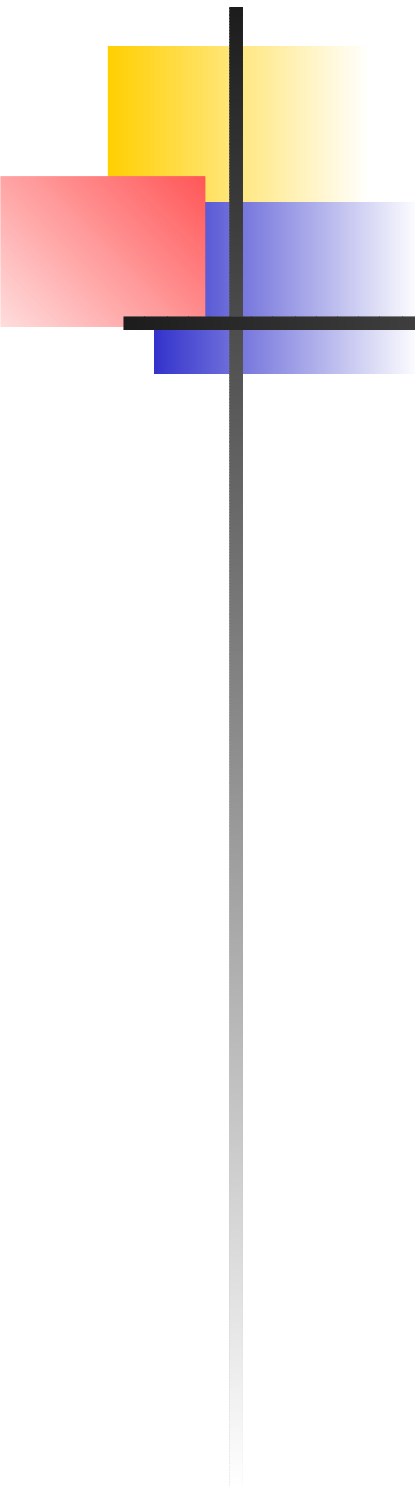




Reduced-Rank Regression

Applications in Time Series

Raja Velu

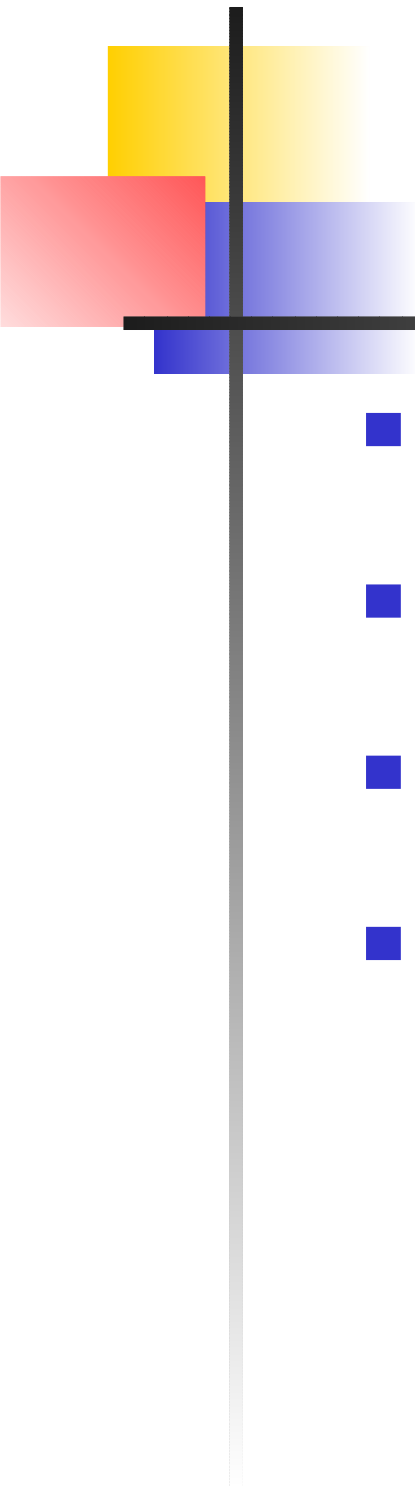
rpvelu@syr.edu

Whitman School of Management

Syracuse University

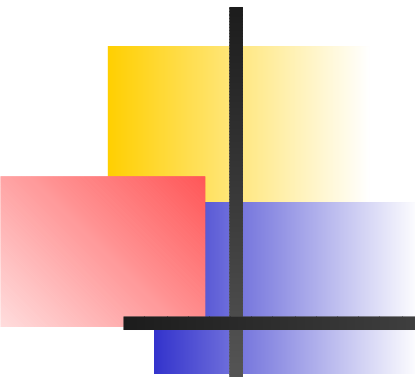
Gratefully to my teachers GCR & TWA

June 6, 2008



Outline

- Brief Review of Reduced Rank Regression
- VAR Model Structure and RR Features
- Numerical Example
- Recent Developments - Forecasting/
RRR-Shrinkage



Review of RRR Results

■ Anderson(1951)

$$Y_t = CX_t + DZ_t + \epsilon_t \quad (1)$$

$$m \times 1 \quad n_1 \times 1 \quad n_2 \times 1$$

$$\text{Rank}(C) = r < m \quad (2)$$

■ Two implications:

$$l_i' C = 0 \quad i = 1, 2, \dots, (m - r) \quad (3)$$

$$C = AB \quad (4)$$

Review (contd.)

■ Estimation of Anderson's Model

Minimize,

$$\begin{aligned} |W| &= \left| \frac{1}{T} (Y - ABX - DZ)(Y - ABX - DX)' \right| \\ &= \left| \tilde{\Sigma}_{\epsilon\epsilon} + (\tilde{C} - AB)\hat{\Sigma}_{xx.z}(\tilde{C} - AB)' \right| \end{aligned} \quad (5)$$

