tq(1984q1) + _n-1
tsset date

dfuller f
dfuller D.f      // f is integrated of order 1

dfuller b
dfuller D.b      // b is integrated with order 1

reg b f
predict e, resid
dfuller e, noconstant
tsline e
```

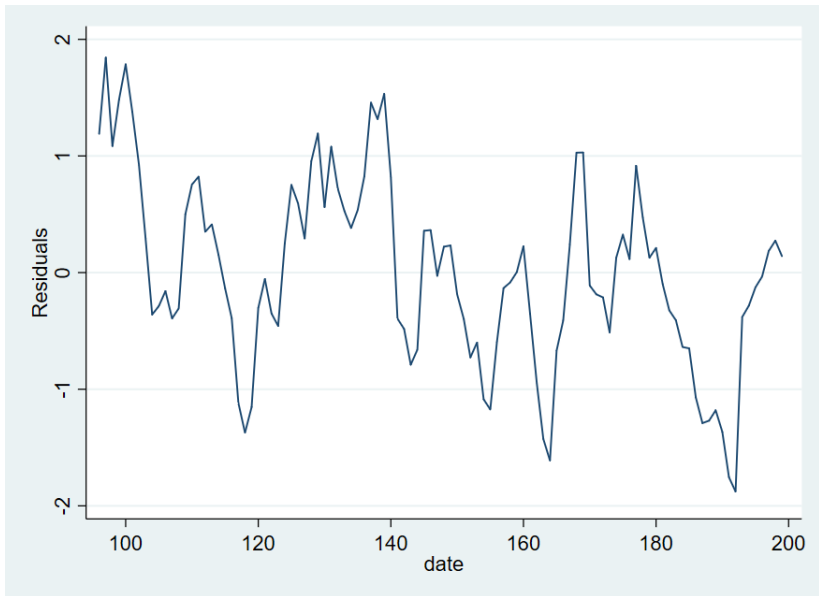
# Engle-Granger (1987): Results

```
. dfuller e, noconstant
```

```
Dickey-Fuller test for unit root                Number of obs   =           103
```

```
----- Interpolated Dickey-Fuller -----  
          Test          1% Critical    5% Critical    10% Critical  
          Statistic     Value          Value          Value  
-----  
Z(t)           -3.188           -2.600           -1.950           -1.610
```

## Engle-Granger (1987): Results 2



## Possible Models for long-run relationships

(<https://davegiles.blogspot.com/2013/06/ardl-models-part-ii-bounds-tests.html>)

If one wants to understand the dynamic relationship between two variables, there is a number of possible cases:

- ▶ Both are  $I(0)$ , i.e. stationary. Then an OLS on the variable levels will be unbiased and efficient.
- ▶ The variables are integrated of the same order (eg.  $I(1)$ ) but *not cointegrated*. Appropriate differentiation (i.e. first difference for first order integration) allows for OLS estimation.
- ▶ The variables are integrated of the same order *and* co-integrated. Then a level OLS provides the long-run relationship, whereas an Error Correction Model (ECM) (which can be estimated using OLS) represents the short-run dynamics.
- ▶ Data might be of different orders and/or co-integrated (“things are not as clear cut”). ARDL analyzes *both* short-run dynamics and long-run relationships.



# ARDL: Pre-Requisites and Procedure

- ▶ none of the variables must be I(2)
- ▶ The model is written as an unrestricted ECM
$$\Delta y_t = \alpha + \sum_i^{p-1} \beta_1 \Delta y_{t-i} + \sum_j^{p-1} \beta_2 \Delta x_{t-j} + \gamma_1 y_{t-1} + \gamma_2 x_{t-1} + \epsilon_t$$
- ▶ an appropriate lag structure is determined, e.g. using information criteria
- ▶ test for *serially independent errors*
- ▶ test for *dynamic stability*
- ▶ Pesaran-Shin-Smith Bounds test for long-run relationship (later in semester)
- ▶ estimate long-run “levels” model and short-run ECM

# ARDL in STATA

```
. ardl eur us, aic //Use Akaike Information Criterion to decide on optimal mode
```

