

ardl: Stata module to estimate autoregressive distributed lag models

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

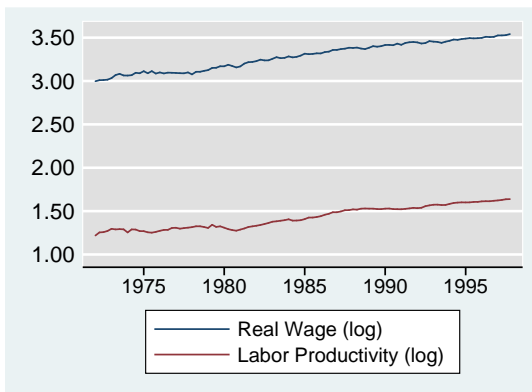
ARDL: autoregressive distributed lag model

- The autoregressive distributed lag (ARDL)¹ model is being used for decades to model the relationship between (economic) variables in a single-equation time-series setup.
- Its popularity also stems from the fact that cointegration of nonstationary variables is equivalent to an error-correction (EC) process, and the ARDL model has a reparameterization in EC form (Engle and Granger, 1987; Hassler and Wolters, 2006).
- The existence of a long-run / cointegrating relationship can be tested based on the EC representation. A bounds testing procedure is available to draw conclusive inference without knowing whether the variables are integrated of order zero or one, $I(0)$ or $I(1)$, respectively (Pesaran, Shin, and Smith, 2001).

¹ Another commonly used abbreviation is ADL.

ARDL: autoregressive distributed lag model

- Long-run relationship: Some time series are bound together due to equilibrium forces even though the individual time series might move considerably.



Data source: Pesaran, Shin, and Smith (2001).

ARDL: autoregressive distributed lag model

- The first public version of the `ardl` command for the estimation of ARDL / EC models and the bounds testing procedure in Stata has been released on August 4, 2014.
- Some indications for the popularity of the ARDL model:
 - Google Scholar returns about 13,200 results when searching for “autoregressive distributed lag”, and more than 5,200 citations for the bounds testing paper by Pesaran, Shin, and Smith (2001).
 - A sequence of blog posts by David Giles on ARDL model estimation attracted more than 500 comments.
 - The discussion topic on the `ardl` command is ranked second on Statalist in terms of replies (>100) and views (>20,000).²
 - There are already at least 2 independent video tutorials available on the web dealing with the `ardl` command for Stata.

² www.statalist.org/forums/forum/general-stata-discussion/general/95329-ardl-in-stata

Estimating long-run relationships

- Engle and Granger (1987) two-step approach for testing the existence of a long-run relationship:
 - Assumption: $(y_t, \mathbf{x}_t)'$ is a vector of $I(1)$ variables.
 - ① Run an OLS regression for the model in levels:

$$y_t = b_0 + \boldsymbol{\theta}'\mathbf{x}_t + v_t,$$

and test whether the residuals $\hat{v}_t = y_t - \hat{b}_0 - \hat{\boldsymbol{\theta}}'\mathbf{x}_t$ are stationary (e.g. with a Dickey-Fuller test).

- ② Estimate an EC model with the lagged residuals from the first step included as EC term (provided they are stationary):

$$\Delta y_t = c_0 + \gamma \hat{v}_{t-1} + \sum_{i=1}^{p-1} \psi_{yi} \Delta y_{t-i} + \sum_{i=0}^{q-1} \psi'_{xi} \Delta \mathbf{x}_{t-i} + u_t,$$

and test whether $-1 \leq \gamma < 0$.

- Stata module `egranger` by Mark E. Schaffer (2010) on SSC.

Estimating long-run relationships

- Disadvantages of the Engle and Granger (1987) approach:
 - The order of integration of the variables needs to be determined first.
 - OLS estimation of the static levels model may create bias in finite samples due to the omitted short-run dynamics (Banerjee, Dolado, Hendry, and Smith, 1986).
 - The bias from the first step transmits to poor second-step estimates.
 - The asymptotic distribution of the OLS estimator for the long-run parameters θ is non-normal, invalidating standard inference based on the t -statistic.
 - General pretesting problems: misclassification of variables as $I(0)$ or $I(1)$; false positives and false negatives at the first step.
- Phillips and Hansen (1990) proposed the fully-modified OLS estimator to overcome some of these problems.

