

SEMIPARAMETRIC INFERENCE IN MULTIVARIATE FRACTIONALLY  
COINTEGRATED SYSTEMS

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International Conference on "Breaks and Persistence in Econometrics",

11 December 2006

Semiparametric modelling is popular in cointegration analysis of  $I(1)$  time series with  $I(0)$  cointegrating errors.

Optimal inference on unknown cointegrating relations loses validity if VAR order is under-specified, or if the process lies outside the VAR class.

One can do as well, in first-order asymptotics, allowing the  $I(0)$  inputs to have nonparametric autocorrelation.

Another source of misspecification is the  $I(1)/I(0)$  framework itself.

In a fractional setting integration orders are unknown, to non-trivially generalize the  $I(1)/I(0)$  assumption.

Optimal estimates have been developed in a fully parametric, and bivariate setting.

We develop partly-optimal inference on cointegrating relations in a semiparametric multivariate fractional setting, with integration orders that can be unknown, and stationary and/or nonstationary.

For a scalar or vector sequence  $v_t$ ,  $t = 0, \pm 1, \dots$ , denote

$$v_t^\# = v_t \mathbf{1}(t > 0),$$

where  $\mathbf{1}(\cdot)$  is the indicator function.

Define  $\Delta = 1 - L$ , where  $L$  is the lag operator, and, for real  $\alpha$ ,  $\alpha \neq -1, -2, \dots$ ,

$$\Delta^{-\alpha} = \sum_{j=0}^{\infty} a_j(\alpha) L^j, \quad a_j(\alpha) = \frac{\Gamma(j + \alpha)}{\Gamma(\alpha)\Gamma(j + 1)}.$$

A scalar process  $\zeta_t \sim I(d)$ , if for any  $l \times 1$  ( $l < \infty$ ) covariance stationary process  $\xi_t = (\xi_{it})$ , whose spectral density matrix is continuous and nonsingular

$$\zeta_t = \sum_{k=1}^l \Delta^{-d_k} \xi_{kt}^\#,$$

for  $d = \max_{1 \leq k \leq l} d_k$ .

A vector process is  $I(d)$  if all its components are  $I(d)$ .

For a  $p \times 1$  vector  $d = (d_1, \dots, d_p)'$ , denote  $\Delta(d) = \text{diag} \{ \Delta^{d_1}, \dots, \Delta^{d_p} \}$ .

Let  $u_t$ ,  $t = 0, \pm 1, \dots$ , be a  $p \times 1$  stationary unobservable process with zero mean and nonparametric spectral density matrix  $f(\lambda)$ ,

$$E(u_0 u_j') = \int_{-\pi}^{\pi} e^{ij\lambda} f(\lambda) d\lambda,$$

that is continuous and nonsingular.

For a  $p \times p$  nonsingular matrix  $\Upsilon$  and a  $p \times 1$  vector  $\delta = (\delta_1, \dots, \delta_p)'$ , define the  $p \times 1$  vector observable process  $z_t$ ,  $t = 0, \pm 1, \dots$  by

$$\Upsilon z_t = \Delta^{-1}(\delta) u_t^\#,$$

where

$$0 \leq \delta_1, \delta_2, \dots, \delta_r < \delta_{r+1} = \delta_{r+2} = \dots = \delta_p,$$

$$\delta_p - \delta_i \neq 1/2, \quad i \in \{1, \dots, r\},$$

$$\Upsilon = \begin{pmatrix} \Upsilon_1 & \Upsilon_2 \\ \mathbf{0}_{p-r,r} & I_{p-r} \end{pmatrix},$$

where  $\Upsilon_1$  is  $r \times r$  upper-triangular with ones in the main diagonal and  $\Upsilon_2$  is  $r \times (p - r)$ , with all rows of  $\Upsilon_1^{-1} \Upsilon_2$  non-null but  $\Upsilon_1$  and  $\Upsilon_2$  otherwise unknown and unrestricted.

$$z_t \sim I(\delta_p).$$

$z_t$  has cointegrating rank  $r$ .

Memories of the  $r$  cointegrating errors can vary,  $u_{it} \sim I(\delta_i)$ ,  $i = 1, \dots, r$ .

Our results are new even if  $r = 1$ , for any  $p \geq 2$ .

Given there no prior restrictions on  $f$ , those on  $\Upsilon$  and  $\delta$  ensure identifiability, and imply that (given consistent estimates of  $\Upsilon$  and  $\delta$ ) consistent estimation of  $f$  is possible.

With

$$\delta_1 = \delta_2 = \dots = \delta_r = 0, \quad \delta_{r+1} = \delta_{r+2} = \dots = \delta_p = 1,$$

we have the usual  $I(1)/I(0)$  cointegrated system.

We could transform our setup with upper-triangular  $\Upsilon_1$  to that with  $\Upsilon_1 = I_r$ , but this reduces the “achievement” of a cointegration analysis, since the relations would generally each have integration order  $\max_{i \in \{1, \dots, r\}} \delta_i$ .