$\tilde{\Sigma}_{\epsilon\epsilon}$ —Residual Covariance matrix under full rank

$\hat{\Sigma}_{xx.z}$ — Partial Covariance matrix

Thus, SVD on

$\tilde{\Sigma}_{\epsilon\epsilon}^{-1/2} \tilde{C} \hat{\Sigma}_{xx.z}^{1/2}$ yields Gaussian Estimates

Review (contd.)

Let $\hat{R} = \tilde{\Sigma}_{\epsilon\epsilon}^{-1/2} \tilde{C} \hat{\Sigma}_{xx.z} \tilde{C}' \tilde{\Sigma}_{\epsilon\epsilon}^{-1/2}$; Let V_j be a normalized eigen vector of $\hat{R}$ associated with j^{th} largest eigen value, $\hat{\lambda}_j^2$

$$\hat{C} = \hat{A}\hat{B} = P\tilde{C} \quad (6)$$

$$\hat{A} = \tilde{\Sigma}_{\epsilon\epsilon}^{-1/2} \hat{V}_{(r)}, \quad \hat{B} = \hat{V}'_{(r)} \tilde{\Sigma}_{\epsilon\epsilon}^{-1/2} \tilde{C}$$

$$\text{where } \hat{V}_{(r)} = [\hat{V}_1, \dots, \hat{V}_r],$$

■ Estimation of l'_i s in (3)

$$\hat{l}'_i = \hat{V}'_{(i)} \tilde{\Sigma}_{\epsilon\epsilon}^{-1/2} \quad i = r + 1, \dots, m \quad (7)$$

■ Unknown Parameters : $mn_1 \rightarrow r(m + n_1 - r)$

Review (contd.)

