Effects of misspecification of seasonal cointegrating ranks – An empirical study

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EFFECTS OF MISSPECIFICATION OF SEASONAL COINTEGRATING RANKS: AN EMPIRICAL STUDY

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We investigate the effects of the misspecification of cointegrating ranks at other frequencies on the inference of seasonal cointegration at the frequency of interest such as test for cointegrating rank and estimation of cointegrating vector. Earlier studies mostly focused on a single frequency corresponding to a seasonal root at a time, ignoring possible cointegration at the remaining frequencies. We investigate the effects of the misspecification, particularly in the case of finite samples by adopting Gaussian reduced rank estimation by Ahn and Reinsel (1994) that considered cointegration at all frequencies of seasonal unit roots simultaneously. It is observed that the identification of the seasonal cointegrating rank at the frequency of interest is robust to the over-specification of the cointegrating ranks at other frequencies, whereas it is very sensitive to under-specification.

KEYWORDS: Gaussian reduced rank estimation, seasonal cointegration.

JEL CLASSIFICATION: C12, C22, C32.

1 Introduction

Since Hylleberg et al. (1990), several approaches to the analysis of seasonal cointegration have been developed. Since these approaches are based on vector autoregressive models, we summarize them in the context of multivariate regression and address the issues associated with them. To achieve this, we consider the following multivariate regression model

\[ z = C_1 x_1 + C_2 x_2 + C_3 x_3 + C_4 x_4 + \varepsilon, \]

where \( z \) is an \( m \)-dimensional random vector, \( x_j \) is an \( m_j \)-dimensional random vector, \( C_j \) is an \( m \times m_j \) matrix for \( j = 1, \ldots, 4 \), and \( \varepsilon \) is an \( m \)-dimensional error vector. It is well

\footnotesize
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known that when $C_j$'s are of full rank and unrestricted, each of the coefficient matrices may be estimated one at a time by regressing $z$ on $x_j$ adjusting for $x_k$ for $k \neq j$, that is, by partial regression that involves regressing the residuals from the regression of $z$ on the $x_k$'s on the residuals from the regression of $x_j$ on the $x_k$'s. Anderson (1951) employed this approach of partial regression and proposed a method to estimate when one of the coefficient matrices, for example, $C_1$, is of reduced rank. This approach is known as partial reduced rank regression and involves the reduced rank regression of $z$ on $x_1$ adjusted for the $x_k$'s for $k \neq 1$. In (non-seasonal) cointegration analysis, Johansen (1988) adopted this approach because the error correction term in the model under consideration is of reduced rank, while the other coefficient matrices are of full rank.

In the context of seasonal cointegration, there are more than one coefficient matrices that are of reduced rank in (1). In such cases, the estimation of a reduced rank matrix one at a time by using partial reduced rank regression amounts to the estimation of the reduced rank matrix treating the other reduced rank matrices as of full rank and unrestricted, that is, it involves the over-specification of the (seasonal cointegrating) ranks of these matrices. This approach has been adopted in Lee (1992), Johansen and Schaumburg (1999), and Cubadda (2001) because it is simple to implement and the regressors, namely, the $x_k$'s, are asymptotically uncorrelated.

If the $x_j$'s are uncorrelated, the matrix $C_j$ can be estimated by the (reduced rank) regression of $z$ on $x_j$ without making any adjustment for the other regressors. In this approach, an under-specification of the ranks of the other coefficients occurs in finite samples when the $x_j$'s are only asymptotically uncorrelated.

In the seasonal cointegration context, not only are the $C_j$'s of reduced rank but also some of them are not functionally independent. For example, when $C_3$ and $C_4$ in (1) are functions of a common parameter vector $\theta$, we re-express the model as

$$z = C_1x_1 + C_2x_2 + C_3(\theta)x_3 + C_4(\theta)x_4 + \varepsilon$$

in order to emphasize their dependence on $\theta$. In this case, $C_3$ and $C_4$ need to be simultaneously estimated through an estimation of $\theta$. However, Cubadda (2001) estimates $C_3$ and $C_4$ separately using the aforementioned partial reduce rank regression.

As in the case of seasonal cointegration, if it is known that the coefficient matrices are of reduced rank and that there are functional dependencies among them, then a sensible approach is to incorporate these and estimate the parameters simultaneously. Ahn and
Reinsel (1994) and Ahn et al. (2004) used an iterative scheme that incorporates the cointegrating ranks at all the seasonal frequencies simultaneously and the dependencies among the coefficient matrices. However, this requires the correct specification of the cointegrating ranks and is thus subject to over- and under-specification of the ranks.

