### Testing Linear Cointegration Against Smooth Transition Cointegration

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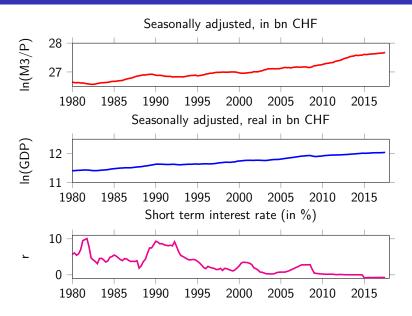
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### A WARNING...

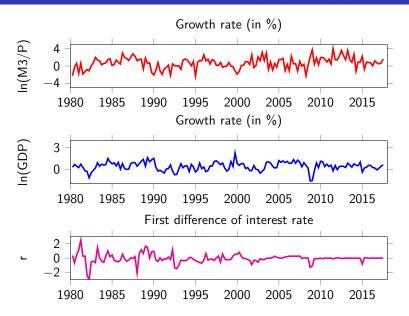


- **2** Model and Theory
- **③** FINITE SAMPLE PERFORMANCE
- Illustration with Long-Run Money Demand
- **5** Summary and Conclusions

#### Switzerland: Logarithms and Levels (1980/I-2017/III)



SWITZERLAND: GROWTH RATES AND FIRST DIFFERENCES (1980/II-2017/III)



SWITZERLAND: MOVING WINDOW ESTIMATION - COEFFICIENT TO INTEREST RATE

$$\ln\left(\frac{M_t}{P_t}\right) = c + \delta t + \beta_1 \ln(Y_t) + \beta_2 r_t + u_t$$

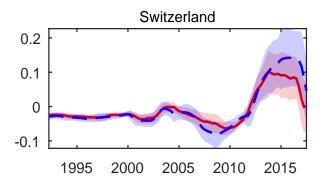


FIGURE: The red solid line displays the FM-OLS estimates and the blue dashed line displays the IM-OLS estimates for  $\beta_2$ . The corresponding 95% confidence bands are given by the red and blue shaded areas.

#### Monitoring Euro Area Money Demand (1980/I-2017/III)

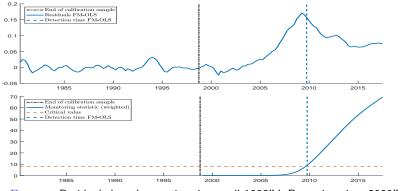


FIGURE: Residuals based on estimation until 1998IV. Detection time 2009IV.

### Model and Theory

DEFINITION & LIMITATIONS BY CONSTRUCTION

LINEAR COINTEGRATING REGRESSION

$$y_t = D'_t \theta_D + \tilde{X}'_t \theta_X + u_t = Z'_t \theta + u_t,$$

where  $Z_t := [D'_t, \tilde{X}'_t]'$ ,  $\theta := [\theta'_D, \theta'_X]'$ , with:

- deterministic regressors D<sub>t</sub>,
- a non-cointegrated I(1) vector  $\tilde{X}_t$ ,
- and a stationary error term  $u_t$ .

Linear cointegration may – by construction – be too restrictive:

- The parameters are assumed to be constant.
- The setting is linear in parameters and I(1) variables.

### Smooth Transition Cointegration

For Simplified Presentation: Same Variables in Both Parts

Smooth Transition Cointegration

$$y_t = Z'_t \theta_L + Z'_t \theta_{NL} \times G(s_t, \theta_G) + u_t$$

with  $Z_t$ ,  $u_t$  as above and:

- a smooth and bounded transition function  $G(\cdot)$ ,
- and integrated variable or time trend as transition variable  $s_t$ .

#### EXAMPLE: LOGISTIC TRANSITION FUNCTIONS

LSTR1: 
$$G_1(s_t, \theta_G) = \frac{1}{1 + \exp(-\gamma(s_t - c))} - \frac{1}{2}$$
, with  $\gamma > 0$   
LSTR2:  $G_2(s_t, \theta_G) = \frac{1}{1 + \exp(-\gamma(s_t - c)^2)} - \frac{1}{2}$ , with  $\gamma > 0$ 

### Smooth Transition Cointegration

TRANSITION VARIABLE

• For the transition variable  $s_t$  we consider two cases:

(i)  $s_t$  is an element of  $\tilde{X}_t$  or is an l(1) process not cointegrated with  $\tilde{X}_t$ , (ii)  $s_t = t$ .

• To have a unified notation we define:

$$X_t := \begin{cases} \tilde{X}_t & \text{ in case } s_t \text{ is an element of } \tilde{X}_t \text{ or } s_t = t, \\ \begin{bmatrix} \tilde{X}_t \\ s_t \end{bmatrix} & \text{ in case } s_t \text{ is } \mathsf{l}(1) \text{ and not cointegrated with } \tilde{X}_t. \end{cases}$$

[Where in the second case  $s_t$  is ordered last w.l.o.g.]

• We furthermore define  $v_t := \Delta X_t$  and denote its long-run variance as usual by  $\Omega_{vv}$ .

NON-IDENTIFICATION UNDER THE NULL HYPOTHESIS

• Testing linear cointegration against the alternative of smooth transition cointegration corresponds to testing:

$$H_0: \theta_{NL} = 0$$
 vs.  $H_1: \theta_{NL} \neq 0$ .

• Under the null hypothesis of linear cointegration with  $\gamma = 0$  some parameters are unidentified, e.g., for LSTR1:

$$y_t = Z'_t \theta_L + Z'_t \theta_{NL} \times \underbrace{\left(\frac{1}{1 + \exp\left(-0(s_t - c)\right)} - \frac{1}{2}\right)}_{=0} + u_t.$$

 This identification problem is tackled by using Taylor approximations of the transition function.

• A Taylor approximation of order n leads to a model of the form

$$y_t = Z'_t \beta_0 + \sum_{j=1}^n (Z_t s^j_t)' \beta_j + u^*_t.$$

• The null hypothesis of linearity of the cointegrating relationship is tested in this auxiliary regression by testing:

$$H_0: [\beta'_1, \ldots, \beta'_n]' = 0 \quad \text{vs.} \quad H_1: [\beta'_1, \ldots, \beta'_n]' \neq 0.$$

#### PROBLEMS

- The asymptotic analysis of LS estimators is complicated by the occurrence of terms of the form  $X_t s_t^j$ .
- Deriving consistency against fixed alternatives is non-trivial, both with standard and "Saikkonen-triangular array" asymptotics.