■ Note $\left| \hat{\Sigma}_{\epsilon\epsilon} \right| = \left| \tilde{\Sigma}_{\epsilon\epsilon} \right| \prod_{j=r+1}^m (1 + \hat{\lambda}_j^2)$ (8)

$$(1 + \hat{\lambda}_j^2) = 1/(1 - \hat{\rho}_j^2)$$

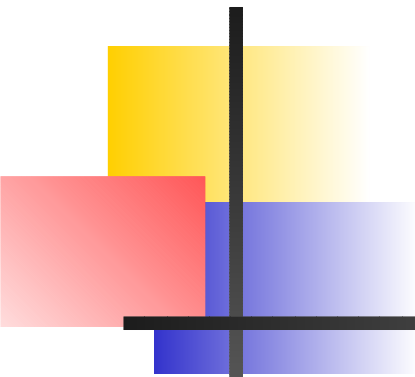
$\hat{\rho}_j^2$: Squared Partial Canonical Correlations

■ LR Test for $H_0 : \text{Rank}(C) \leq r$

$$[T - n_1 + (n_1 - m - 1)/2] \cdot \sum_{j=r+1}^m \log(1 - \hat{\rho}_j^2) \quad (9)$$

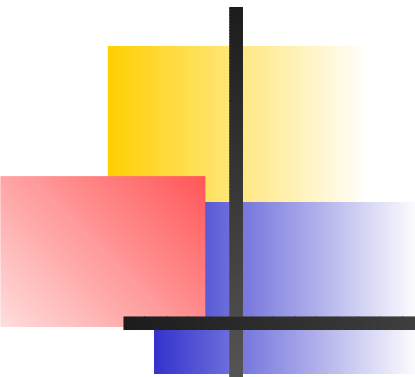
$$\sim \chi_{(m-r)(n_1-r)}^2$$

■ Hence, RRR $\Leftrightarrow$ Canonical Correlation Analysis



VAR Models

- Number of Parameters depend on order ' p ' and dimension ' m '
- Stationarity imposes constraints on the AR Coefficient matrices
- Anderson (2002) : Canon Corr / VAR RR
- Box & Tiao (1977): Cannon Corr/Non-stationarity – Cointegration ideas



VAR/RR - Features

$$Y_t = \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \epsilon_t \quad (10)$$

- Φ_2 – reduced-rank; Φ_1 – Full rank – Anderson's Model

- Rank $(\Phi_1 : \Phi_2)$ lower rank;

- $$Y_t = A(B_1 : B_2) \begin{pmatrix} Y_{t-1} \\ Y_{t-2} \end{pmatrix} + \epsilon_t \quad (11)$$

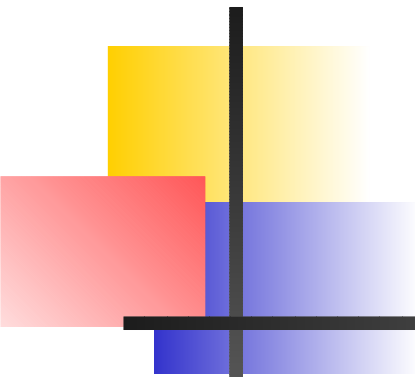
(Velu et al 1986)

- $$Y_t = A_1 B Y_{t-1} + A_2 B Y_{t-2} + \epsilon_t \quad (12)$$

(Reinsel 1985) -Index Model

- Let $\Phi_j = A_j B_j$ and $\text{range}(A_{j+1}) \subset \text{range}(A_j)$

(Ahn and Reinsel, 1988) –Nested RR



VAR- Unit Root Features

- Model (10) : $Y_t - \Phi_1 Y_{t-1} - \Phi_2 Y_{t-2} = \Phi(L)Y_t = \epsilon_t$
 $|\Phi(L)| = 0$, has $d \leq m$ unit roots; rest are outside unit circle
- Error Correction (Granger) form:
$$W_t = CY_{t-1} - \Phi_2 W_{t-1} + \epsilon_t \quad (13)$$
$$\text{Rank}(C) = \text{Rank}(-\Phi(1)) \leq r = m - d \quad (14)$$
- Thus, non-stationarity can be checked via reduced-rank test; Anderson (1951)
- Implications of (14); $W_t = Y_t - Y_{t-1}$ is stationary