Because the aforementioned approaches of Lee (1992), Johansen and Schaumburg (1999), and Cubadda (2001) are subject to over-specification and those of Ahn and Reinsel (1994) and Ahn et al. (2004) are subject to both over- and under-specification, we investigate the effects of misspecification through the Monte Carlo simulation.

### 2 Seasonally Cointegrated Time Series and its Estimations

We let \( \mathbf{y}_t \) be an \( m \)-vector time series with non-stationary seasonal behavior in period \( s \) such that

\[
\Phi(L)\mathbf{y}_t = (I_m - \sum_{j=1}^{s} \Phi_j L^j)\mathbf{y}_{t-1} = \mathbf{D}\mathbf{I} + \mathbf{e}_t, \tag{3}
\]

where \( \mathbf{e}_t \) are i.i.d. \( N_n(0, \Omega) \), and \( \mathbf{D} \) is a deterministic term that may contain a constant, a linear term, or seasonal dummies. We assume that the initial values \( \mathbf{y}_0, \ldots, \mathbf{y}_{-p+1} \) are fixed and that the roots of the determinant \( |\Phi(z)| = 0 \) are on or outside the unit circle.

For simplicity of presentation, we consider that the series \( \mathbf{y}_t \) is observed quarterly, that is, \( s = 4 \). If the series are cointegrated at the frequencies 0, 1/2, and 1/4 (0, \( \pi \), and \( \pi/2 \), respectively), model (3) may be rewritten in the following error correction model (ECM) as in Ahn and Reinsel (1994) and Ahn et al. (2004):

\[
\Phi^*(L)(1-L^4)\mathbf{y}_t = \mathbf{D}\mathbf{I} + \alpha_{1R} \beta_{1R}^t (1+L)(1+L^2)\mathbf{y}_{t-1} + \alpha_{2R} \beta_{2R}^t (1-L)(1+L^2)\mathbf{y}_{t-1} + \alpha_{3R} \beta_{3R}^t (1-L^2)\mathbf{y}_{t-1} + \epsilon_t, \tag{4}
\]

where \( \alpha_{1R} \beta_{1R}^t = -\Phi(1)/4 \); \( \alpha_{2R} \beta_{2R}^t = \Phi(-1)/4 \); \( (\alpha_{3R} + i\alpha_{3R})(\beta_{3R} + i\beta_{3R})' = -\Phi(i)/2 \); \( \alpha_{jR} \), \( \beta_{jR} \), and \( \beta_{jI} \) are \( m \times r_j \) real-valued matrices with a rank equal to \( r_j \); \( \beta_{jR} = [I_{r_j}, \beta_{0jR}]' \); and \( \beta_{jI} = [O_{r_j}, \beta_{0jI}]' \). \( I_{r_j} \) and \( O_{r_j} \) are an \( r_j \times r_j \) identity matrix and an \( r_j \times r_j \) zero matrix, respectively. We note that the subscript \( j = 1, 2, \) and 3 corresponds to the frequencies 0, 1/2, and 1/4, respectively. We also note that the model in (4) takes the form of the model in (2) with \( \Phi^*(L) = L , \ (1-L^4)\mathbf{y}_t = \mathbf{z} , \ (1+L)(1+L^2)\mathbf{y}_{t-1} = \mathbf{x}_1 , \ (1-L)(1+L^2)\mathbf{y}_{t-1} = \mathbf{x}_2 , \ (1-L^2)\mathbf{y}_{t-1} = \mathbf{x}_3 , \ (1-L^2)\mathbf{y}_{t-2} = \mathbf{x}_4 , \ \alpha_{1R} \beta_{1R}^t = C_1 , \ \alpha_{2R} \beta_{2R}^t = C_2 , \ \alpha_{3R} \beta_{3R}^t + \alpha_{3I} \beta_{3I}^t = C_3 , \) and \( -\alpha_{3R} \beta_{3R}^t + \alpha_{3I} \beta_{3I}^t = C_4 \) and that \( C_3 \) and \( C_4 \) depend on the common parameters \( \alpha_{3R} , \ \alpha_{3I} , \ \beta_{3R} , \) and \( \beta_{3I} \).
The Gaussian reduced rank estimation of Ahn and Reinsel (1994) uses the iterative Newton-Raphson method that can be computationally complicated because of the nonlinear nature of the parameters $\alpha_j$’s and $\beta_j$’s. Its advantage is to simultaneously incorporate the reduced rank structures attributable to cointegration at all different frequencies in model (4). Therefore, the efficiency of inference, such as the test for cointegrating ranks and the estimation of cointegrating vectors, may be improved for finite samples. However, it requires the correct specification of the cointegrating ranks at all seasonal frequencies, and it is not easy to correctly specify these ranks simultaneously. We may pre-specify the cointegrating rank at each of the frequencies while ignoring the cointegrating ranks at the other frequencies, for example, by partial reduced rank regression as in Cubadda (2001). This pre-specification may result in over- or under-specification of some of the cointegrating ranks. Although we may be able to correctly specify the cointegrating ranks by iteratively applying the likelihood ratio test, it is interesting to investigate the effects of misspecification of the cointegrating ranks.

