MACROECONOMETRIC MODELLING OF THE LITHUANIAN ECONOMY

FROM OUTER EXPERIENCE TO DATA CONSISTENT APPROACH

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Some Lithuanian models

Model	Economic principles	Experience used	Econometric model	Specification of CI
LITMOD	The demand side based with I-O relationships to derive the cost structure	Danish MONA	ECM	Informal (eye-based)
EcoRET for Lithuania	Neoclassical (static optimization)	Hungarian EcoRet	ECM	Assumed
ECB MCM Lithuanian block	Neoclassical synthesis (supply side determines the long-run, demand side – the short run behaviour)	French, Spanish, Irish MCM	ECM	Tested using standard means

Cointegration and the ECM

- Cointegration

  Suppose $Y_t \sim I(1)$ and $\exists\ \beta \neq 0$ such that $\beta' Y_t \sim I(0)$, then Y_t components are cointegrated.

- Error Correction Model (ECM)

  Given the cointegrated Y_t, it has the ECM representation

  $\Delta Y_t = \Pi Y_{t-1} + \Sigma_{i=1}^{k} \Gamma_i \Delta Y_{t-i} + \varepsilon_t$

  with $rank(\Pi) > 0$.

Modelling constraints

- As in many other post-Soviet economies time series are very short: mostly available since 1995-1998
  - modelling with quarterly data leans on about 30-40 observations
- Transition period is turbulent and full of various crises, surprises, etc.
  - dummy variables are usually used to account for structural breaks

Some events important for the Lithuanian economy

- 1995 – the first year of increase in GDP, the EU association, banking crises (end of the year)
- 1996 – further influence of banking crises
- 1997 – the Asian crisis
- 1998 – the Russian crisis
- 1999 – the consequences of the Russian crisis, political turmoil with governmental changes
- 2000 – exceptionally high growth in Germany and the EU, governmental changes
- 2001 – oil prices started increasing sharply
- 2002 – the prospects to join the EU in the first wave became clear, Litas re-pegged to euro
- 2003 – the beginning of the presidential turmoil
- 2004 – the EU accession, Parliament elections
- 2005 – the post accession period, the euro-associated expectations
- … and hundreds of other case-specific reasons to add a dummy variable

P.S. This illustrates that for any year one could find an event to justify an inclusion of some dummy variables

The sequence of modelling usually used

- Utilize some structure of the models developed for the other countries

- Estimate the parameters

- Use dummy variables to adjust for ‘bad’ observations – the most sizable deviations

- Drop insignificant or incorrectly signed variables

Any problems?

The effect of inclusion of a dummy variable on the CI inference in the EG procedure under the null hypothesis of no CI (simulation results based on 1000 repetitions)

- Nearly no effect when sample size is 1000 observations

- Small sample (40 observations)

nominal size	critical value without a dummy	critical value with one dummy	critical value with two dummies
0.05	-2.97	-3.46	-3.67
0.1	-2.59	-3.06	-3.28

The effect is even more sever in the actual models as:

- we have seen some equations in the Lithuanian models having up to four (!) dummy variables
- in the models based on the quarterly data a dummy variable for the whole year rather than a particular quarter is included
- dummy variables to account for permanent change (0 before, and 1 thereafter) have much higher influence
- inclusion of a linear trend makes the case worse

The other way around case – the effect of ignored lags in the CI relationship on the power of CI test

- Let $Y_t \sim I(1)$ and $X_t \sim I(1)$ be cointegrated as follows

(1) $Y_t = \beta X_{t-\tau} + u_t$,

where for a fixed τ stationary process $\{u\}$ is not correlated with $\{X\}$.

- Then for any $j=0, 1,\ldots$ holds

(2) $Y_t = \beta X_{t-j} + v_t(j)$, $v_t(j) = u_t - \beta(X_{t-j} - X_{t-\tau})$.

- In the standard Engle-Granger procedure $j=0$ is assumed. When (1) is the DGP with $\tau \neq 0$, this produces, in general, $Cov(X_t, v_t) \neq 0$ as well as autocorrelated v_t, even if u_t and ΔX_t were uncorrelated white noise processes.

The effects of ignored lags in the CI relationship on the power of the EG-CI test

- Asymptotically the created correlation and autocorrelation effects have no influence on the parameter estimates in (2) due to superconsistency of the OLS

- In small samples it causes biases of the estimates of the cointegrating regression parameters. Consequently, in small samples it will be hard to reject the null of no cointegration using (2) with $j=0$ when (1) is true with $\tau \neq 0$.

How important is the small sample bias induced loss of power when contemporaneous CI is estimated?

		T = 30		T = 50	
CI parameter	Lag (tau)	DF	ADF	DF	ADF
β = 1	k = 0	0, 998	0, 969	1	0, 988
	k = 1	0, 999	0, 957	1	0, 985
	k = 2	0, 943	0, 908	0, 993	0, 971
	k = 3	0, 723	0, 689	0, 901	0, 87
	k = 4	0, 584	0, 539	0, 805	0, 742
β = 0	k = 0	0, 046	0, 07	0, 048	0, 056

Suggested procedure

- It is better to test whether $\{u\}$ is nonstationary instead of testing nonstationarity of $\{v\}$. Given uncorrelated $\{u\}$ and $\{X\}$ it is straightforward to see from (2) that

$$\forall\beta, j\neq\tau \;\; Var[v_t(j)] > Var(u_t) \;\; \text{and} \;\; \tau = argmin_j \, E(Y_t - \beta X_{t-j})^2.$$

- This gives a rule based on minimization of the residuals sum of squares. As β is not known, however, it follows that

$$min_b \, E[(u_t + \beta X_{t-\tau} - bX_{t-j})^2] > E(u_t^2), \;\; \text{unless } b=\beta, j=\tau.$$

- Therefore we look for the best shift τ by using an empirical analogue of

$$\tau = argmin_j \, [\, E(Y_t - b(j)X_{t-j})^2].$$

How effective it is?

T = 30	Lag (tau)	DF	MDF	ADF	MADF
β = 1	k = 0	0, 998	0, 997	0, 969	0, 97
	k = 1	0, 999	0, 998	0, 957	0, 952
	k = 2	0, 943	0, 995	0, 908	0, 946
	k = 3	0, 723	0, 994	0, 689	0, 951
	k = 4	0, 584	0, 989	0, 539	0, 927
β = 0	k = 0	0, 046	0, 061	0, 07	0, 085

Final remarks

- One period lag does not create problems, but…
- In >60 percent of equations in our models are specified with lags in the cointegrating regressions and the respective ECM.
- A lag of 3-4 quarters is very usual. There is one case – in a labour demand equation – with a lag of about two years.
- This does not seem to happen by accident: 3 years we are updating the model quarter by quarter (and with many revisions of the data !), but the lag structure and coefficients are stable.

Thank you for your attention
and
your questions