VAR- Unit Root Features - Interpretation

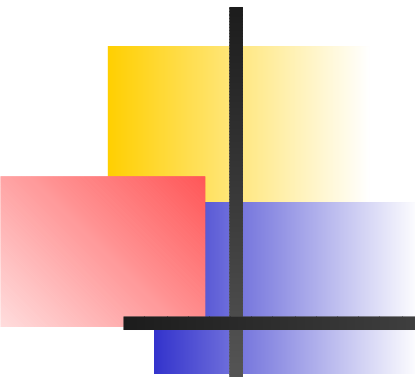
- Johansen (1988,1991)

Note (13) is: $W_t = ABY_{t-1} - \Phi_2 W_{t-1} + \epsilon_t \dots \dots \dots (14)$

- BY_t are stationary; rows of B are co-integrating vectors

- Let $Z_t = \begin{pmatrix} B \\ B^* \end{pmatrix} Y_t$, $B^* (d \times m)$ is orthogonal to B

- $B^* Y_t$ are non-stationary – “Common Trends”



VAR-Unit Root-RRR - Advantages

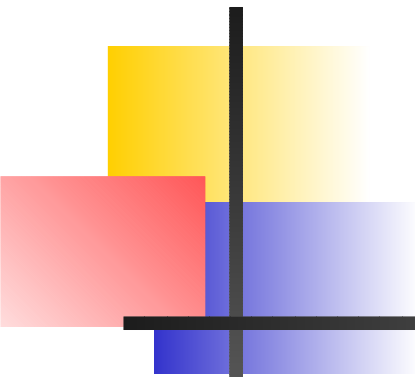
- Parsimonious Parametrization
- Exhibit any “co-features” or “common features”
- Improves forecasting
- Other References are :

Tiao and Tsay (1988)

Hannan and Deistler (1988)

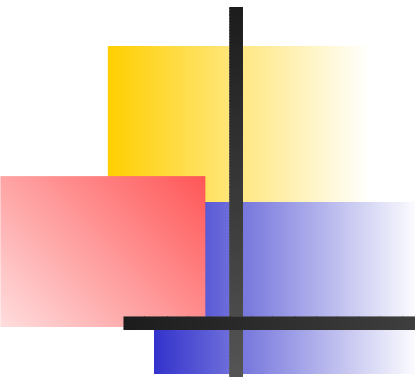
Engle and Kozicki (1993)

Min and Tsay (2005)



Cointegration-Unit Root-Tests

- $H_0: \text{Rank}(C) = r \quad \text{vs} \quad H_1: \text{Rank}(C) < r$
- Johansen's Trace Statistics:
$$L_{tr}(r) = -(T - mp) \sum_{j=r+1}^m \ln(1 - \hat{\rho}_j^2) \dots\dots\dots(9)$$
- Limiting distribution of L_{tr} is a standard Brownian motion, depends only on 'r'
- Estimation of C, A, B etc. all follow from Anderson (1951)



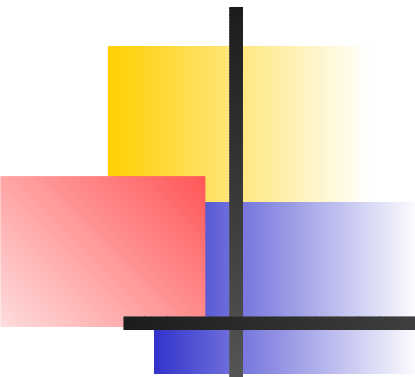
Beyond Cointegration – Common Features

- Note that in Model

$$W_t = ABY_{t-1} - \Phi_2 W_{t-1} + \epsilon_t,$$

the component BY_{t-1} is stationary

- Find $l'_i \ni l'_i A = 0$ spans the co-feature space (Anderson 1951)
- Find $l'_i \ni l'_i A = 0$ and $l'_i \Phi_2 = 0$, Serial Correlation Common Feature (Engle & Kozicki 1993)
- Common Seasonality (Hecq et al 2006)
- Review Paper : Urga (2007)