```
ARDL(4,0) regression
```

```
Sample:          424 -          614                Number of obs   =          191
                                                F(   5,   185)   =        3004.38
                                                Prob > F         =          0.0000
                                                R-squared       =          0.9878
                                                Adj R-squared   =          0.9875
Log likelihood = -75.256023                Root MSE        =          0.3646
```

```
-----+-----
```

eur	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
eur					
L1.	1.055477	.0698777	15.10	0.000	.9176176 1.193337
L2.	.0733688	.1042555	0.70	0.482	-.1323138 .2790513
L3.	.1138271	.1057457	1.08	0.283	-.0947953 .3224496
L4.	-.2835677	.0690439	-4.11	0.000	-.4197823 -.147353
us	.0526194	.0142578	3.69	0.000	.0244906 .0807482
_cons	-.0077393	.0609519	-0.13	0.899	-.1279894 .1125109

```
-----+-----
```

([http://repec.org/usug2018/uk18\\_Kripfganz.pdf](http://repec.org/usug2018/uk18_Kripfganz.pdf))

$$y_t = \alpha_0 + \alpha_1 t + \sum_i^p \phi_i y_{t-i} + \sum_j^q \beta_j' x_{t-j} + u_t$$

- ▶ Coefficients represent the long-term relationship between variable levels
- ▶ Include auto-regressive terms
- ▶ Include a time trend (trend stationarity)

# ARDL in STATA 3 (ECM)

```
. ardl eur us, bic ec
```

```
ARDL(4,0) regression
```

```
Sample:          424 -          614
```

```
Number of obs   =          191
```

```
R-squared       =          0.2943
```

```
Adj R-squared  =          0.2753
```

```
Root MSE      =          0.3646
```

```
Log likelihood = -75.256023
```

		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----							
ADJ	eur						
	L1.	-.0408945	.0103098	-3.97	0.000	-.0612345	-.0205546
-----+-----							
LR	us	1.286711	.3021187	4.26	0.000	.6906697	1.882751
-----+-----							
SR	eur						
	LD.	.0963718	.0681707	1.41	0.159	-.0381202	.2308637
	L2D.	.1697405	.0678472	2.50	0.013	.0358869	.3035941
	L3D.	.2835677	.0690439	4.11	0.000	.147353	.4197823
	cons	-.0077393	.0609519	-0.13	0.899	-.1279894	.1125109

## ARDL in STATA 4: Interpretation of the Conditional EC Formulation

$$\Delta y_t = \alpha_0 + \alpha_1 t + \alpha_2 (y_{t-1} - \theta x_t) + \sum_{i=1}^{p-1} \psi_{yi} \Delta y_{t-i} + \sum_{i=0}^{q-1} \psi'_{xi} \Delta x_{t-i} + u_t$$

- ▶  $\alpha_2$  is the *speed-of-adjustment* parameter, measuring how fast the system returns to equilibrium. It is denoted as a negative (“ADJ”).
- ▶  $\alpha_2 = 1 - \sum_{j=1}^p \phi_j$  (from the level-ARDL regression).
- ▶  $\theta = \frac{\sum_{j=0}^q \beta_j}{\alpha_2}$  denotes the long run coefficients from the same *first step*. (“LR”)
- ▶  $\psi$  just denote the short-run coefficients from the second, error-correcting step (“SR”)

# ARDL in STATA 5: Alternative Error Correction Representation

```
. ardl eur us, bic ec1
```

```
ARDL(4,0) regression
```

```
Sample:          424 -          614          Number of obs   =          191
                                     R-squared           =          0.2943
                                     Adj R-squared        =          0.2753
Log likelihood = -75.256023          Root MSE           =          0.3646
```