While this transformation seems innocuous in the traditional framework where  $\delta_i = 0, i = 1, \dots, r$ , in our fractional setting it could reduce cointegrating gaps.

We include:

stationary cointegration,  $\delta_p \in (0, 1/2)$

weak cointegration,  $\delta_p - \delta_i < 1/2$

strong cointegration,  $\delta_p - \delta_i > 1/2$

We extend nontrivially the bivariate model to a richer multivariate framework,

allow for nonparametric  $f$ ,

simultaneously cover relations of weak and strong cointegration.

Asymptotics for point estimates for  $\Upsilon$  differ significantly across these cases, the same rules of inference prevail throughout, the same Wald test statistic (for a linear hypothesis) having a null limit  $\chi^2$  distribution.

We treat the nonparametric autocorrelation in the frequency domain.

We use a ratio of weighted periodogram averages either across all frequencies or within a shrinking neighbourhood of zero frequency.

The weighting is inverse with respect to smoothed estimates of  $f$ .

Because of the concentration of spectral mass around zero frequency, where  $f$  changes little, computationally simpler estimates, with the same asymptotic properties, use just an estimate of  $f(0)$ .

Form unknown elements of  $\Upsilon$  into the  $q \times 1$  vector  $\nu$ , where  $q = r(p - (r + 1) / 2)$ .

Equivalently write

$$vec\Upsilon = C\nu - c,$$

for suitable  $C$  and  $c$ .

Define the  $p^2 \times p$  matrix-valued process  $z_t^d$ , whose  $i$ th  $p \times p$  sub-matrix is diagonal with  $(j, j)$ th element  $\Delta^{d_j} z_{it}$ .

Define the DFT

$$w_\xi(\lambda) = \frac{1}{(2\pi n)^{\frac{1}{2}}} \sum_{t=1}^n \xi_t e^{it\lambda},$$

for real  $\lambda$ .

Denote by  $\lambda_j = 2\pi j/n$ ,  $j = 0, \dots, [n/2]$ , the Fourier frequencies.

Given  $z_t, t = 1, \dots, n$ , a nonsingular estimate  $\hat{f}(\lambda)$  of  $f(\lambda)$ , for integer  $m$  such that

$$m \rightarrow \infty \text{ as } n \rightarrow \infty, \quad 1 \leq m \leq n/2,$$

and  $s_j = 1, j = 0, n/2, s_j = 2$ , otherwise, define

$$\hat{a}_m(d) = C' \sum_{j=0}^m s_j \operatorname{Re} \left\{ w_{z^d}(-\lambda_j) \hat{f}^{-1}(\lambda_j) w'_{z^d}(\lambda_j) \right\} c,$$

$$\hat{b}_m(d) = C' \sum_{j=0}^m s_j \operatorname{Re} \left\{ w_{z^d}(-\lambda_j) \hat{f}^{-1}(\lambda_j) w'_{z^d}(\lambda_j) \right\} C,$$

$$\hat{a}_m^{\circ}(d) = C' \sum_{j=0}^m s_j \operatorname{Re} \left\{ w_{z^d}(-\lambda_j) \hat{f}^{-1}(0) w'_{z^d}(\lambda_j) \right\} c,$$

$$\hat{b}_m^{\circ}(d) = C' \sum_{j=0}^m s_j \operatorname{Re} \left\{ w_{z^d}(-\lambda_j) \hat{f}^{-1}(0) w'_{z^d}(\lambda_j) \right\} C.$$

Defining

$$\hat{\nu}_m(d) = \hat{b}_m^{-1}(d) \hat{a}_m(d), \quad \hat{\nu}_m^{\circ}(d) = \hat{b}_m^{\circ}(d)^{-1} \hat{a}_m^{\circ}(d),$$

consider the estimates of  $\nu$  :

$$\begin{aligned} \text{W ("weighted")} & : \hat{\nu}_m(\delta), \hat{\nu}_m(\hat{\delta}); \\ \text{Z ("zero-frequency")} & : \hat{\nu}_m^{\circ}(\delta), \hat{\nu}_m^{\circ}(\hat{\delta}), \end{aligned}$$

where  $\hat{\delta}$  estimates  $\delta$ .

The estimates are of GLS type, and effectively “whiten” the data, as their desirable asymptotic properties will confirm.

$\hat{\nu}_m(\delta)$ ,  $\hat{\nu}_m^o(\delta)$ , treat  $\delta$  as known (as is usual in the  $I(1)/I(0)$  case), but in our context they are generally regarded as infeasible, and included in part for completeness and to demonstrate that estimation of  $\delta$  makes no asymptotic difference, as well as to imply, with  $\hat{\nu}_m(\hat{\delta})$ ,  $\hat{\nu}_m^o(\hat{\delta})$ , cases where  $\delta$  is partly known (e.g.  $\delta_p = 1$  is known but  $\delta_1, \dots, \delta_r$  are unknown).