Numerical Example

- Four Quarterly Series : Private Investment, GNP, Consumption and Unemployment, 1951-1988, $T = 148$ (See Figure 1)
- VAR(2) is specified; also $rank(\Phi_2) = 1$ based on partial Canonical Correlations (See Table 2)
- Recall that Partial Canonical analysis between W_t and Y_{t-1} , given $W_{t-1} \Leftrightarrow LR$ for Unit Roots;

Results suggests $d = 2$ unit roots, thus $r = 2$ cointegrating ranks; (See Table 3)

- Model (14) : $W_t = CY_{t-1} - \Phi_2 W_{t-1} + \epsilon_t$

Figure 1

Fig. 1. Logs of Quarterly US Economy Time Series, 1951 - 1988

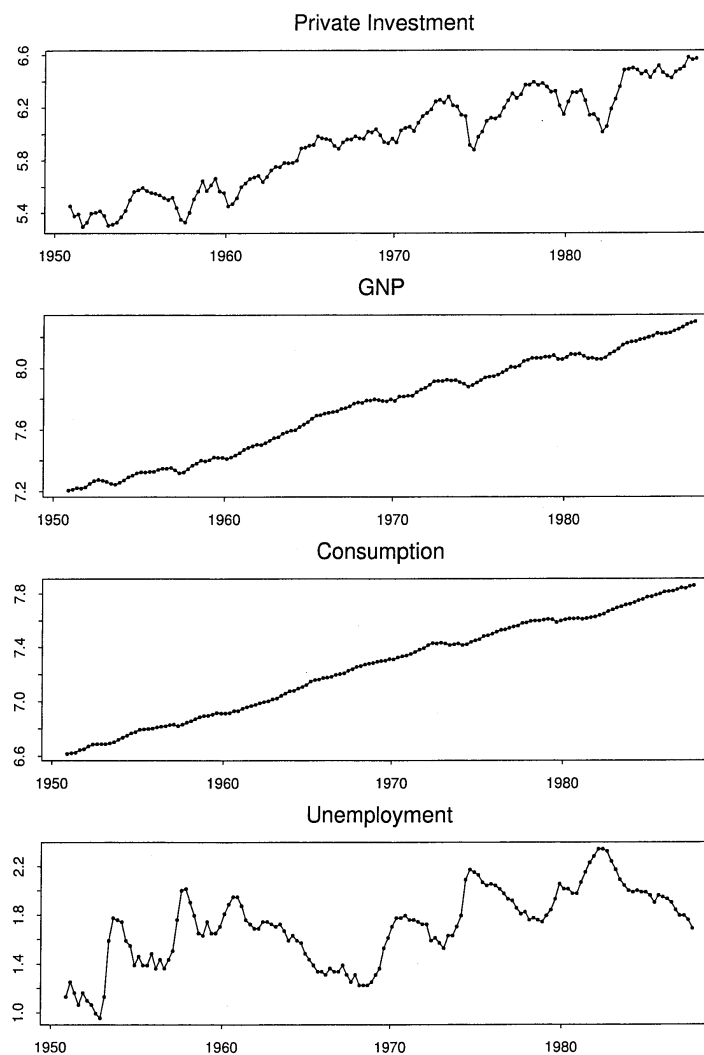


Table 2

SPECIFICATION OF AR ORDER AND REDUCED RANKS

Table 2. Summary of Test Statistics for AR Order j and Ranks $r_j = m - s$ of Coefficients Φ_j for US Economy Data, Partial Canonical Correlation Analysis between Y_t and Y_{t-j} , given $Y_{t-1}, \dots$

j	Eigenvalues	$C(j, s)$			
		$s=4$ ($r=0$)	$s=3$ ($r=1$)	$s=2$ ($r=2$)	$s=1$ ($r=3$)
1	0.999, 0.931, 0.825, 0.540	1895.95	734.00	356.22	109.88
2	0.374, 0.057, 0.004, 0.001	72.69	8.77	0.70	0.09
3	0.098, 0.051, 0.027, 0.002	24.23	10.71	3.88	0.23
4	0.107, 0.071, 0.011, 0.001	25.34	10.99	1.61	0.16
5	0.146, 0.033, 0.012, 0.002	25.02	5.81	1.67	0.22
6	0.102, 0.064, 0.012, 0.004	22.10	9.58	1.85	0.45