```
-----+-----
          D.eur |          Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
ADJ      |
          eur |
          L1. |   -.0408945   .0103098    -3.97   0.000   -.0612345   -.0205546
-----+-----
LR       |
          us  |
          L1. |    1.286711   .3021187     4.26   0.000    .6906697    1.882751
```

# # ARDL in STATA 6: Alternative Error Correction Representation

SR							
eur							
LD.		.0963718	.0681707	1.41	0.159	-.0381202	.2308637
L2D.		.1697405	.0678472	2.50	0.013	.0358869	.3035941
L3D.		.2835677	.0690439	4.11	0.000	.147353	.4197823
us							
D1.		.0526194	.0142578	3.69	0.000	.0244906	.0807482
_cons		-.0077393	.0609519	-0.13	0.899	-.1279894	.1125109

---

## ARDL in STATA 7: Alternative Error Correction Representation

$$\Delta y_t = \alpha_0 + \alpha_1 t + \alpha_2 (y_{t-1} - \theta x_{t-1}) + \sum_{i=1}^{p-1} \psi_{yi} \Delta y_{t-i} + \omega' \Delta x_{t-1} + \sum_{i=1}^{q-1} \psi'_{xi} \Delta x_{t-i} + u_t$$

- ▶  $\Delta x_{t-1}$  is isolated with coefficient  $\omega$  (“SR”: “D1”)
- ▶ Thus, the long-run dynamics only include lag levels (“LR”: “L1”).



## Extending Arellano-Bond 1 (Repetition)

A dynamic panel model can be written in fixed effects.

$$y_{it} = \alpha_i + \sum_j^p \gamma_j y_{it-j} + x_t' \beta + \epsilon_{it}$$

$y$  can be correlated (1) directly through lags of  $y$  (“true state dependency”), (2) directly through  $x$  (“observed heterogeneity”) or (3) indirectly through individual effects  $\alpha_i$  (“unobserved heterogeneity”). Keep in mind that individual effects respond to unobserved characteristics.

Note that mean difference (“within”) is inconsistent, as is instrumented mean difference estimation, as mean differences will be correlated with the mean error term.

First Difference estimation is also inconsistent, but instrumented first difference estimation is permitted.

$$\Delta y_{it} = \sum_j^{p-1} \gamma_j \Delta y_{i,t-j} + \Delta x_t' \beta + \Delta \epsilon_{it}$$

Note that  $\Delta \epsilon_{it} = \epsilon_{i,t} - \epsilon_{i,t-1}$  is correlated with  $\Delta y_{it-1} = y_{it-1} - y_{it-2}$ .

## Extending Arellano-Bond 2 (Repetition)

- ▶ Anderson-Hsiao:  $y_{t-2}$  is uncorrelated with  $\Delta\epsilon_{it}$  and can be used as an instrument for  $\Delta y_{it-1}$
- ▶ Arellano-Bond: Adding more lags as instruments makes estimation more efficient
- ▶ Using the General Method of Moments (GMM) is even more efficient. Restricting lags in long and narrow samples (large  $T$ ) increases asymptotic performance. `vce(robust)` includes Windmeijer (2005) robust standard errors.

# Extending Arellano-Bond 3 (Repetition 2)

```
. xtabond lwage, lags(2) twostep vce(robust)
```

```
Arellano-Bond dynamic panel-data estimation  
Group variable: id  
Time variable: t
```

```
Number of obs      =      2,380  
Number of groups   =        595
```

```
Obs per group:  
      min =          4  
      avg =          4  
      max =          4
```

```
Number of instruments =      15
```

```
Wald chi2(2)       =     1974.40  
Prob > chi2        =          0.0000
```

```
Two-step results
```

```
(Std. Err. adjusted for clustering on id)
```

---

	Coef.	WC-Robust Std. Err.	z	P> z	[95% Conf. Interval]	
lwage						
L1.	.6095931	.0330542	18.44	0.000	.544808	.6743782
L2.	.2708335	.0279226	9.70	0.000	.2161061	.3255608
_cons	.9182262	.1339978	6.85	0.000	.6555952	1.180857

---

```
Instruments for differenced equation
```

```
GMM-type: I(2/ ) lwage
```

## Extending Arellano-Bond 3

Both Arellano-Bover and Blundell-Bond introduce a restriction  $E(\Delta y_{it-1} \epsilon_{it}) = 0$  such that  $\Delta y_{it-1}$  can be introduced as an instrument.

This is a solution for the problem that the pure Arellano-Bond instruments tend to suffer from weak instrumental variable problems.