- Order of Taylor Approximation
  - As discussed in detail, e.g., in Luukkonen *et al.* (1988), there are situations in which a first order Taylor approximation leads to tests with trivial power.
  - Consider the following smooth transition model with the "nonlinear" part only containing the intercept and with  $s_t = x_t$ :

$$y_t = \theta_1 + \theta_2 x_t + \theta_3 \times G(x_t, \theta_G) + u_t.$$

• A first order Taylor approximation leads to

$$y_t = \beta_1 + \beta_2 x_t + u_t^*,$$

and therefore tests based on this approximation have trivial power.

• In such cases higher order Taylor approximations, typically third order, are used.

### TESTING FOR SMOOTH TRANSITION COINTEGRATION Multi-Collinearity by Design

- Another issue that requires some care is multi-collinearity of regressors in the Taylor approximation.
- First, consider  $s_t = t$  and  $D_t = (1, t, \dots, t^{p-1})'$  with p > 1, then  $D_t \otimes s_t = D_t \otimes t = (t, t^2, \dots, t^p)'$ .
- Clearly, for p > 1 at least the linear trend appears in  $D_t$  and  $D_t \otimes s_t$ .
- Second, if a constant is included (in the "linear" term) and  $s_t$  is already an element of the regressors  $X_{t,L}$  the regressor  $s_t$  appears twice.
- This "multi-collinearity by construction" is easily overcome by excluding the corresponding regressor(s) in the Taylor approximation term(s).

### **OLS ASYMPTOTICS**

Asymptotic Behavior of the "X'u-Term"

In case that  $s_t$  is an I(1) process:

$$T^{-\frac{j+2}{2}} \sum_{t=1}^{T} x_{t_i} s_t^j u_t \Rightarrow \int_0^1 B_{v_i}(r) B_s^j(r) dB_u(r)$$
$$+ j \Delta_{su} \int_0^1 B_{v_i}(r) B_s^{j-1}(r) dr$$
$$+ \Delta_{vu} \int_0^1 B_s^j(r) dr$$

In case that  $s_t = t$ :

$$T^{-(j+1)} \sum_{t=1}^{T} x_{t_i} t^j u_t \Rightarrow \int_0^1 B_{v_i}(r) r^j dB_u(r) + \Delta_{vu} \int_0^1 r^j dr$$

### Fully Modified OLS Estimation

- The idea of FM-OLS is to correct for bias terms arising in the OLS limit and to correct for the correlation between *X<sub>t</sub>*, *s<sub>t</sub>* and *u<sub>t</sub>*.
- The auxiliary model can be written in more compact form:

$$y_t = F_t'\beta + u_t^*,$$

with 
$$F_t = [1, s_t, \dots, s_t^n]' \otimes Z_t$$
 and  $\beta = [\beta'_0, \dots, \beta'_n]'$ .

#### Fully Modified OLS

The FM-OLS estimator of  $\beta$  in the above model is given by

$$\hat{\beta}^+ = \left(\sum_{t=1}^T F_t F_t'\right)^{-1} \left(\sum_{t=1}^T F_t y_t^+ - M^*\right),$$

with  $y_t^+ := y_t - v_t' \hat{\Omega}_{vv}^{-1} \hat{\Omega}_{vu}$  and model specific correction term  $M^*$ .

#### INTEGRATED MODIFIED OLS

IM-OLS estimation is OLS estimation of the partial summed auxiliary model augmented by  $X_t$ , i.e.,

$$\begin{split} S_t^{\gamma} &= S_t^{F\prime} \beta + X_t^{\prime} \gamma + S_t^{u*}, \\ &= S_t^{\tilde{F}\prime} \beta_* + S_t^{u*}, \end{split}$$

where  $S_t^{y} := \sum_{i=1}^t y_i$  and similarly for  $S_t^{F}$  and  $S_t^{u*}$ .

- Adding  $X_t$  "soaks up" all dynamic correlation between the regressors and the errors.
- Partial summation lets us get rid of "integrated×stationary"-terms.
- For IM-OLS estimation no choices with respect to tuning parameters have to be made.
- By using properly modified residuals fixed-b inference is possible.

### INTEGRATED MODIFIED OLS ESTIMATION

FURTHER ORTHOGONALIZATION OF THE RESIDUALS

• As in Vogelsang and Wagner (2014) construct some additional regressors:

$$a_t := t \sum_{j=1}^T S_j^{\tilde{F}} - \sum_{j=1}^{t-1} \sum_{s=1}^j S_s^{\tilde{F}}, \qquad S_t^{\tilde{F}} := [S_t^{F'}, X_t']'.$$

• The fixed-*b* long-run variance estimator is based on the residuals from the IM-OLS regression augmented by *a<sub>t</sub>*:

$$S_t^y = S_t^{\tilde{F}'} \beta_* + a_t' \kappa + S_t^{u*}.$$

• Denoting the residuals with  $\tilde{S}_t^{u*}$  we use:

$$\hat{\omega}_{u \cdot v}^* := T^{-1} \sum_{i=2}^T \sum_{j=2}^T k\left(\frac{|i-j|}{M}\right) \Delta \tilde{S}_i^{u*} \Delta \tilde{S}_j^{u*}.$$

### TESTING FOR SMOOTH TRANSITION COINTEGRATION FM-OLS: Wald-Type Test

• The Wald-type test is based on FM-OLS estimation of:

$$y_t = Z_t'\beta_0 + Q_t'\beta_Q + u_t$$

 The null hypothesis is H<sub>0</sub> : β<sub>Q</sub> = 0; and the corresponding test statistic is given by:

$$W_{FM} := rac{\hat{eta}_Q^{+\prime}( ilde{Q}' ilde{Q})\hat{eta}_Q^+}{\hat{\omega}_{u\cdot v}},$$

with  $\tilde{Q} := Q - Z(Z'Z)^{-1}Z'Q$ .

• The conditional long-run variance estimator used is given by:

$$\hat{\omega}_{u\cdot v} := \hat{\Omega}_{uu} - \hat{\Omega}_{uv} \hat{\Omega}_{vv}^{-1} \hat{\Omega}_{vu},$$

using the OLS residuals of the above Taylor approximation and  $v_t = \Delta X_t$ .

### TESTING FOR SMOOTH TRANSITION COINTEGRATION FM-OLS: LM-TYPE TEST

• The starting point is FM-OLS estimation of the null model:

$$y_t = Z_t'\beta_0 + u_t$$

• The resulting FM-OLS residuals  $\hat{u}_t^+ := y_t^+ - Z_t' \hat{\beta}_0^+$  are then used as dependent variable in:

$$\hat{u}_t^+ = \tilde{Q}_t' \beta_{\tilde{Q}} + \psi_t,$$

with  $\tilde{Q} := Q - Z(Z'Z)^{-1}Z'Q$ .