The computational simplicity of the Z over the W estimates is due not only to having to estimate  $f$  at only frequency zero, but to

$$\hat{a}_{[n/2]}^{\circ}(d) = \frac{1}{2\pi} C' \sum_{t=1}^n z_t^d \hat{f}^{-1}(0) (z_t^d)' c, \quad \hat{b}_{[n/2]}^{\circ}(d) = \frac{1}{2\pi} C' \sum_{t=1}^n z_t^d \hat{f}^{-1}(0) (z_t^d)' C.$$

In a parametric setting with strong cointegration, Z estimates only do as well as W ones when the cointegrating gap  $> 1$ ;

when it is 1, a “second-order bias” appears, when it is less than 1 (but greater than 1/2) convergence is slower due to sub-optimal weighting, and in each case the null  $\chi^2$  limit distribution of Wald test statistics is lost.

Limiting the increase of  $m$  repairs this defect

Consider

$$H_0 : R\nu = v,$$

where  $v$  is a given  $J \times 1$  vector and  $R$  is a given  $J \times q$  matrix with full row rank and constraints don't link different rows of  $\Upsilon$  (to avoid commutativity problems due to different convergence rates).

We permit linear restrictions among coefficients in the same cointegrating relation, including the possibility that one or more of the  $\nu_k$  is known *a priori*, and also exclusion restrictions.

The W and Z Wald statistics on which tests are based are

$$W_m(d) = (R\hat{\nu}_m(d) - v)' (Rb_m^{-1}(d) R')^{-1} (R\hat{\nu}_m(d) - v),$$

$$W_m^\circ(d) = (R\hat{\nu}_m^\circ(d) - v)' (Rb_m^\circ(d)^{-1} R')^{-1} (R\hat{\nu}_m^\circ(d) - v),$$

with  $d = \delta$  or  $\hat{\delta}$ .

Assume for the W estimates that

$$u_t = A(L) \varepsilon_t, \quad A(z) = I_p + \sum_{j=1}^{\infty} A_j z^j,$$

where the  $A_j$  are  $p \times p$  such that

$$\det \{A(z)\} \neq 0, \quad |z| = 1 \text{ (W) or } \det \{A(1)\} \neq 0 \text{ (Z)}$$

$A(e^{i\lambda})$  is differentiable in  $\lambda \in [-\pi, \pi]$  with derivative in  $Lip(\eta)$ ,  $\eta > 1/2$ , the  $\varepsilon_t$  are iid with mean 0, pd covariance matrix  $\Omega$ , and  $E \|\varepsilon_t\|^\mu < \infty$ ,  $\mu \geq 4$ , and if  $\delta_p - \delta_i > 1/2$  for some  $i \in \{1, \dots, r\}$ ,  $\mu > 2/(2 \min_{i: \delta_p - \delta_i > 1/2} (\delta_p - \delta_i) - 1)$ .

This is easily satisfied if  $u_t$  is a stationary and invertible ARMA.

The rates in our conditions have implications for the choice of  $m$ .

The usual estimates of integration orders and spectral densities have convergence rates no better than  $n^{2/5}$ , so that not all conditions can hold when  $m$  grows as fast as  $n$ , and  $\delta_p - \delta_i \leq 3/5$ .

Since bias increases with  $m$ , bias-reduction may be needed.

Various devices are available.

Our  $\nu$  estimates have mixed normal asymptotics when all cointegrating relations are strong, normal asymptotics when all are weak, and when both kinds of relation are present there is a corresponding combination of limiting distributions.

The final, global, outcome is that Wald statistics the same, standard, limit behaviour:

Under  $H_0$ ,

$$W_m(\delta), W_m(\hat{\delta}) \rightarrow_d \chi_J^2,$$

$$W_m^o(\delta), W_m^o(\hat{\delta}) \rightarrow_d \chi_J^2.$$

Thus, the limit theory of Wald tests, familiar in many classical situations in econometrics and associated with optimal procedures in the  $I(1)/I(0)$  cointegration literature, holds here simultaneously for weak (including stationary) and strong cointegration, and in the possible presence of unknown integration orders of observables and/or cointegrating errors.

Extensions:

Over-identifying restrictions

Variable integration orders of observables.

Parametric counterpart:  $f(\lambda) = f(\lambda; \tau)$ ,  $\lambda \in (-\pi, \pi]$ , where  $f(\lambda; \tau)$  is a known function of  $\lambda$  and an unknown finite-dimensional vector  $\tau$  (e.g.  $u_t$  is a VAR of prescribed degree).

Given an estimate  $\hat{\tau}$  of  $\tau$ , the  $f(\lambda_j; \hat{\tau})$  can replace the  $\hat{f}(\lambda_j)$  with  $m = \lfloor n/2 \rfloor$ .

Under strong cointegration the resulting estimate of  $\nu$  does not do better than ours.

Under weak cointegration, it is, like ours, asymptotically normal but with a faster,  $\sqrt{n}$ , rate and is not asymptotically independent of  $\hat{\tau}$ , or of the estimate of  $\delta$ , which also needs to be  $\sqrt{n}$ -consistent.

We can obtain optimal estimates of  $\nu$ ,  $\delta$  and  $\tau$  by jointly optimizing a Gaussian likelihood.