Estimating long-run relationships

- Pesaran and Shin (1998) suggest to obtain the long-run parameters from an ARDL model:
 - OLS estimators of the short-run parameters are \sqrt{T} -consistent and asymptotically normal.
 - The corresponding estimators of the long-run parameters are super-consistent if the regressors are $I(1)$, and asymptotically normally distributed irrespective of the order of integration.
- Bounds procedure for testing the existence of a long-run relationship based on the EC representation of the ARDL model:
 - Pesaran, Shin, and Smith (2001) tabulate asymptotic critical values that span a band from all regressors being purely $I(0)$ to all regressors being purely $I(1)$.
 - Narayan (2005) computes corresponding small-sample critical values for various sample sizes.

ARDL model

- ARDL(p, q, \dots, q) model:

$$y_t = c_0 + c_1 t + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{i=0}^q \beta'_i \mathbf{x}_{t-i} + u_t,$$

$t = \max(p, q), \dots, T$, for simplicity assuming that the lag order q is the same for all variables in the $K \times 1$ vector \mathbf{x}_t .

- The variables in $(y_t, \mathbf{x}'_t)'$ are allowed to be purely $I(0)$, purely $I(1)$, or cointegrated.³
- The optimal lag orders p and q (possibly different across regressors) can be obtained by minimizing a model selection criterion, e.g. the Akaike information criterion (AIC) or the Bayesian information criterion (BIC).⁴

³For a full set of assumptions see Pesaran, Shin, and Smith (2001).

⁴The BIC is also known as the Schwarz or Schwarz-Bayesian information criterion.

EC representation

- Reparameterization in conditional EC form:

$$\Delta y_t = c_0 + c_1 t - \alpha(y_{t-1} - \boldsymbol{\theta} \mathbf{x}_{t-1}) + \sum_{i=1}^{p-1} \psi_{yi} \Delta y_{t-i} + \boldsymbol{\omega}' \Delta \mathbf{x}_t + \sum_{i=1}^{q-1} \psi'_{xi} \Delta \mathbf{x}_{t-i} + u_t,$$

with the speed-of-adjustment coefficient $\alpha = 1 - \sum_{j=1}^p \phi_j$ and the long-run coefficients $\boldsymbol{\theta} = \frac{\sum_{j=0}^q \beta_j}{\alpha}$.

- Alternative EC parameterization:

$$\Delta y_t = c_0 + c_1 t - \alpha(y_{t-1} - \boldsymbol{\theta} \mathbf{x}_t) + \sum_{i=1}^{p-1} \psi_{yi} \Delta y_{t-i} + \sum_{i=0}^{q-1} \psi'_{xi} \Delta \mathbf{x}_{t-i} + u_t.$$

Testing the existence of a long-run relationship

- Pesaran, Shin, and Smith (2001) approach:
 - 1 Decide about the inclusion of deterministic model components and obtain the optimal lag orders p and q based on a suitable model selection criterion, e.g. AIC or BIC. (When in doubt, choose higher lag orders for testing purposes.)
 - 2 Estimate the chosen $ARDL(p, q, \dots, q)$ model by OLS.
 - 3 Compute the F -statistic for the joint null hypothesis $H_0^F : (\alpha = 0) \cap \left(\sum_{j=0}^q \beta_j = \mathbf{0} \right)$ and compare it to the critical values.
 - 4 If H_0^F is rejected, compute the t -statistic for the single null hypothesis $H_0^t : \alpha = 0$ and compare it to the critical values.
 - 5 Potentially re-estimate a parsimonious version of the ARDL / EC model.

Testing the existence of a long-run relationship

- Pesaran, Shin, and Smith (2001) provide lower and upper bounds for the asymptotic critical values depending on the number of regressors, their order of integration, and the deterministic model components:
 - 1 No intercept, no time trend.
 - 2 Restricted intercept, no time trend.
 - 3 Unrestricted intercept, no time trend.
 - 4 Unrestricted intercept, restricted time trend.
 - 5 Unrestricted intercept, unrestricted time trend.
- Test decisions:
 - Do not reject H_0^F or H_0^t , respectively, if the test statistic is closer to zero than the lower bound of the critical values.
 - Reject the H_0^F or H_0^t , respectively, if the test statistic is more extreme than the upper bound of the critical values.
- The existence of a (conditional) long-run relationship is confirmed if both H_0^F and H_0^t are rejected.