- The parameter  $\beta_{\tilde{Q}}$  needs to be estimated with a suitable correction to FM-OLS; similar to Wagner and Hong (2016, Proposition 4).
- This results in the test statistic:

$$LM_{FM} := \frac{\hat{\beta}_{\breve{Q}}^{+\prime}(\breve{Q}'\breve{Q})\hat{\beta}_{\breve{Q}}^{+}}{\tilde{\omega}_{u \cdot v}},$$

with  $\tilde{\omega}_{u \cdot v}$  based on the residuals from the linear (null) model.

IM-OLS Tests: Only the Variance Estimator Differs

• For IM-OLS testing is based on the equation:

$$S_t^y = S_t^{Z'} \beta_0 + S_t^{Q'} \beta_Q + X_t' \gamma + S_t^u,$$

with the null being again  $H_0$ :  $\beta_Q = 0$ , which is now part of a "bigger" parameter vector  $\beta_*$ , i.e.,

$$\beta_Q = R_Q \beta_* = \begin{bmatrix} 0 & I_{\dim(\beta_Q)} & 0 \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_Q \\ \gamma \end{bmatrix} = 0.$$

• Since we use OLS in a linear regression model, Wald- and LM-type tests only differ by the variance estimator chosen, and we end up with:

$$\{W, LM, Fb\}_{IM} := \frac{\hat{\beta}'_{Q,*} \left(R_Q \hat{V}_{IM} R'_Q\right)^{-1} \hat{\beta}_{Q,*}}{\omega_{u \cdot v}},$$

with  $\omega_{u \cdot v} \in {\{\hat{\omega}_{u \cdot v}, \tilde{\omega}_{u \cdot v}, \hat{\omega}_{u \cdot v}^*\}}$  and  $\hat{V}_{IM}$  an estimator of the "X'X"-part of the estimator variance.

STANDARD LIMIT NULL DISTRIBUTIONS

#### PROPOSITION

Under the null hypothesis of linear cointegration it holds that:

$$W_{\rm FM}, LM_{\rm FM}, W_{\rm IM}, LM_{\rm IM} \stackrel{d}{\rightarrow} \chi_q^2,$$

with  $q = \dim(\beta_Q)$  depending on the model and the Taylor approximation order.

FIXED-b LIMIT NULL DISTRIBUTION

#### PROPOSITION

If M = bT with  $b \in (0, 1]$  being held fixed as  $T \to \infty$ , then it holds for the fixed-*b* test statistic under the null hypothesis that:

$$Fb_{\mathrm{IM}} \xrightarrow{d} \frac{\chi_q^2}{N(\tilde{P}^*)},$$

with  $\chi_q^2$  independent of  $N(\tilde{P}^*)$ , where  $N(\cdot)$  is a function of (a function of) standard Wiener processes  $\tilde{P}$  that depends upon bandwidth and kernel function.

CONSISTENCY AGAINST FIXED ALTERNATIVES: TRIANGULAR ARRAY ASYMPTOTICS

#### PROPOSITION

Under the alternative hypothesis of smooth transition cointegration:

$$y_t = Z'_t \theta_L + Z'_t \theta_{NL} \times G(s_{t,T}, \theta_G) + u_t,$$

with  $\theta_{NL} \neq 0$ ,  $\gamma \neq 0$  and  $s_{t,T} := \frac{T_0}{T}t$  for time as transition variable and  $s_{t,T} := \sqrt{\frac{T_0}{T}}s_t$  otherwise it holds that:

$$LM_{\rm FM}, LM_{\rm IM} = O_{\mathbb{P}}(T/M_T),$$

with  $M_T$  denoting the bandwidth used for long-run covariance estimation.

SIMULATION DESIGN: SIZE

Under the null hypothesis we generate data according to:

$$y_t = \theta_0 + \theta_1 x_{1t} + \theta_2 x_{2t} + u_t,$$

with the errors  $u_t$  and  $v_t = \Delta x_t$  generated as:

$$u_t = \rho_1 u_{t-1} + \varepsilon_t + \rho_2 (e_{1t} + e_{2t}), \quad u_0 = 0,$$
  
$$v_{it} = e_{it} + 0.5 e_{i,t-1}, \quad i = 1, 2,$$

with  $(\varepsilon_t, e_{1t}, e_{2t})' \sim \mathcal{N}(0, I_3)$ .

- $\rho_1$  controls the level of serial correlation in the error term  $u_t$ , and  $\rho_2$  controls regressor endogeneity.
- The parameter values are set to  $\theta_0 = \theta_1 = \theta_2 = 1$ .
- $T \in \{100, 200, 500\}$  and  $\rho_1 = \rho_2 \in \{0, 0.3, 0.6, 0.8\}.$
- The number of replications is 5,000 in all cases and all tests are carried out at the nominal 5% level.
- We use the Bartlett kernel and the Andrews (1991) bandwidth.

### Empirical Null Rejection Probabilities

#### TRANSITION VARIABLE $s_t = x_{2t}$

т	$ ho_1, ho_2$	D-OLS		FM-OLS		IM-OLS		
		W <sub>D,AIC</sub>	W <sub>D,BIC</sub>	W <sub>FM</sub>	$LM_{FM}$	WIM	LMIM	Fb <sub>IM</sub>
Panel A	: First order	Taylor app	roximation	(n = 1)				
100	.0	.0872	.0770	.1460	.0582	.1168	.0542	.0548
	.3	.1474	.1392	.1540	.0672	.1526	.0800	.1304
	.6	.2348	.1822	.1826	.0586	.1976	.1006	.2502
	.8	.4256	.2630	.2536	.0610	.3028	.1544	.5190
200	.0	.0660	.0654	.1100	.0530	.0974	.0598	.0532
	.3	.1116	.1112	.1260	.0636	.1164	.0780	.0936
	.6	.1690	.1506	.1538	.0574	.1454	.0892	.1394
	.8	.2742	.1948	.1940	.0498	.1960	.1020	.2918
Panel B	: Third orde	er Taylor ap	proximation	n ( <i>n</i> = 3)				
100	.0	.1756	.1530	.3136	.0884	.2426	.0372	.0704
	.3	.2588	.2380	.3006	.0578	.3128	.0690	.2350
	.6	.4146	.3056	.3080	.0312	.3868	.0736	.6072
	.8	.6482	.3916	.3874	.0678	.5590	.1110	.9030
200	.0	.0964	.0884	.2058	.0566	.1658	.0386	.0538
	.3	.1784	.1742	.2096	.0510	.2178	.0686	.1346
	.6	.2764	.2452	.2358	.0274	.2770	.0742	.3202
	.8	.4490	.3126	.3022	.0286	.3976	.0720	.6646

