Time-series–Cross Section Data: Modeling Dynamics: Continuous DV

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Outline

- Introduction
- General time-series issues
- Testing
- Lagged Dependent Variables
- Error Correction
- Comparing specifications
- What to do?
- Non-stationarity
- Binary DV (Workshop 3)

Focus on dynamics

- Looking today at dynamic issues
- modeling issues related to time
- Assume from first workshop have dealt with cross-sectional issues correctly
- Dynamics in TSCS data is very similar to dynamics in time series data
- Continuous DV only today

Correlated errors

- "Nuisance" assumption - errors are serially correlated
- for yearly data usually AR, could easily generalize/test)

$$\epsilon_{i,t} = \rho\epsilon_{i,t-1} + \mu_{i,t} \tag{1}$$

  where the μ are independently distributed across time.
- Correct for this serial correlation in the usual (GLS) manner

GLS estimation

- First run OLS
- Compute the serial correlation of the residuals
- (that is, regress the residuals on the lagged residuals and take the coefficient on the lagged residual as $\hat{\rho}$.)
- Then transform by subtracting $\hat{\rho}$ of the prior observation from the current one
- and run OLS on the transformed observations.
- Can do better by transforming rather than dropping first obs (Prais-Winsten)

Testing

- Test for serially correlated errors (with or without a lagged dependent variable)
- via the TSCS analogue of the standard Lagrange multiplier test
- Explain why so useful for TS
- All estimation done under null of temporal independence
- Run OLS
- compute residuals
- regress the residuals on all the independent variables (including the lagged dependent variable if present) and the lagged residual
- If the coefficient on the lagged residual is significant (with the usual *t*-test), we can reject the null of independent errors.
- or TR^2 is χ^2_1
- Can do similar for higher order process, but with yearly data may not be needed (but why not test?)

Lagged Dependent Variable

- Just as with any time series, we could also model dynamics with a lagged dependent variable
- they make the dynamics part of the model, not just a nuisance
- there is seldom any reason to prefer serially correlated errors to a lagged dependent variable
- the LDV model assumes that the effects of all variables, measured and unmeasured (errors?) have impacts that die out exponentially
- whereas the AR1 error model assumes that the measured variables have only immediate impact
- but the unmeasured variables have impacts which die out exponentially
- lagged dependent variables usually simple to estimate and interpret (even if testing indicates SMALL remaining serial correlation)
- Can test for remaining serial correlation easily using LM test from previous slide
- If do not reject independence, need more complex model

LDV vs AR1 errors

The LDV model is (using ν to denote iid errors)

$$y_{i,t} = \mathbf{x}_{i,t}\boldsymbol{\beta} + \phi y_{i,t} + \nu_{i,t} \tag{2}$$

while the AR1 error model is

$$y_{i,t} = \mathbf{x}_{i,t}\boldsymbol{\beta} + \nu_{i,t} + \rho\epsilon_{i,t-1} \tag{3}$$

since

$$\epsilon_{i,t} = \nu_{i,t} + \rho\epsilon_{i,t-1} \tag{4}$$

and hence

$$y_{i,t} = \mathbf{x}_{i,t}\boldsymbol{\beta} + \rho y_{i,t-1} - \mathbf{x}_{i,t-1}\boldsymbol{\beta}\rho + \nu_{i,t} \tag{5}$$

so both LDV and AR1 errors are special cases of ADL model

$$y_{i,t} = \mathbf{x}_{i,t}\boldsymbol{\beta} + \rho y_{i,t-1} - \mathbf{x}_{i,t-1}\gamma + \nu_{i,t} \tag{6}$$

Choosing which spec

- Thus, following Hendry's advice to test from general to specific
- start with the ADL setup
- and then test the null that either $\gamma = 0$ or $\gamma = -\beta\rho$
- ADL equivalent to the single equation DHSY "error correction model" model

$$\Delta y_{i,t} = \Delta x_{i,t}\boldsymbol{\beta} - \phi(y_{t-1} - x_{t-1}\boldsymbol{\gamma}) + \nu_t. \tag{7}$$

- with coefficients suitably interpreted

DHSY

- DHSY model very nice
- Long term equilibrium and short term adjustment
- Solves problems for integrated series but also fine for any series that adjusts slowly (if it fits!)