Stata syntax of the ardl command

- Syntax:
`ardl depvar [indepvars] [if] [in] [, options]`
- Selected options:
 - `lags(numlist)`: set lag lengths,
 - `maxlags(numlist)`: set maximum lag lengths,
 - `ec`: display output in error-correction form,
 - `ec1`: like option `ec`, but level variables in $t - 1$ instead of t ,
 - `aic`: use AIC as information criterion instead of BIC,
 - `exog(varlist)`: exogenous variables in the regression,
 - `noconstant`: suppress constant term,
 - `trendvar(varname)`: specify trend variable,
 - `restricted`: restrict constant or trend term.
- Postestimation commands:
 - `estat btest`: bounds test,
 - `predict`: fitted values, residuals, and error-correction term,
 - `estat ic, nlcom, test, ...`

Example

- Pesaran, Shin, and Smith (2001) estimate a UK earnings equation. We focus on the model with unrestricted intercept and no time trend (case 3).

```
. describe w prod ur wedge union d*
```

variable name	storage type	display format	value label	variable label
w	double	%6.2fc		Real Wage (log)
prod	double	%6.2fc		Labor Productivity (log)
ur	double	%6.2fc		Unemployment Rate (log)
wedge	double	%7.3fc		Wedge (log)
union	double	%7.3fc		Union Power (log)
d7475	byte	%3.0fc		Dummy: Years 1974-1975
d7579	byte	%3.0fc		Dummy: Years 1975-1979

```
. summarize w prod ur wedge union d*, separator(7)
```

Variable	Obs	Mean	Std. Dev.	Min	Max
w	116	3.252843	.1792393	2.91503	3.54119
prod	116	1.402628	.1411384	1.155336	1.63873
ur	112	1.838737	.6734774	.0262613	2.53305
wedge	116	-.3412168	.0402661	-.4151654	-.2330282
union	116	-.6886907	.0602385	-.8461587	-.650586
d7475	116	.0689655	.2544948	0	1
d7579	116	.1724138	.3793785	0	1

Example: ARDL model with optimal lag orders

```
. ardl w prod ur wedge union if tin(1972q1,1997q4), exog(d7475 d7579) maxlags(6) aic
> maxcombs(15000) fast
```

	w	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
	w					
	L1.	.3346901	.0998041	3.35	0.001	.1359548 .5334255
	L2.	.0810293	.1087734	0.74	0.459	-.1355661 .2976248
	L3.	-.198378	.1011595	-1.96	0.053	-.3998123 .0030563
	L4.	.4030251	.0989762	4.07	0.000	.2059382 .6001119
	L5.	-.0693079	.0949025	-0.73	0.467	-.2582829 .1196671
	L6.	.2017837	.0800474	2.52	0.014	.042389 .3611783
	prod	.2642678	.0587165	4.50	0.000	.1473483 .3811872
	ur					
	--.	.0038742	.008252	0.47	0.640	-.0125575 .020306
	L1.	-.01077	.0120686	-0.89	0.375	-.0348018 .0132617
	L2.	-.0116548	.0145987	-0.80	0.427	-.0407246 .0174151
	L3.	.0212508	.0153697	1.38	0.171	-.0093542 .0518557
	L4.	.0028227	.0151775	0.19	0.853	-.0273995 .033045
	L5.	-.0304991	.0109952	-2.77	0.007	-.0523934 -.0086049

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Example: ARDL model with optimal lag orders

```

wedge |
  --. | -.3059897   .051594   -5.93   0.000   -.4087265   -.2032528
  L1. |   .032749   .060641    0.54   0.591   -.0880027   .1535007
  L2. | -.0494003   .0626044   -0.79   0.432   -.1740615   .0752609
  L3. | -.0963634   .0611009   -1.58   0.119   -.2180308   .025304
  L4. |   .188605   .0558292    3.38   0.001    .077435    .2997751
union |
  --. | -.955714   .8138684   -1.17   0.244   -2.576333    .664905
  L1. | -1.467002   1.350003   -1.09   0.281   -4.155202    1.221197
  L2. |  2.527384   1.401008    1.80   0.075   -.2623798    5.317149
  L3. |   .311388   1.349422    0.23   0.818   -2.375655    2.998431
  L4. | -2.241151   1.106961   -2.02   0.046   -4.445392   -.0369088
  L5. |  2.185799   .6535696    3.34   0.001    .8843756    3.487222
d7475 |   .0301088   .006154    4.89   0.000    .0178547    .042363
d7579 |   .0169541   .0062481    2.71   0.008    .0045126    .0293956
_cons |   .6604224   .1425601    4.63   0.000    .376549    .9442958

```

```
-----
```

```
. matrix list e(lags)
```

```
e(lags)[1,5]
```

```

      w   prod      ur  wedge  union
r1      6     0     5     4     5

```

Example: error-correction representation

```
. ardl w prod ur wedge union if tin(1972q1,1997q4), exog(d7475 d7579) eci lags(6 0 5 4 5)
```