### EMPIRICAL NULL REJECTION PROBABILITIES

#### Transition variable $s_t = t$

	$ ho_1, ho_2$	D-OLS		FM-OLS		IM-OLS		
Т		W <sub>D,AIC</sub>	W <sub>D,BIC</sub>	W <sub>FM</sub>	$LM_{FM}$	WIM	LMIM	$Fb_IM$
Panel A	: First order	Taylor app	roximation	(n = 1)				
100	.0	.1168	.1014	.1260	.0542	.0926	.0546	.0592
	.3	.1982	.1876	.2448	.1254	.1784	.1110	.1676
	.6	.4100	.3312	.4622	.2344	.2824	.1346	.3676
	.8	.7182	.5972	.6778	.3822	.5170	.2628	.7334
200	.0	.0598	.0568	.0592	.0476	.0544	.0512	.0498
	.3	.1002	.0984	.1054	.0584	.0940	.0730	.0672
	.6	.1788	.1750	.1568	.0460	.1024	.0740	.1060
	.8	.3448	.3530	.2686	.0288	.1242	.0666	.1946
Panel B	: Third orde	er Taylor ap	proximatior	n ( <i>n</i> = 3)				
100	.0	.3040	.2620	.3352	.0808	.2404	.0498	.0862
	.3	.4734	.4444	.5250	.2542	.4406	.1048	.3308
	.6	.8300	.7438	.8578	.4638	.6844	.0932	.8158
	.8	.9794	.9434	.9704	.6338	.9312	.2102	.9884
200	.0	.1352	.1272	.1650	.0616	.1146	.0486	.0588
	.3	.2914	.2854	.4182	.2038	.2960	.0968	.1664
	.6	.6146	.5542	.7010	.3656	.4432	.0732	.4900
	.8	.9202	.8804	.9130	.5344	.7738	.1712	.8800

SIMULATION DESIGN: POWER

For the alternative we use the following DGP:

$$y_t = Z'_t heta_L + Z'_t heta_{NL} imes G(s_t, \gamma, c) + u_t,$$

with  $Z_t = [1, x_t']'$  and errors  $u_t$ ,  $v_t = \Delta x_t$  as generated for the null.

- The parameter values are set again to  $\theta_L = [1, 1, 1]'$ .
- As transition function we consider  $G(\cdot) \in \{G_1(\cdot), G_2(\cdot)\}$  and transition variable  $s_t \in \{x_{2t}, t\}$ .
- We consider location parameter c = 0 for  $s_t = x_{2t}$  and c = T/2 for  $s_t = t$  and use the scaling parameters  $\gamma \in \{0.01, 0.1, 1, 10\}$ .
- We consider a grid of (including the null) 21 points for  $\theta_{NL} := \kappa \theta_L$ , with values for  $\kappa$  chosen from the interval [0, 2] on an equidistant grid with mesh 0.1.

SIZE-CORRECTED POWER: LSTR1 WITH  $s_t = x_{2t}$ 

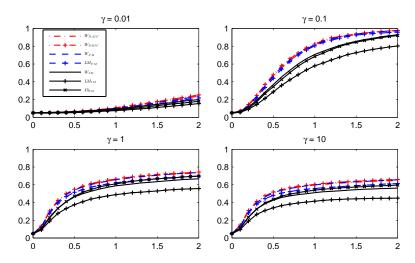


FIGURE: Size-corrected power for T = 100, Taylor approximation of order q = 1 and  $\rho_1 = \rho_2 = 0.3$ .

SIZE-CORRECTED POWER: LSTR2 WITH  $s_t = x_{2t}$ 

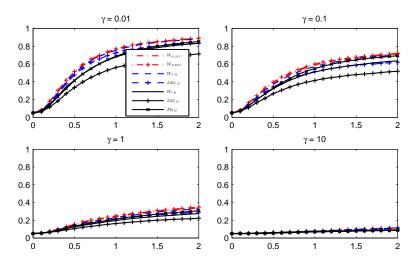


FIGURE: Size-corrected power for T = 100, Taylor approximation of order q = 1 and  $\rho_1 = \rho_2 = 0.3$ .

SIZE-CORRECTED POWER: LSTR2 WITH  $s_t = x_{2t}$ 

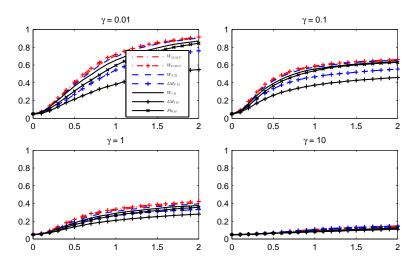


FIGURE: Size-corrected power for T = 100, Taylor approximation of order q = 3 and  $\rho_1 = \rho_2 = 0.3$ .

Size-Corrected Power: LSTR1 with  $s_t = t$ 

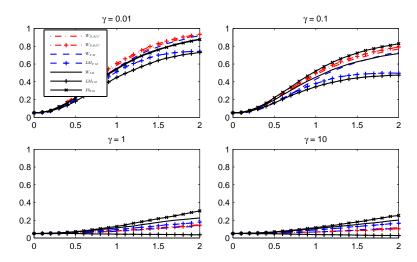


FIGURE: Size-corrected power for T = 100, Taylor approximation of order q = 1 and  $\rho_1 = \rho_2 = 0.3$ .

Size-Corrected Power: LSTR2 with  $s_t = t$ 

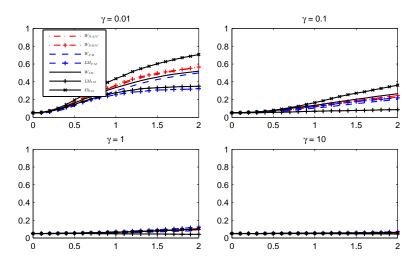


FIGURE: Size-corrected power for T = 100, Taylor approximation of order q = 1 and  $\rho_1 = \rho_2 = 0.3$ .

# Illustration with Long-Run Money Demand

We consider the simple long-run money demand equation:

$$\ln\left(\frac{M_t}{P_t}\right) = c + \delta t + \beta_1 \ln(Y_t) + \beta_2 r_t + u_t,$$

with (non-cointegrated) I(1) processes  $ln(Y_t)$  and  $r_t$ .

