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- The multivariate nonlinear test not only takes into consideration both dependent and joint effects among variables but is also able to detect a multivariate nonlinear deterministic process that cannot be detected by using any linear causality test.

- To overcome this limitation, this paper suggests including cointegration in the analysis.

Cointegration

Johansen cointegration test proposed by Johansen (1988), Johansen and Juselius (1990) and Johansen (1991) as some studies, for example, Gonzalo (1994), confirm that the Johansen cointegration test performs better than the other cointegration tests, namely the ADF test (Engle and Granger, 1987). In addition, when GARCH errors exist in the model, Lee and Tse (1996) conclude that the bias is not too serious when using Johansen's cointegration test if we compare its performance with other cointegration tests

Johansen and Juselius (1990) and Johansen (1991) develop a multivariate maximum likelihood (ML) procedure for the estimation of the cointegrating vectors. According to Johansen's procedure, the p-dimensional unrestricted Vector Autoregression (VAR) model should be first specified with k lags:

$$\boldsymbol{Z_t} = \sum_{i=1}^{k} \boldsymbol{A_i Z_{t-i}} + \Psi \boldsymbol{D_t} + U_t \qquad (1)$$

where $\boldsymbol{Z_t} = [M_t, D_t, Y_t\ ]'$ is a 3×1vector of stochastic variables and M_t, D_t, and Y_t are to be the logarithms of the ratio of bank deposit liabilities to nominal GDP, the ratio of claims on private sector to nominal GDP, and real GDP per capita in period t, respectively. $\boldsymbol{D_t}$ is a vector of dummies and $\boldsymbol{A_i}$ is a vector of parameters. This VAR could be rewritten as:

$$\Delta \boldsymbol{Z_t} = \sum_{i=1}^{k-1} \Phi_i \Delta \boldsymbol{Z_{t-i}} + \boldsymbol{\Pi Z_{t-i}} + \Psi \boldsymbol{D_t} + U_t\ . \qquad (2)$$

The hypothesis of cointegration is formulated as a reduced rank of the $\mathbf{\Pi}$ matrix where $\mathbf{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta}'$ such that $\boldsymbol{\alpha}$ is the vector or matrix of the adjustment parameter and $\boldsymbol{\beta}$ is the vector or matrix of the cointegrating vectors. According to Engle and Granger (1987), if the rank of $\mathbf{\Pi}$ (r) is not equal to zero, then r cointegrating vectors exist. The number of cointegrating vectors is less than or equal to the number of variables, which is 3 in our case. The likelihood ratio (LR) reduced the rank test for the null hypothesis of at most r cointegrating vectors is given by the following Trace statistic, and for the null hypothesis of r against the alternative of r+1 cointegrating vectors is known as the maximal eigenvalue statistic

$$3\lambda_{trace} = -\mathrm{T}\sum_{i=r}^{m} \ln\left(1-\lambda_{i+1}\right) \quad , \qquad \lambda_{max}$$
$$= -\mathrm{T}\ln(1-\lambda_{r+1}) \qquad (3)$$

where m is the maximum number of possible cointegrating vectors which is 3 in our case, in this paper, $r = 0, 1, 2$ and $\lambda_1 > \lambda_2 > \lambda_3$ denote eigenvalues of their corresponding eigenvectors $\mathrm{v} = (v_1, v_2, v_3)$.If the null hypothesis of r cointegrating vectors is accepted, then the rank of the $\mathbf{\Pi}$ matrix equal to r and there is exactly r cointegrating vector.

Granger Causality

Since our analysis presented in next section (see Table 1) confirms that all the variables $M_t, D_t,$ and Y_t are I(1), academics and practitioners are interested in testing whether there is any causality relationship among the differences of the variables $M_t, D_t,$ and Y_t. We let $m_t = \Delta M_t$, $d_t = \Delta D_t$, and $y_t = \Delta Y_t$. This means that academics and practitioners are interested in testing whether there is any causality relationship among m_t, d_t, and y_t. Thus, in this paper we will test whether there is any linear Granger causality and thereafter examine whether there is any nonlinear Granger causality among the variables m_t, d_t, and y_t.