- Eigenvalues are squared partial canonical correlations $\hat{\rho}_i^2(j)$. Test for

$$H_0: \text{rank}(\Phi_j) = m - s \text{ is } C(j, s) = -(T - j - mj - 1) \sum_{i=(m-s)+1}^m \log[1 - \hat{\rho}_i^2(j)] \sim \chi_{s^2}^2$$

Table 3

SPECIFICATION OF $rank(C)$ OR NUMBER d OF UNIT ROOTS

Table 3. Summary of LR Tests for $rank(C) = r$ (cointegration) or number of unit roots $d = m - r$ for US Economy Data, Partial Canonical Correlation Analysis between W_t and Y_{t-1} , given $W_{t-1}, \dots$

j	Eigenvalues	LR statistics			
		$r=0$ ($d=4$)	$r=1$ ($d=3$)	$r=2$ ($d=2$)	$r=3$ ($d=1$)
1	0.304, 0.115, 0.060, 0.011	81.20	28.36	10.56	1.56
2	0.207, 0.086, 0.053, 0.012	56.43	22.81	9.72	1.78
3	0.196, 0.085, 0.074, 0.010	56.60	25.24	12.52	1.41
4	0.219, 0.078, 0.072, 0.011	59.20	23.93	12.26	1.59
5	0.179, 0.089, 0.066, 0.013	52.80	24.84	11.57	1.83
6	0.196, 0.099, 0.068, 0.008	56.50	25.75	11.11	1.17

- Eigenvalues are squared partial canonical correlations $\hat{\rho}_i^2$ of W_t and Y_{t-1} ,

$$-(T - j) \log(\lambda) = -(T - mp) \sum_{i=r+1}^m \log(1 - \hat{\rho}_i^2) \text{ is LR statistic.}$$

Numerical Example (contd.)

■ Estimation with 'Cointegrating' Reduced Rank Imposed

$$\hat{C} = \hat{A}\hat{B} = \begin{bmatrix} -0.241 & 0 \\ -0.022 & 0 \\ -.01 & .107 \\ -.209 & -.921 \end{bmatrix} \begin{bmatrix} 1 & 0 & -.997 & .092 \\ 0 & 1 & -.942 & .094 \end{bmatrix}$$

$$= \begin{bmatrix} -0.241 & 0 & 0.24 & -.0222 \\ -0.022 & 0 & .022 & -.002 \\ -0.01 & 0.107 & -.09 & .009 \\ -0.209 & -.921 & 1.07 & -.105 \end{bmatrix}$$

$$-\hat{\Phi}_2 = \begin{bmatrix} 1 \\ .167 \\ .070 \\ -1.673 \end{bmatrix} \begin{bmatrix} .239 & 0 & 2.724 & 0 \end{bmatrix} = \begin{bmatrix} 0.239 & 0 & 2.724 & 0 \\ .04 & 0 & 0.45491 & 0 \\ 0.017 & 0 & 0.19068 & 0 \\ -0.400 & 0 & -4.5573 & 0 \end{bmatrix}$$

$$|\hat{\Sigma}_\epsilon| = 4.503 \times 10^{-15} \text{ -Estimates } \sim \text{Full Rank LSES}$$

Numerical Example (contd.)