- $M_t$  is given by  $M_3$ .
- *P<sub>t</sub>* is the consumer price index.
- $Y_t$  is real gross domestic product.
- $r_t$  is a 3-month interest rate.

#### DATA DESCRIPTION

Variable	Description	Source
Y <sub>t</sub>	Gross Domestic Product, Expenditure Approach, Chained Volume Estimates, National Currency, Quarterly Levels, Seasonally Adjusted, National Reference Year, Reference Period: 2015 – 16.	OECD
r <sub>t</sub>	Nominal Short-Term Interest Rate, Per Cent per Annum, Quarterly.	OECD
M <sub>t</sub>	Broad Money (M3), Seasonally Adjusted, National Currency, Quarterly.	FRED
P <sub>t</sub>	Consumer Price Index (CPI), All Items, Reference Period: $2015 - 16 = 100$ , Quarterly.	OECD

- All variables quarterly, seasonally adjusted with country specific starting points and last observation 2017/III.
- Australia, Canada, Czech Republic, Denmark, Israel, New Zealand, Norway, South Korea, Sweden, Switzerland, UK, USA and Euro Area

Augmented Dickey-Fuller and Phillips-Perron Tests

	In(M3/P)			In(GDP)			Interest Rate		
	ADF	PP	PP(fb)	ADF	PP	PP(fb)	ADF	PP	PP(fb)
AUS	-1.76	-1.64	-1.61	-2.90	-3.74	-3.55	-2.92	-2.83	-2.84
CAN	-2.54	-2.08	-1.81	-2.17	-2.35	-2.38	-3.36	-2.82	-2.80
CHE	-1.59	-1.31	-1.05	-2.68	-2.58	-2.63	-2.95	-2.98	-2.97
CZE	-2.32	-2.19	-2.25	-2.28	-1.86	-1.83	-1.96	-1.75	-1.70
DEN	-2.25	-2.25	-2.26	-2.47	-1.99	-1.97	-2.62	-2.64	-2.66
ISR	-2.62	-2.59	-2.57	-2.67	-2.76	-2.70	-2.23	-2.47	-2.46
KOR	-3.61	-4.14	-4.49	-1.73	-1.56	-1.77	-2.70	-2.97	-2.95
NZL	-3.10	-2.93	-2.90	-2.11	-2.26	-2.26	-2.81	-4.56	-4.62
NOR	-1.93	-1.66	-1.57	-3.16	-3.16	-3.45	-2.82	-3.25	-3.22
SWE	-2.19	-2.01	-1.88	-1.81	-1.99	-2.01	-4.33	-2.91	-3.06
UK	-2.09	-1.08	-0.70	-1.49	-1.77	-1.71	-3.57	-2.72	-2.72
USA	-0.72	-0.94	-0.92	-1.32	-1.61	-1.60	-3.24	-2.96	-2.94
EA	-2.16	-1.18	-0.79	-2.18	-1.71	-1.81	-3.02	-2.79	-2.88

TABLE: Bold entries indicate rejection at the 5% level. PP(fb) denotes the one-step version of the Vogelsang and Wagner (2013) test.

(NO-)COINTEGRATION TESTS

	Shin Test		PU Test
D-OLS	FM-OLS	IM-OLS	
0.1968	0.1670	0.0726	7.7920
0.2249	0.1139	0.0593	5.2664
0.6087	0.6440	0.1707	17.2928
0.2113	0.1479	0.0736	19.6403
0.1111	0.0848	0.0551	3.1702
0.2498	0.1533	0.0461	3.0915
0.2835	0.2270	0.0855	28.5091
0.1112	0.1015	0.0528	10.1979
0.1430	0.1351	0.0640	11.7283
0.0725	0.0572	0.0555	5.1052
0.5892	0.4693	0.2325	6.3602
0.0975	0.0418	0.0338	7.2720
0.1642	0.0698	0.0430	8.2181
	0.1968 0.2249 0.6087 0.2113 0.1111 0.2498 0.2835 0.1112 0.1430 0.0725 0.5892 0.0975	D-OLS         FM-OLS           0.1968         0.1670           0.2249         0.1139           0.6087         0.6440           0.2113         0.1479           0.1111         0.0848           0.2498         0.1533           0.2835         0.2270           0.1112         0.1015           0.1430         0.1351           0.0725         0.0572           0.5892         0.4693           0.0975         0.0418	D-OLS         FM-OLS         IM-OLS           0.1968         0.1670         0.0726           0.2249         0.1139         0.0593           0.6087         0.6440         0.1707           0.2113         0.1479         0.0736           0.1111         0.0848         0.0551           0.2498         0.1533         0.0461           0.2835         0.2270         0.0855           0.1112         0.1015         0.0528           0.1430         0.1351         0.0640           0.0725         0.0572         0.0555           0.5892         0.4693         0.2325           0.0975         0.0418         0.0338

TABLE: Results of the cointegration test by Shin (1994) and the no-cointegration test of Phillips and Ouliaris (1990) for the linear regression using Andrews (1991) bandwidth and the Bartlett kernel. Bold entries indicate rejection at the 5% level.

MOVING WINDOW ESTIMATION - COEFFICIENT TO INTEREST RATE

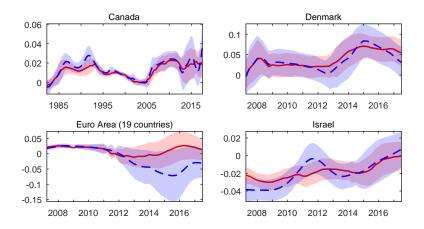


FIGURE: The red solid line displays the FM-OLS estimates and the blue dashed line displays the IM-OLS estimates for  $\beta_2$ . The corresponding 95% confidence bands are given by the red and blue shaded areas.

MOVING WINDOW ESTIMATION - COEFFICIENT TO INTEREST RATE

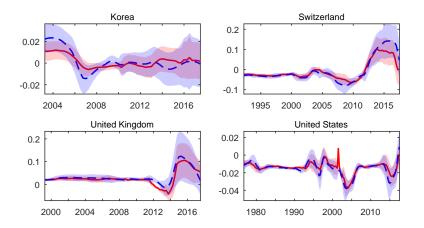


FIGURE: The red solid line displays the FM-OLS estimates and the blue dashed line displays the IM-OLS estimates for  $\beta_2$ . The corresponding 95% confidence bands are given by the red and blue shaded areas.