```
use mus08psidextract.dta, clear
xtdpdsys lwage, lags(2) twostep
```

```
System dynamic panel-data estimation
Group variable: id
Time variable: t
```

```
Number of obs      =      2,975
Number of groups   =         595
```

```
Obs per group:
      min =          5
      avg =          5
      max =          5
```

```
Number of instruments =      20
```

```
Wald chi2(2)      =      4174.06
Prob > chi2       =          0.0000
```

```
Two-step results
```

```
-----+-----
      lwage |          Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      lwage |
      L1. |   .6017105   .019114   31.48   0.000   .5642477   .6391732
      L2. |   .2880127   .0179783   16.02   0.000   .2527759   .3232496
      |
```

# Compare Arellano-Bond and Arellano-Bover

```
. quietly xtabond lwage, lags(2) twostep  
. estimates store abond2  
  
. quietly xtdpdsys lwage, lags(2) twostep  
. estimates store abover1  
  
. esttab abond2 abover1, mtitles("Arellan-Bond" "Arellano-Bover")
```

	Ar.nd lwage	Ar.er lwage
L.lwage	0.610*** (26.70)	0.602*** (31.48)
L2.lwage	0.271*** (14.30)	0.288*** (16.02)
_cons	0.918*** (7.17)	0.856*** (9.34)
N	2380	2975

# Serial Corellation

Both Arellano-Bond and Arellano-Bover/Blundell-Bond methdoologies require the error terms to be serially uncorrelated.

Autocorrelation in  $\epsilon_{it}$  and  $\epsilon_{it-1}$  (absent individual effects) would render  $y_{t-2}$  be endogenous to  $v_{it-1}$ .

This can be tested using `estat abond`.

```
. estat abond //Test for serial correlation of error terms
```

Arellano-Bond test for zero autocorrelation in first-differenced errors

```
+-----+
|Order | z      Prob > z|
+-----+-----+
|  1  |-4.3902 0.0000 |
|  2  |-2.1733 0.0298 |
+-----+-----+
H0: no autocorrelation
```

## Treating Serial Correlation in the error term

- ▶ Include more and earlier lags, then re-do the test
- ▶ Model a moving average process in the error term:  $v_{it} = \epsilon_{it} + \theta v_{it-1}$
- ▶ In STATA, `xtdpd` allows for this (`dpd` denotes “dynamic panel data”)

# Arellano-Bover in xtddpd

Reproduce earlier model

```
xtddpd L(0/2).lwage, dgmiv(lwage) twostep
```

Dynamic panel-data estimation

Group variable: id

Time variable: t

Number of obs = 2,975

Number of groups = 595

Obs per group:

min = 5

avg = 5

max = 5

Number of instruments = 15

Wald chi2(2) = 1471.72

Prob > chi2 = 0.0000

One-step results

lwage	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
lwage					
L1.	.5707517	.024875	22.94	0.000	.5219976 .6195058
L2.	.2675649	.0203552	13.14	0.000	.2276694 .3074605
_cons	1.203588	.1455457	8.27	0.000	.9183232 1.488852



## Arellano-Bover with Moving Average: Results 2

```
. esttab abond1 abover1 xtdpd1, mtitles("Arellano-Bond" "Arellano-Bover 1" "Are
```

	(1)	(2)	(3)
	Arellano-B~d	Arellano-B~1	Arellano-B~2
L.lwage	0.946*** (82.32)	0.602*** (31.48)	0.610*** (26.70)
L2.lwage		0.288*** (16.02)	0.271*** (14.30)
_cons	0.451*** (5.93)	0.856*** (9.34)	0.918*** (7.17)
N	2975	2975	2975

t statistics in parentheses

\* p<0.05, \*\* p<0.01, \*\*\* p<0.001

## Arellano-Bover with Moving Average: Results 3

```
. estat abond //test for serial autocorrelation again
```

Arellano-Bond test for zero autocorrelation in first-differenced errors

```
+-----+
|Order | z      Prob > z|
+-----+-----+
|  1  |-4.5381 0.0000 |
|  2  |-1.9946 0.0461 |
+-----+-----+
H0: no autocorrelation
```

⇒ Problem is not solved by reroducing model in a different package! (Shocker.)

## Arellano-Bover with Moving Average: Results 4