- Implications / Interpretation

- Cointegration : Stationary Combinations:

$$Z_{3t}^* = Y_{1t} - 0.997Y_{3t} + 0.042Y_{4t}$$

$$Z_{4t}^* = Y_{2t} - 0.942Y_{3t} + 0.094Y_{4t}$$

- Common Trend Components:

$$Z_{1t}^* = b_1' Y_t \text{ and } Z_{2t}^* = b_2' Y_t$$

where $b_1' A$ and $b_2' A = 0$;

choose $b_1 \ni b_1' \Phi_2 = b_1' a_3 d' = 0$

Thus, $b_1' W_t = b_1' \xi_t$, so

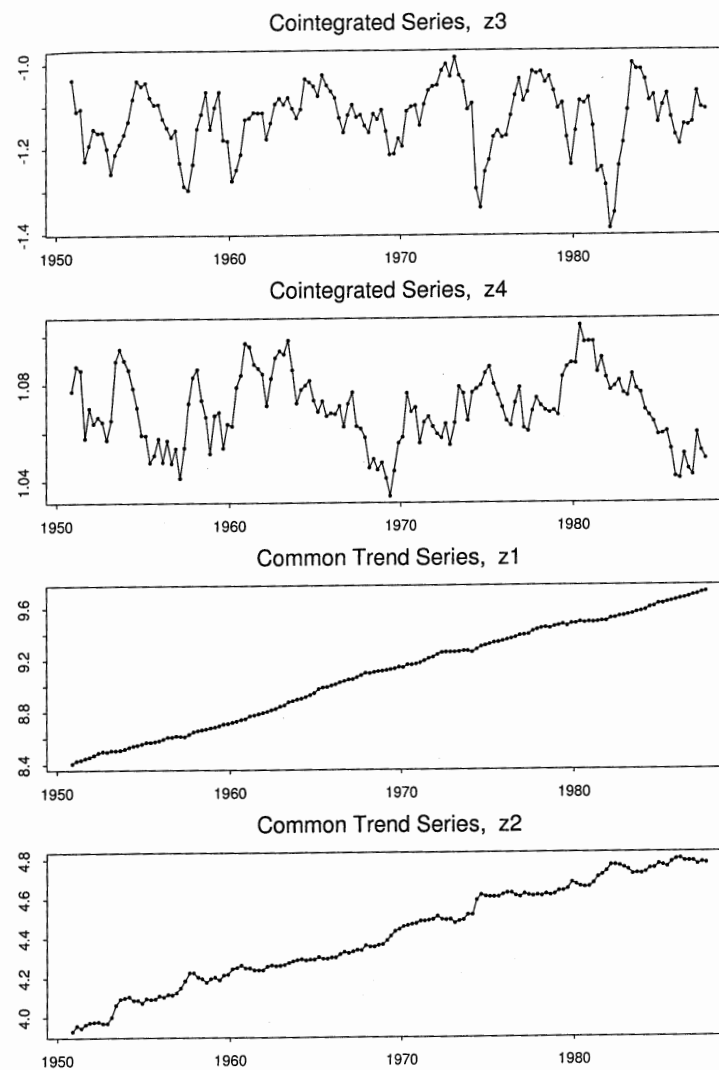
$Z_{1t}^* = b_1' Y_t$ is a random walk

$$Z_{1t}^* = -0.132Y_{1t} + Y_{2t} + 0.285Y_{3t} + 0.033Y_{4t}$$

See Figure 2

Figure 2

Fig. 2. Cointegrating & Common Trend Series for US Economy Data, 1951 - 1988



Numerical Example (contd.)

- Overall interpretation;

$$Z_t^* = \begin{pmatrix} B \\ B^* \end{pmatrix} Y_t = \begin{pmatrix} Z_{1t} \\ Z_{2t} \end{pmatrix}$$

$$Z_{1t}^* - Z_{1t-1}^* = (B^* a_3) d' W_{t-1} + \epsilon_{1t}^*$$

$$Z_{2t}^* = (I + BA) Z_{2t-1}^* + (Ba_3) d' W_{t-1} + \epsilon_{2t}^*$$

$$B^* a_3 = \begin{bmatrix} 0 \\ -.289 \end{bmatrix}, \quad Ba_3 = \begin{bmatrix} 0.776 \\ -.055 \end{bmatrix},$$

$$I + BA = \begin{bmatrix} .750 & -.191 \\ -.032 & .814 \end{bmatrix}$$

$$Z_{1t}^* \sim RW ; Z_{2t}^* - Z_{2t-1}^* \sim \text{with AR(1) structure}, Z_{3t}^* \sim \text{AR(2)};$$

$$Z_{4t}^* \sim \text{AR(1)}$$

Forecasting-Applications

- Effect of RR estimation on prediction, $\text{Rank}(C) = 1$; $C = \alpha\beta'$