		D.w	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
ADJ		w					
	L1.		-.2471578	.0521006	-4.74	0.000	-.3509034 - .1434121
LR		prod					
	L1.		1.069227	.045147	23.68	0.000	.979328 1.159126
	ur						
	L1.		-.1010536	.0303893	-3.33	0.001	-.1615664 -.0405409
	wedge						
	L1.		-.9321955	.2432139	-3.83	0.000	-1.416496 -.4478946
	union						
	L1.		1.45941	.2847566	5.13	0.000	.892387 2.026433
SR		w					
	LD.		-.4181521	.0970869	-4.31	0.000	-.6114769 -.2248273
	L2D.		-.3371228	.1076478	-3.13	0.002	-.551477 -.1227686
	L3D.		-.5355008	.1024435	-5.23	0.000	-.7394918 -.3315098
	L4D.		-.1324758	.0889041	-1.49	0.140	-.3095064 .0445549
	L5D.		-.2017837	.0800474	-2.52	0.014	-.3611783 -.042389

(Continued on next page)

Example: error-correction representation

prod							
D1.		.2642678	.0587165	4.50	0.000	.1473483	.3811872
ur							
D1.		.0038742	.008252	0.47	0.640	-.0125575	.020306
LD.		.0180804	.0112588	1.61	0.112	-.0043387	.0404995
L2D.		.0064256	.0106366	0.60	0.548	-.0147545	.0276058
L3D.		.0276764	.01116	2.48	0.015	.005454	.0498988
L4D.		.0304991	.0109952	2.77	0.007	.0086049	.0523934
wedge							
D1.		-.3059897	.051594	-5.93	0.000	-.4087265	-.2032528
LD.		-.0428413	.0584202	-0.73	0.466	-.1591708	.0734882
L2D.		-.0922416	.0566866	-1.63	0.108	-.205119	.0206358
L3D.		-.188605	.0558292	-3.38	0.001	-.2997751	-.077435
union							
D1.		-.955714	.8138684	-1.17	0.244	-2.576333	.664905
LD.		-2.783421	.8141048	-3.42	0.001	-4.404511	-1.162331
L2D.		-.2560365	.8307344	-0.31	0.759	-1.91024	1.398167
L3D.		.0553516	.743211	0.07	0.941	-1.424571	1.535274
L4D.		-2.185799	.6535696	-3.34	0.001	-3.487222	-.8843756
d7475		.0301088	.006154	4.89	0.000	.0178547	.042363
d7579		.0169541	.0062481	2.71	0.008	.0045126	.0293956
_cons		.6604224	.1425601	4.63	0.000	.376549	.9442958

Example: bounds testing

```
. estat bttest
```

```
Pesaran/Shin/Smith (2001) ARDL Bounds Test
HO: no levels relationship           F = 7.367
                                     t = -4.744
```

```
Critical Values (0.1-0.01), F-statistic, Case 3
```

	[I_0]	[I_1]	[I_0]	[I_1]	[I_0]	[I_1]	[I_0]	[I_1]
	L_1	L_1	L_05	L_05	L_025	L_025	L_01	L_01
k_4	2.45	3.52	2.86	4.01	3.25	4.49	3.74	5.06

accept if $F <$ critical value for I(0) regressors
reject if $F >$ critical value for I(1) regressors

```
Critical Values (0.1-0.01), t-statistic, Case 3
```

	[I_0]	[I_1]	[I_0]	[I_1]	[I_0]	[I_1]	[I_0]	[I_1]
	L_1	L_1	L_05	L_05	L_025	L_025	L_01	L_01
k_4	-2.57	-3.66	-2.86	-3.99	-3.13	-4.26	-3.43	-4.60

accept if $t >$ critical value for I(0) regressors
reject if $t <$ critical value for I(1) regressors

```
k: # of non-deterministic regressors in long-run relationship
Critical values from Pesaran/Shin/Smith (2001)
```

- Bounds test confirms the existence of a long-run relationship.

Summary: the new ardl package for Stata

- The estimation of ARDL / EC models has become increasingly popular over the last decades. The associated bounds testing procedure is an attractive alternative to other cointegration tests.
- The new `ardl` command estimates an ARDL model with optimal or pre-specified lag orders.
- Two different reparameterizations of the ARDL model in EC form are available.
- The bounds procedure for testing the existence of a long-run relationship is implemented as a postestimation command. Asymptotic and finite-sample critical value bands are available.

```
net install ardl, from(http://www.kripfganz.de/stata/)
help ardl
help ardl postestimation
help ardlbounds
```

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