```
. xtddpd L(0/2).lwage, dgmmiv(lwage, lagrange(3 4)) lgmmiv(L.lwage) twostep //ch
```

```
Dynamic panel-data estimation      Number of obs   =      2,975  
Group variable: id                Number of groups =      595  
Time variable: t
```

```
Obs per group:  
    min =      5  
    avg =      5  
    max =      5
```

```
Number of instruments =      12      Wald chi2(2)      =      4078.49  
Prob > chi2          =      0.0000
```

Two-step results

lwage	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
lwage						
L1.	.7553581	.0632078	11.95	0.000	.631473	.8792432
L2.	.1270523	.0527304	2.41	0.016	.0237026	.2304021
_cons	.8918238	.1147999	7.77	0.000	.6668201	1.116827

## Arellano-Bover with Moving Average: Results 5

```
. esttab abond1 abover1 xtdpd1 xtdpd2, mtitles("Arellano-Bond" "Arellano-Bover
```

---

	(1)	(2)	(3)	(4)
	Arellano-B~d	Arellano-B~1	Arellano-B~2	Arellano-~1)
L.lwage	0.946*** (82.32)	0.602*** (31.48)	0.605*** (30.20)	0.755*** (11.95)
L2.lwage		0.288*** (16.02)	0.276*** (14.40)	0.127* (2.41)
_cons	0.451*** (5.93)	0.856*** (9.34)	0.917*** (9.12)	0.892*** (7.77)
N	2975	2975	2975	2975

---

t statistics in parentheses

\* p<0.05, \*\* p<0.01, \*\*\* p<0.001

## Arellano-Bover with Moving Average: Results 6

```
. estat abond
```

```
Arellano-Bond test for zero autocorrelation in first-differenced errors
```

```
+-----+  
|Order | z      Prob > z|  
+-----+  
|  1  |-3.0078  0.0026 |  
|  2  | .22473  0.8222 |  
+-----+  
H0: no autocorrelation
```

## Arellano-Bover with Moving Average: Full Model

Results up to now have been shoddy at best, as we only used one variable for simplicity.

```
quietly xtabond lwage occ south smsa ind, lags(2) pre(wks, lag(1,2)) endogenous
estimates store abond_full
quietly xtdpsys lwage occ south smsa ind, lags(2) pre(wks, lag(1,2)) endogenous
estimates store abover_full
quietly xtdpd L(0/2).lwage L(0/1).wks occ south smsa ind ms union, div(occ south)
estimates store abover_ma
```

## Arellano-Bover with Moving Average: Full Model 2

```
. esttab abond_full abover_full abover_ma
```

	(1)	(2)	(3)
	lwage	lwage	lwage
L.lwage	0.597*** (15.98)	0.599*** (21.18)	0.851*** (8.95)
L2.lwage	0.250*** (8.04)	0.287*** (9.94)	0.0497 (0.59)
wks	-0.0155* (-2.03)	-0.00396 (-0.65)	-0.00114 (-0.24)
L.wks	0.00384 (1.44)	0.00113 (0.64)	0.000108 (0.08)

## Arellano-Bover with Moving Average: Full Model 3

ms	0.136 (1.09)	0.0347 (0.60)	0.0405 (0.84)
union	-0.178 (-1.00)	-0.0642 (-0.86)	-0.0257 (-0.37)
occ	-0.0355 (-0.99)	-0.0458 (-1.39)	-0.0496 (-1.58)
south	-0.0101 (-0.05)	-0.106 (-1.14)	-0.149* (-2.00)
smsa	-0.0827 (-1.55)	-0.0546 (-1.16)	-0.0647 (-1.23)
ind	0.0252 (0.56)	0.0146 (0.47)	0.0137 (0.39)
_cons	1.710*** (3.56)	1.097** (2.79)	0.890** (2.58)
-----			
N	2380	2975	2975
-----			

t statistics in parentheses

\* p<0.05 \*\* p<0.01 \*\*\* p<0.001