Linear Granger Causality

To test the linear causality relationship between two vectors of stationary time series, we set $x_t = (x_{1,t}, \dots, x_{n_1,t})'$ and $y_t = (y_{1,t}, \dots, y_{n_2,t})'$ say $x_t = (m_t, d_t)'$ and $y_t = (y_t)'$, where there are 3 series in total. Under this setting, one could construct the following vector autoregressive regression (VAR) model:

$$\begin{pmatrix} x_t \\ y_t \end{pmatrix} = \begin{pmatrix} A_{x[2\times1]} \\ A_{y[1\times1]} \end{pmatrix} + \begin{pmatrix} A_{xx}(L)_{[2\times2]} & A_{xy}(L)_{[2\times1]} \\ A_{yx}(L)_{[1\times2]} & A_{yy}(L)_{[1\times1]} \end{pmatrix} \begin{pmatrix} x_{t-1} \\ y_{t-1} \end{pmatrix} + \begin{pmatrix} e_{x,t} \\ e_{y,t} \end{pmatrix}$$

(4)

where $A_{x[2\times1]}$ and $A_{y[1\times1]}$ are two vectors of intercept terms, $A_{xx}(L)_{[2\times2]}$, $A_{xy}(L)_{[2\times1]}$, $A_{yx}(L)_{[2\times1]}$, and $A_{yy}(L)_{[1\times1]}$ are matrices of lag polynomials, $e_{x,t}$ and $e_{y,t}$ are the corresponding error terms.

Testing the following null hypotheses: $H_0^1: A_{xy}(L) = 0$ and $H_0^2: A_{yx}(L) = 0$ is equivalent to testing the linear causality relationship between x_t and y_t.There are four different situations for the causality relationships between x_t and y_t in (1): (a) rejecting H_0^1 but not rejecting H_0^2 implies a unidirectional causality from y_t to x_t, (b) rejecting H_0^2 but not rejecting H_0^1 implies a unidirectional causality from x_t to y_t, (c) rejecting both H_0^1 and H_0^2 implies the existence of feedback relations, and (d) not rejecting both H_0^1 and H_0^2 implies that x_t and y_t are not rejected to be independent. Readers may refer to Bai, et al. (2010) for the details of testing H_0^1 and/or H_0^2.

If the time series are cointegrated, one should impose the error-correction mechanism (ECM) on the VAR to construct a vector error correction model (VECM) in order to test Granger causality between the variables of interest. In particular, when testing the causality relationship between two vectors of non-stationary time series, we let $\Delta x_t = (\Delta M_t, \Delta D_t)'$ and $\Delta y_t = (\Delta Y_t)'$ be the corresponding stationary differencing series such that there are 3 series in total. If x_t and y_t are cointegrated, then instead of using the VAR in (1), one should adopt the following VECM model:

$$\begin{pmatrix}\Delta x_t \\ \Delta y_t\end{pmatrix} = \begin{pmatrix}A_{x[2\times1]} \\ A_{y[1\times1]}\end{pmatrix} + \begin{pmatrix}A_{xx}(L)_{[2\times2]} & A_{xy}(L)_{[2\times1]} \\ A_{yx}(L)_{[1\times2]} & A_{yy}(L)_{[1\times1]}\end{pmatrix}\begin{pmatrix}\Delta x_{t-1} \\ \Delta y_{t-1}\end{pmatrix} + \begin{pmatrix}\alpha_{x[2\times1]} \\ \alpha_{y[1\times1]}\end{pmatrix} \cdot ecm_{t-1} + \begin{pmatrix}e_{x,t} \\ e_{y,t}\end{pmatrix} \quad (5)$$

where ecm_{t-1} is lag one of the error correction term, and $\alpha_{x[2\times1]}$ and $\alpha_{y[1\times1]}$ are the coefficient vectors for the error correction term ecm_{t-1}. There are now two sources of causation of $y_t(x_t)$ by $x_t(y_t)$, either through the lagged dynamic terms $\Delta x_{t-1}(\Delta y_{t-1})$, or through the error correction term ecm_{t-1}. Thereafter, one could test the null hypothesis $H_0 : A_{xy}(L) = 0\big(H_0 : A_{yx}(L) = 0\big)$ and/or $H_0 : \alpha_x = 0\big(H_0 : \alpha_y = 0\big)$ to identify Granger causality relation using the LR test.