The approaches of Lee (1992), Johansen and Schaumburg (1999), and Cubadda (2001) are different from the Gaussian reduced rank estimation of Ahn and Reinsel (1994). As the terms $(1 + L)(1 + L^2)y_{t-1}$, $(1 - L)(1 + L^2)y_{t-1}$, and $(1 - L^2)y_{t-1}$ on the right-hand side of model (2) are asymptotically uncorrelated, they focused on a single frequency at a time by adjusting for the variables at the other frequencies. Because the adjustment is based on full rank regression, the reduced rank structures at the other frequencies are treated as of full rank. This amounts to an over-specification of the cointegrating ranks. Alternatively, one may consider reduced rank regression without the adjustment because of the asymptotic uncorrelatedness among those terms. However, this amounts to under-specification of the cointegrating ranks. These approaches may be simpler than that of Ahn and Reinsel (1994), but they may be accompanied by a loss of efficiency. Therefore, it may be interesting to investigate the efficiency in the inference of cointegration when over- or under-specification occurs.

3 Monte Carlo experiment

In this section, we conduct a Monte Carlo experiment to investigate the effects of misspecification of cointegrating ranks at other frequencies on the test for the cointegrating rank and the estimation of cointegrating vectors at the frequency of interest by adopting the Gaussian reduced rank estimation.

For a Monte Carlo experiment, the data generating process considered is the bivariate quarterly vector autoregressive (VAR) process of order 4, which has the following error
correction representation:
\[(1 - L^4)y_t = a_1 \beta_1' u_{t-1} + a_2 \beta_2' v_{t-1} + (a_3 \beta_3' + a_4 \beta_4') w_{t-1} + (-a_3 \beta_3' + a_4 \beta_4') w_{t-2} + \varepsilon_t, \]
(5)

where \(a_1 = (a_{11}, a_{21})' = (0.6, 0.6)'\), \(a_2 = (a_{12}, a_{22})' = (-0.4, 0.6)'\), \(a_3 = (a_{13}, a_{23})' = (0.6, -0.6)'\), \(a_4 = (a_{14}, a_{24})' = (0.4, -0.8)'\), \(\beta_1 = (1, b_1)' = (1, -0.7)'\), \(\beta_2 = (1, b_2)' = (1, 0.3)'\), \(\beta_3 = (1, b_3)' = (1, 0.7)'\), \(\beta_4 = (0, b_4)' = (0, -0.2)'\), \(u_{t-1} = (1 + L)(1 + L^2)y_{t-1}\), \(v_{t-1} = (1 - L)(1 + L^2)y_{t-1}\), and \(w_{t-1} = (1 - L^2)y_{t-1}\). The covariance matrix \(\Omega\) of \(\varepsilon_t\) is taken to be
\[
\Omega = \begin{pmatrix}
\sigma^2 & \rho \sigma \\
\rho \sigma & 1
\end{pmatrix}
\]
for \(\rho = -0.5, 0, 0.5\) and \(\sigma^2 = 0.5, 1, 2\). We note that the roots of the characteristic equation \(\det\{\Phi(L)\} = 0\) are \(\pm 1, \pm i, 0.9715 \pm 0.7328i\), and \(-1.3508 \pm 0.3406i\), and \(y_t\) is seasonally cointegrated with the cointegrating rank of 1 at each of the frequencies 0, 1/2, and 1/4.

For examining the effects on the test for cointegrating rank at given a frequency, we are interested in the following hypothesis:
\[H_0 : r_f \leq 1 \quad \text{vs} \quad H_1 : r_f > 1 \quad \text{for} \quad f = 0, 1/2, 1/4.\]
(6)

In each test, at a given frequency \(f\), the cointegrating ranks at other frequencies are set to be under-specified as 0, exact-specified as 1, or over-specified as 2. (We omit reporting the powers of the cointegrating rank test \(H_0 : r_f = 0\) because almost all the empirical powers were 100% irrespective of the misspecification of cointegrating ranks at the other frequencies.) For testing the hypotheses, we used the following likelihood ratio test statistic:
\[LR = \ln \left( \frac{\max_{H_0} L}{\max_{H_1} L} \right) = -T \ln \left( \frac{\max_{H_1} |\hat{\Omega}|}{\max_{H_0} |\hat{\Omega}|} \right),\]
where \(L\) is the likelihood function based on the normality assumption and \(\hat{\Omega}\) is the covariance matrix of the residuals resulting from the Gaussian reduced rank estimation.