#### Long-Run Money Demand: $s_t = r_t$

$s_t = r_t$		D-OLS		FM-OLS		IM-OLS		
	Start	$W_{D,AIC}$	W <sub>D,BIC</sub>	W <sub>FM</sub>	$LM_{FM}$	WIM	$LM_IM$	Fb <sub>IM</sub>
Panel A:	First Order	<sup>r</sup> Taylor Ap	proximatio	n ( $n = 1$ )				
CAN	1970Q1	36.15	35.45	87.49	9.91	55.65	7.84	375.95
CHE	1980Q1	13.23	13.23	11.52	13.55	18.64	31.89	615.11
DEN	1995Q1	8.83	8.83	19.24	7.82	18.75	9.11	105.36
ISR	1995Q1	20.10	20.10	27.44	4.62	22.77	10.55	169.55
KOR	1991Q1	208.03	191.31	202.21	31.86	128.72	16.17	504.30
UK	1987Q1	5.55	4.28	5.10	55.05	13.28	59.11	814.81
USA	1964Q1	18.83	18.83	12.65	6.37	20.25	9.76	760.90
EA	1995Q1	36.79	34.95	25.59	3.74	26.31	8.54	1058.57
Panel B:	Panel B: Third Order Taylor Approximation $(n = 3)$							
CAN	1970Q1	40.95	40.95	106.06	30.41	114.92	14.78	4786.17
CHE	1980Q1	106.90	106.90	132.06	39.87	153.55	42.09	6411.93
DEN	1995Q1	33.45	33.45	28.08	15.58	34.38	12.87	299.86
ISR	1995Q1	344.29	344.29	453.20	33.11	405.33	26.91	1579.14
KOR	1991Q1	602.69	602.69	623.73	39.45	545.76	25.71	2085.52
UK	1987Q1	175.69	271.37	271.63	285.23	277.68	70.45	2968.68
USA	1964Q1	23.19	23.19	61.97	17.32	86.37	13.94	2951.75
EA	1995Q1	398.03	129.51	103.86	15.02	112.53	11.80	4735.91

TABLE: Bold numbers indicate rejection at the 5% level. For the standard tests the corresponding critical values of the  $\chi^2_{3}$ - and  $\chi^2_{9}$ -distribution are given by 7.81 and 16.92.

#### Long-Run Money Demand: $s_t = t$

$s_t = t$		D-OLS		FM-OLS		IM-OLS		
	Start	$W_{D,AIC}$	W <sub>D,BIC</sub>	W <sub>FM</sub>	$LM_FM$	WIM	$LM_IM$	Fb <sub>IM</sub>
Panel A:	First Order	· Taylor Ap	proximatio	n ( $n = 1$ )				
CAN	1970Q1	49.04	54.99	126.11	5.98	87.54	9.96	673.71
CHE	1980Q1	18.20	18.20	32.26	33.34	40.60	34.88	483.29
DEN	1995Q1	22.68	22.68	23.98	6.39	34.03	11.65	153.86
ISR	1995Q1	41.06	41.06	49.23	6.98	44.79	14.72	375.84
KOR	1991Q1	288.21	288.21	289.45	20.67	171.98	17.10	525.56
UK	1987Q1	22.24	4.44	3.53	37.03	11.71	49.54	917.39
USA	1964Q1	24.90	24.90	13.74	1.58	16.28	9.30	618.54
EA	1995Q1	50.95	68.41	36.19	4.27	34.30	8.38	2035.80
Panel B:	Panel B: Third Order Taylor Approximation $(n = 3)$							
CAN	1970Q1	135.49	138.93	253.43	33.96	242.83	15.97	6252.21
CHE	1980Q1	1271.84	256.79	-	64.73	358.60	41.50	6332.94
DEN	1995Q1	71.59	71.59	84.76	22.35	97.21	13.22	357.12
ISR	1995Q1	529.44	529.44	183.54	40.04	232.44	23.63	1334.70
KOR	1991Q1	662.97	662.97	623.19	44.82	530.29	24.85	1563.99
UK	1987Q1	242.11	349.44	292.65	322.31	316.10	69.50	2420.62
USA	1964Q1	163.31	163.31	433.14	10.58	381.73	15.02	6729.98
EA	1995Q1	355.05	355.05	208.76	25.15	164.12	11.15	5223.22

TABLE: Bold numbers indicate rejection at the 5% level. For the standard tests the corresponding critical values of the  $\chi^2_{3}$ - and  $\chi^2_{9}$ -distribution are given by 7.81 and 16.92.

Summary of Test Findings

• A large amount of rejections throughout across *n* and *s*<sub>t</sub>.

Panel A: First Order Taylor Approximation $(n=1)$					
$egin{aligned} s_t &= r_t \ s_t &= t \end{aligned}$	Canada, Denmark, South Korea, Switzerland South Korea, Switzerland				
Panel B: Third Order Taylor Approximation $(n = 3)$					
$s_t \in \{r_t, t\}$	Israel, South Korea, Switzerland, United Kingdom				

TABLE: List of countries with rejections throughout.

### SUMMARY AND CONCLUSIONS

- We have provided tests for the null of linear cointegration against the alternative of smooth transition cointegration.
- The tests are based on FM-OLS and IM-OLS estimators considered for this type of Taylor approximation polynomial.
- We face some limitations in the setting, both with respect to  $X_t$  and also  $s_t$ .
- Roughly, the LM-tests perform better than the Wald-tests.
- The next step is to develop FM- and IM-type estimation for smooth transition cointegration models.

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### ASSUMPTIONS

REGRESSORS AND ERRORS

• Let  $\{\Delta X_t\}_{t\in\mathbb{Z}} = \{v_t\}_{t\in\mathbb{Z}}$  and denote with  $\{\xi_t\}_{t\in\mathbb{Z}} = \{[u_t, v'_t])'\}_{t\in\mathbb{Z}}$  the process generated by:

$$\xi_t = C(L)\xi_t = \sum_{j=0}^{\infty} C_j \xi_{t-j}^0,$$

with  $\sum_{j=1}^{\infty} j ||C_j|| < \infty$  and  $\det(C(1)) \neq 0$ .

- The process  $\{\xi_t^0\}_{t\in\mathbb{Z}}$  is a strictly stationary and ergodic martingale difference sequence (MDS) with natural filtration  $\mathcal{F}_t = \sigma(\{\xi_s^0\}_{-\infty}^t)$ .
- Moreover, we assume a positive definite covariance matrix  $\Sigma_{\xi^0\xi^0}$  and  $\sup_{t\in\mathbb{Z}}\mathbb{E}[\|\xi^0_t\|^r|\mathcal{F}_{t-1}]<\infty$  a.s. for some r>4.