Back to specification

- To see how the specifications differ, it is easiest to look at the impact of a permanent one unit level change in x.
- AR1 model: y instantaneously adjusts, increasing by β_{ar1}.
- LDV model: y adjusts to the change in x geometrically; the initial impact of the change is β_{ldv}, with steady-state impact $\frac{\beta_{ldv}}{1-\phi}$
- The ADL model is more complicated; initially y responds to the level shift in x by increasing β_{adl} units, with the long run change in y being $\frac{\beta_{adl}+\gamma_{adl}}{1-\phi}$.
- If x is similar to the variables that make up the error process, one might expect the LDV model to be suitable.
- If x represents a change in regime that we expect to have an immediate one time impact, the AR1 formulation seems plausible.
- If the data are willing to speak, the ADL or DHSY model is a good compromise between the two
- and allows for testing the specializations

When does all this matter?

- If ϕ is relatively small, then shocks quickly die out in AR1 error model
- In a model with AR1 errors, the impact of any of the independent variables is felt only immediately.
- In the LDV model, where the long run impact of any given x is $\frac{\beta_x}{(1-\phi)}$, most of the long run effect is seen quickly if ϕ is small
- In this situation, the LDV and AR1 error specification will appear quite similar.
- As ϕ gets larger, the difference between the two models get larger.
- As ϕ gets towards one neither approach is correct
- we move into the world of non-stationary time series.
- One example with a small ϕ.

Garrett model of economic growth in 14 OECD nations, 1966–1990 (with fixed effects)

	LDV		AR1 Errors		AR1	
Variable	$\hat{\beta}$	PCSE	$\hat{\beta}$	PCSE	$\hat{\beta}$	PCSE
GDP_{-1}	.16	.07			.15	.08
DEMAND	.72	.16	.70	.18	.70	.17
CORP	−.72	.60	−.78	.70	−.92	1.16
LEFT	−.77	.34	−.88	.38	−.63	.53
LEFTxCORP	.27	.14	.31	.15	.19	.20
PER6673	1.64	.37	1.98	.41	1.65	.37
CONSTANT	2.76	1.77	3.42	2.08	2.45	1.82
$DEMAND_{-1}$					.07	.18
$CORP_{-1}$					.23	1.09
$LEFT_{-1}$					−.23	.53
$LEFTxCORP_{-1}$					.14	.20
ϕ			.15	.08		
N	336		336		336	
BIC	4.3846		4.3945		4.4504	
SSE	1116.131		1127.226		1112.210	

Modeling non-stationary TSCS data

- While estimation of TSCS models with unit root data is just beginning to be studied
- Experience from single time series analysis tells us that we cannot simply use stationary methods
- Example: Huber and Stephens analysis of the determinants of social security spending
- 16 OECD countries in the post-World War II period (26 years)
- *SSBEN* is very smooth:

$$SSBEN_t = 1.003 SSBEN_{t-1} + \nu_t$$

  (se = .008)
- In the absence of co-integration, we can only explain short run changes in *SSBEN* by short run changes in the independent variable.
- Short run changes in SSBEN NOT explained by short run changes in political variables
- Conclusion very different from Huber and Stephens
- Try error correction if series appear to be cointegrated

Integration and Political Economy

- Would we ever expect a political economy series to be integrated
- Could variance wander to infinity
- Things like SSBEN are bounded by 0 and 100%
- Do we expect when SSBEN is very high that is equally likely to go up or down
- Note: Error correction still fine even if series not integrated
- Difference of DHSY model and standard vector autoregressive methods for integrated series

Summing up

- Choose dyn spec for TSCS as you would for TS
- But remember the TSCS data have (usually) only low frequency (yearly) data
- Testing as in TS - LM test
- LDV's simplify, can test if appropriate, not atheoretical
- Worry about non-stationarity - less clear what to do