- Covariance matrix of the prediction error:

$$(1 + x_0'(XX')^{-1}x_0)\Sigma_{\epsilon\epsilon} - \left\{ x_0'(XX')^{-1}x_0 - \frac{(\beta'x_0)^2}{\beta'(XX')^{-1}\beta} \right\} (\Sigma_{\epsilon\epsilon} - \Sigma_{\epsilon\epsilon}^{1/2}V_1V_1'\Sigma_{\epsilon\epsilon}^{1/2})$$

(Reinsel and Velu, 1998, p46)

- Empirical Analysis of Hog data indicate accounting for both non-stationarity and rank reduction consistently outperforms well at all forecasting horizons (Wang and Bessler 2004)

RRR and Shrinkage

■ Recall $\hat{C} = \hat{A}\hat{B} = \hat{\Sigma}_{yy}^{1/2} \hat{V}_*^{(r)} \hat{V}_*^{(r)'} \Sigma_{yy}^{-1/2} \tilde{C}$
 $= \hat{H}_1^{-1} \hat{\Delta}_1 \hat{H}_1 \tilde{C}$

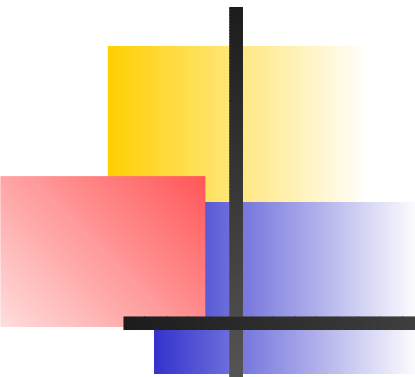
where $\hat{\Delta}_1 = \text{Diag}(1, 1, \dots, 1, 0 \dots 0)$, $m \times m$ diagonal matrix

GCV - Breiman and Friedman (1997)

Reinsel (1998)

$$\hat{\Delta}_1 = \text{Diag}(\hat{d}_j), \hat{d}_j = \frac{(1-p_1)(\hat{\rho}_j^2 - p_1)}{(1-p_1)^2 \hat{\rho}_j^2 + p_1^2 (1 - \hat{\rho}_j^2)} \quad j = 1 \dots m$$

where $p_1 = n_1 / (T - n_2)$



Forecasting Applications -Contd.

- Forecasting Large Datasets (Carriero, Kapetanios & Marcellino 2007)

- RRR (Reinsel and Velu, 1998)
- BVAR (Doan et al, 1984)
- BRR (Geweke, 1996)
- RRP (Restrictions on the posterior mean)
- MB (Brieman, 1996)
- FM (Stock and Watson 2002)

Data: 52 US Macroeconomic series (Real, Monetary & Financial)

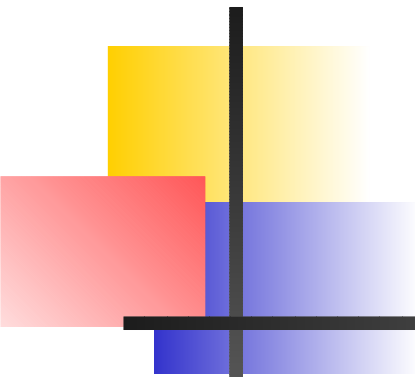
- Three Benchmarks: AR (1), BVAR and RW;

- Among the six models: BRR -Short horizons

RRP -Long Horizons

FM- Best for 1-step ahead.

- Conclusion: Using Shrinkage and Rank reduction in combination



Future Work

- Shrinkage -RRR, Needs further investigation
Yuan et al 2007-RRR/ LASSO
- Impact of Rank Misspecification : Anderson (2002)
- More broadly, in VAR context, the impact of misspecification of both the order 'p' and rank 'r' need to be studied.