Samples of series with length \(T = 100\) are generated with 1,000 replications. The initial values are set to zero, and we discard the first 50 observations in order to alleviate the dependence on the initial values. The estimated model is a VAR(5) with unrestricted seasonal deterministic terms. All the tests are based on the 5% asymptotic critical values that are obtained from Johansen and Schaumburg (1999) and Lee and Siklos (1995).

The results of the simulations are summarized in Tables 1 through 3. The tables show the rejection rates of the tests for the hypothesis in (6) in all cases for \(f = 1/2, 0, 1/4,\)
respectively. In the tables, the columns under the triplet (1,1,1) report the empirical sizes.

For the tests at $f = 1/2$, which are summarized in Table 1, the empirical sizes are not significantly different from the nominal level of 0.05 in general. When the cointegrating rank at $f = 0$ or 1/4 is over-specified, the empirical sizes that are displayed under the triplets (1,2,1), (2,1,1), and (2,2,1) are larger than those of the tests with the correct rank specification at these two frequencies, although they are not significantly different. When the cointegrating ranks at $f = 0$ and 1/4 are over-specified, the empirical sizes that are displayed under the triplet (0,0,1) are significantly larger than those of the tests with the correct rank specification at these two frequencies. When the cointegrating rank at either $f = 0$ or 1/4 is under-specified, the empirical sizes that are displayed under the triplets (0,1,1) and (1,0,1) are significantly smaller than those of the tests with the correct rank specification at these two frequencies except for the case of $\rho = -0.5$ and $\sigma^2 = 2$. When under-specification occurs at one of the frequencies and over-specification at the other, the empirical sizes are smaller, and those frequencies with under-specification at $f = 0$ and over-specification at $f = 1/4$ are much smaller in general.

For the tests at $f = 0$, which are summarized in Table 2, the empirical sizes are significantly smaller than the nominal size and become smaller as the correlation $\rho$ changes from negative to positive. These size biases for the tests at $f = 0$ may be attributable to the inappropriate use of critical values that are obtained based on large samples, while the sample size of 100 in this study is small. The effect of over-specification is similar to that of over-specification for the tests at $f = 1/2$. However, significant upward size biases (compared with the empirical sizes with the correct rank specification at all the frequencies) occurs when the under-specification occurs at $f = 1/4$. When under-specification occurs at $f = 1/2$, there are no significant differences among the empirical sizes with $\rho = -0.5$, while the empirical sizes are significantly larger with $\rho = 0$ and 0.5.

For the tests at $f = 1/4$, which are summarized in Table 3, the empirical sizes are significantly smaller for $\rho = -0.5, 0$ and significantly larger for $\rho = 0.5$ than at the nominal level when the ranks are correctly specified at the other frequencies. These size biases can also be attributable to the inappropriate use of critical values that are obtained based on large samples, while the sample size of 100 in this study is small. The different directions of the size biases require further investigation. The effect of over-specification is similar to that of over-specification for the tests at $f = 1/2$. Significant upward size biases (compared with the empirical sizes with correct rank specification at all the frequencies) occur when under-specification occurs at $f = 0$. When under-specification occurs only at $f = 1/2$, there are no significant differences among the empirical sizes.
The interesting observation is that for \( f = 0 \) and \( 1/4 \) the results are symmetric in that the empirical sizes of the tests for one of the frequencies are significantly larger when the cointegrating rank of the other frequency is under-specified. However, the commonly-accepted fact that the frequencies \( f = 0 \) and \( 1/2 \) are symmetric does not appear to hold in our simulation for the finite sample.

Based on the limited simulation study presented here, over-specification rather than under-specification of the cointegrating ranks is generally recommended. Under-specification is avoided, particularly at the zero frequency.

4 Acknowledgement

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References


Table 1: Comparison of the rejection rates of 5% level tests for hypotheses in (6) for the frequency $f = 1/2$.

<table>
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<tr>
<th>$\rho$</th>
<th>$\sigma^2$</th>
<th>Cointegrating ranks $(r_0, r_{1/4}, r_{1/2})$</th>
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<td>-0.5</td>
<td>0.5</td>
<td>0.084 0.024 0.029 0.037 0.050 0.055 0.035 0.050 0.055</td>
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<td></td>
<td>1</td>
<td>0.084 0.037 0.043 0.039 0.058 0.059 0.040 0.059 0.059</td>
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Table 2: Comparison of the rejection rates of 5% level tests for hypotheses in (6) for the frequency $f = 0$.

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Table 3: Comparison of the rejection rates of 5% level tests for hypotheses in (6) for the frequency $f = 1/4$.

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