For the deterministic component we assume that there exists a sequence of  $p \times p$  scaling matrices  $A_D = A_D(T)$  and a *p*-dimensional vector of càdlàg functions D(s), with  $0 < \int_0^s D(z)D(z)'dz < \infty$  for  $0 < s \le 1$ , such that for 0 < s < 1 it holds that:

$$\lim_{T\to\infty} T^{1/2}A_D D_{[sT]} = D(s).$$

[For the leading case of polynomial time trends, the deterministic component has the form  $D_t = [1, t, t^2, \dots, t^{q-1}]'$  with  $G_D = \text{diag}(T^{-1/2}, T^{-3/2}, T^{-5/2}, \dots, T^{-(q-1/2)})$  and  $D(s) = [1, s, s^2, \dots, s^{q-1}]'$ .]

The kernel function  $k(\cdot)$  satisfies:

**(**) 
$$k(0) = 1, \ k(\cdot)$$
 is continuous at 0 and  $ar{k}(0) := \sup_{x \geq 0} |k(x)| < \infty$ 

② 
$$\int_0^\infty ar k(x) dx < \infty$$
, where  $ar k(x) = \sup_{y \ge x} |k(y)|$ 

The bandwidth satisfies  $M_T \to \infty$  with  $\lim_{T \to \infty} (M_T^{-1} + T^{-1/2} M_T) = 0.$ 

TRANSITION FUNCTION

• The transition function is given by

$$G(s_t, \theta_G) := G_*(h(s_t, \theta_G)),$$

where

$$h(s_t, \theta_G) := \gamma \prod_{i=1}^n (s_t - c_i),$$

with  $c_n \geq \ldots \geq c_1$ ,  $\gamma > 0$ .

- The function G<sub>\*</sub>(·): ℝ → ℝ is n-times continuously differentiable in an open interval including zero with G<sub>\*</sub>(0) = 0 and bounded.
- With respect to the derivatives we assume that:

$$\frac{\partial G_*(s)}{\partial s}|_{s=0} \neq 0 \quad \text{and} \quad \frac{\partial^n G_*(s)}{\partial^n s}|_{s=0} \neq 0.$$

## REGRESSION WITH INTEGRATED VARIABLES

#### REGRESSION WITH INTEGRATED VARIABLES

OLS IN COINTEGRATING REGRESSION

$$y_{t} = x_{t}\beta + u_{t}, x_{t} = x_{t-1} + v_{t}, \hat{\beta} - \beta = \left(\sum_{t=1}^{T} x_{t}^{2}\right)^{-1} \sum_{t=1}^{T} x_{t} u_{t}$$
$$T\left(\hat{\beta} - \beta\right) \Rightarrow \left(\int_{0}^{1} B_{v}^{2}(r)dr\right)^{-1} \left(\int_{0}^{1} B_{v}(r)dB_{u}(r) + \Delta_{vu}\right),$$
with  $\Delta_{vu} := \sum_{j=0}^{\infty} \mathbb{E}v_{t-j}u_{t} \ [\mathbb{E}x_{t}u_{t} = \mathbb{E}(\sum_{j=0}^{t-1} v_{t-j})u_{t}]$ 

$$\frac{1}{\sqrt{T}} x_{\lfloor rT \rfloor} = \frac{1}{\sqrt{T}} \sum_{t=1}^{\lfloor rT \rfloor} v_t \Rightarrow B_v(r) = \Omega_{vv}^{1/2} W_v(r)$$
$$\frac{1}{T^2} \sum_{t=1}^T x_t^2 = \frac{1}{T} \sum_{t=1}^T \left(\frac{x_t}{\sqrt{T}}\right)^2 \Rightarrow \int_0^1 B_v^2(r) dr$$
$$\frac{1}{T} \sum_{t=1}^T x_t u_t = \frac{1}{\sqrt{T}} \sum_{t=1}^T \left(\frac{x_t}{\sqrt{T}}\right) u_t \Rightarrow \int_0^1 B_v(r) dB_u(r) + \Delta_{vu}$$

## Regression with Integrated Variables $_{\rm FM-OLS}$

$$\begin{aligned} y_{t} &= x_{t}\beta + u_{t}, \ \hat{\beta}^{+} := \left(\sum_{t=1}^{T} x_{t}^{2}\right)^{-1} \left(\sum_{t=1}^{T} x_{t}y_{t}^{+} - \hat{\Delta}_{vu}^{+}T\right), \\ y_{t}^{+} &:= y_{t} - v_{t}\hat{\Omega}_{vv}^{-1}\hat{\Omega}_{vu}, \ \hat{\Delta}_{vu}^{+} := \hat{\Delta}_{vu} - \hat{\Delta}_{vv}\hat{\Omega}_{vv}^{-1}\hat{\Omega}_{vu} \\ \mathcal{T}\left(\hat{\beta}^{+} - \beta\right) &= \left(\frac{1}{T^{2}}\sum_{t=1}^{T} x_{t}^{2}\right)^{-1} \left(\frac{1}{T}\sum_{t=1}^{T} x_{t}u_{t}^{+} - \hat{\Delta}_{vu}^{+}\right) \\ &= \left(\frac{1}{T^{2}}\sum_{t=1}^{T} x_{t}^{2}\right)^{-1} \left(\frac{1}{T}\sum_{t=1}^{T} x_{t}u_{t}^{-} - \frac{1}{T}\sum_{t=1}^{T} x_{t}v_{t}\hat{\Omega}_{vv}^{-1}\hat{\Omega}_{vu} - \hat{\Delta}_{vu}^{+}\right) \\ &\Rightarrow \left(\int_{0}^{1} B_{v}^{2}(r)dr\right)^{-1} \left(\int_{0}^{1} B_{v}(r)dB_{u}(r) + \Delta_{vu} - \int_{0}^{1} B_{v}(r)dB_{v}(r)\Omega_{vv}^{-1}\Omega_{vu} - \Delta_{vv}\Omega_{vv}^{-1}\Omega_{vu} - \Delta_{vv}\Omega_{vv}^{-1}\Omega_{vu} - \Delta_{vu}^{+}\right) \\ &= \left(\int_{0}^{1} B_{v}^{2}(r)dr\right)^{-1} \int_{0}^{1} B_{v}(r)dB_{u\cdot v}(r), \quad B_{u\cdot v}(\cdot) := B_{u}(\cdot) - B_{v}(\cdot)\Omega_{vv}^{-1}\Omega_{vu} \right) \end{aligned}$$

## Some Asymptotic Results

#### PROPOSITION

Under the assumptions given in the paper it holds under the null hypothesis, with  $\beta_0 = [\beta'_0, 0', \dots, 0']'$ , that:

$$A^{-1}\left(\hat{\beta}^+-eta_0
ight)\stackrel{d}{
ightarrow}\left(\int_0^1 J(r)J(r)'dr
ight)^{-1}\int_0^1 J(r)dB_{u\cdot v}(r)dr$$

with  $B_{u \cdot v}(r) := B_u(r) - B_v(r)' \Omega_{vv}^{-1} \Omega_{vu}$ , A the scaling matrix, and

$$J(r) := \begin{cases} \mathbf{B}_{s}^{(0,n)}(r) \otimes \begin{bmatrix} D(r) \\ B_{v}(r) \end{bmatrix} & \text{ in case (i)} \\ \mathbf{r}^{(0,n)} \otimes \begin{bmatrix} D(r) \\ B_{v}(r) \end{bmatrix} & \text{ in case (ii)} \end{cases}$$

where  $\mathbf{B}_{s}^{(0,n)}(r) := [1, B_{s}(r), \dots, B_{s}^{n}(r)]'$  and  $\mathbf{r}^{(0,n)} := [1, r, \dots, r^{n}]'$ .

The correction term  $M^* := [M_0^{*\prime}, M_1^{*\prime}, \dots, M_n^{*\prime}]'$  depends on the approximation order and transition variable and is given by:

$$M_{j}^{*} := \begin{cases} \begin{bmatrix} j\hat{\Delta}_{su}^{+}\sum_{t=1}^{T}D_{t}s_{t}^{j-1} \\ \hat{\Delta}_{vu}^{+}\sum_{t=1}^{T}s_{t}^{j}+j\hat{\Delta}_{su}^{+}\sum_{t=1}^{T}X_{t}s_{t}^{j-1} \end{bmatrix} & \text{ in case (i)} \\ \begin{bmatrix} 0_{p} \\ \hat{\Delta}_{vu}^{+}\sum_{t=1}^{T}t^{j} \end{bmatrix} & \text{ in case (ii)} \end{cases}$$

#### PROPOSITION

Under the assumptions given in the paper it holds under the null hypothesis, with  $\beta_{*,0} := [\beta'_0, (\Omega_{vv}^{-1}\Omega_{vu})']'$ , that:

$$\begin{split} \tilde{A}^{-1}\left(\hat{\beta}_{*}-\beta_{*,0}\right) \stackrel{d}{\to} \left(\int_{0}^{1}f(r)f(r)'dr\right)^{-1}\int_{0}^{1}f(r)B_{u\cdot\nu}(r)dr\\ &= \left(\int_{0}^{1}f(r)f(r)'dr\right)^{-1}\int_{0}^{1}[F(1)-F(r)]dB_{u\cdot\nu}(r), \end{split}$$

where

$$f(r) := \begin{bmatrix} \int_0^r J(s) ds \\ B_v(r) \end{bmatrix}, \quad F(r) := \int_0^r f(s) ds$$

and J(r) as defined before.

### FIXED-**b** INFERENCE

#### FIXED-*b* INFERENCE: SIMPLE EXAMPLE I

• Consider a simple "almost standard" (i.e. HAC) regression:

$$y_t = x_t\beta + u_t,$$

with  $T^{-1}\sum_{t=1}^{\lfloor rT \rfloor} x_t^2 \rightarrow rQ$ , Q > 0 and  $z_t = x_t u_t$  such that:

$$\frac{1}{T^{1/2}}\sum_{t=1}^{\lfloor rT\rfloor} z_t \Rightarrow \omega^{1/2} W(r).$$

• Then: 
$$\sqrt{T} \left( \hat{\beta} - \beta \right) \Rightarrow \mathcal{N}(0, \omega Q^{-2}).$$

• With a consistent estimator  $\hat{\omega} \to \omega$  it follows that:

$$t_{\beta} = \frac{\hat{\beta} - \beta_0}{\sqrt{\hat{V}ar(\hat{\beta})}} = \frac{\hat{\beta} - \beta_0}{\hat{\omega}^{1/2}\hat{Q}^{-1}} \Rightarrow \mathcal{N}(0, 1).$$

Using a consistent estimator 
 *û* = 
 *f*<sub>0</sub> + 2 ∑<sub>j=1</sub><sup>T-1</sup> k(j/M) 
 *f*<sub>j</sub>, with
 *f*<sub>j</sub> = T<sup>-1</sup> ∑<sub>t=j+1</sub><sup>T</sup> 
 *ź*<sub>t</sub> 
 *ż*<sub>t-j</sub> and 
 *ž*<sub>t</sub> = x<sub>t</sub> 
 *û*<sub>t</sub>, "hides" finite sample effects of kernel function k(·) and bandwidth M.

#### FIXED-*b* INFERENCE: SIMPLE EXAMPLE II

- Consider a bandwidth proportional to sample size, i.e. M = bT.
- Then under appropriate assumptions it holds that ŵ ⇒ ωP(b, k), where P(b, k) is a function of W(r) that depends upon bandwidth b and kernel function k(·).
- This leads to a fixed-b limit distribution of the *t*-statistic of the form:

$$t_eta \Rightarrow rac{W(1)}{P(b,k)}$$

- See, e.g., Kiefer and Vogelsang (2005).
- Critical values can be tabulated for (a grid of) values of b and different kernel functions  $k(\cdot)$ .

Residuals from Linear Cointegrating Regression

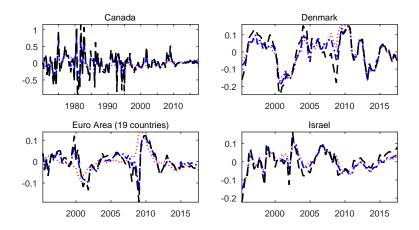


FIGURE: The red dotted line shows the D-OLS residuals, the blue dashed dotted line the FM-OLS residuals and the black dashed line the IM-OLS residuals.

Residuals from Linear Cointegrating Regression

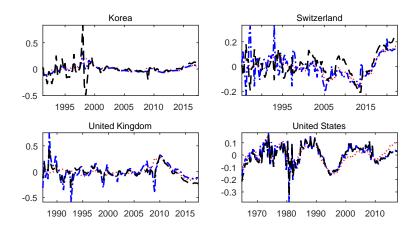


FIGURE: The red dotted line shows the D-OLS residuals, the blue dashed dotted line the FM-OLS residuals and the black dashed line the IM-OLS residuals.