Nonlinear Granger Causality

Bai, et al. (2010, 2011, 2018) and Chow, et al. (2018) extend the nonlinear causality test developed by Hiemstra and Jones (1994) and others to the multivariate setting. To identify any nonlinear Granger causality relationship from any two series, say $\{x_t\}$ and $\{y_t\}$ in the bivariate setting, one has to first apply the linear model to $\{x_t\}$ and $\{y_t\}$ to identify their linear causal relationships and obtain the corresponding residuals, $\{\hat{\varepsilon}_{1t}\}$ and $\{\hat{\varepsilon}_{2t}\}$. Thereafter, one has to apply a nonlinear Granger causality test to the residual series, $\{\hat{\varepsilon}_{1t}\}$ and $\{\hat{\varepsilon}_{2t}\}$, of the two variables being examined to identify the remaining nonlinear causal relationships between their residuals. This is also true if one would like to identify the existence of any nonlinear Granger causality relation between two vectors of time series, say $x_t = (x_{1,t}, \dots, x_{n1,t})'$ and $y_t = (y_{1,t}, \dots, y_{n2,t})'$ in the multivariate setting. One has to apply the VAR model or the VECM model to the series to identify their linear causal relationships and obtain their corresponding residuals. Thereafter, one has to apply a nonlinear Granger causality test to the residual series. For simplicity, in this section we denote $X_t = (X_{1,t}, \dots, X_{n1,t})'$ and $Y_t = (Y_{1,t}, \dots, Y_{n2,t})'$ to be the corresponding residuals of any two vectors of variables being examined. We first define the lead vector and lag vector of a time series, say $X_{i,t}$, as follows: for

$X_{i,t}$, i = 1,2, the m_{x_i}-length lead vector and the L_{x_i}-length lag vector of $X_{i,t}$ are:

$$X_{i,t}^{m_{x_i}} \equiv \left(X_{i,t}, X_{i,t+1}, \dots, X_{i,t+m_{x_i}-1}\right), m_{x_i} = 1,2, \dots, t = 1, 2, \dots,$$

$$X_{i,t-L_{x_i}}^{L_{x_i}} \equiv \left(X_{i,t-L_{x_i}}, X_{i,t-L_{x_i}+1}, \dots, X_{i,t-1}\right), L_{x_i} = 1, 2, \dots, \mathrm{t}$$
$$= L_{x_i} + 1, L_{x_i} + 2, \dots,$$

respectively. We denote $M_x = \left(m_{x1}, \dots, m_{x_{n_1}}\right)$, $L_x = \left(L_{x1}, \dots, L_{x_{n_1}}\right)$, $m_x = \max\left(m_{x1}, \dots, m_{n_1}\right)$, and $l_x = \max\left(L_{x1}, \dots, L_{x_{n_1}}\right)$. The m_{y_i}-length lead vector, $Y_{i,t}^{m_{y_i}}$, the L_{y_i}-length lag vector, $Y_{i,t-L_{y_i}}^{L_{y_i}}$, of $Y_{i,t}$, and M_y, L_y, m_y, and l_y can be defined similarly.

Given m_x, m_y, L_x, L_y, and $e > 0$, we define the following four events:

$$\{\|X_t^{M_x} - X_s^{M_x}\| < e\} \equiv \left\{\left\|X_{i,t}^{M_{x_i}} - X_{i,s}^{m_{x_i}}\right\| < e, \text{for any } i = 1, \dots, n_1\right\};$$

$$\left\{\|X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x}\| < e\right\}$$
$$\equiv \left\{\left\|X_{i,t-L_{x_i}}^{L_{x_i}} - X_{i,s-L_{x_i}}^{L_{x_i}}\right\| < e, \text{for any } i = 1, \dots, n_1\right\};$$

$$\left\{\left\|Y_t^{M_y} - Y_s^{M_y}\right\| < e\right\}$$
$$\equiv \left\{\left\|Y_{i,t}^{m_{y_i}} - Y_{i,s}^{m_{y_i}}\right\| < e, \text{for any } i = 1, \dots, n_2\right\}; and$$

$$\left\{\left\|Y_{t-L_y}^{L_y} - Y_{s-L_y}^{L_y}\right\| < e\right\}$$
$$\equiv \left\{\left\|Y_{i,t-L_{y_i}}^{L_{y_i}} - Y_{i,s-L_{y_i}}^{L_{y_i}}\right\| < e, \text{for any } i = 1, \dots, n_2\right\};$$

where $\|\cdot\|$ denotes the maximum norm which is defined as $\|X - Y\| = \max(|x_1 - y_1|, |x_2 - y_2|, \dots, |x_n - y_n|)$ for any two vectors $X = (x_1, \dots, x_n)$ and $Y = (y_1, \dots, y_n)$. The vector series $\{Y_t\}$ is said not to strictly Granger cause another vector series $\{X_t\}$ if

$$Pr\left(\|X_t^{M_x} - X_s^{M_x}\| < e \middle| \|X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x}\| < e, \left\|Y_{t-L_y}^{L_y} - Y_{s-L_y}^{L_y}\right\| < e,\right)$$

$$= Pr\left(\|X_t^{M_x} - X_s^{M_x}\| < e \middle| \|X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x}\| < e\right)$$

(6)

where Pr (· | ·) denotes conditional probability. Applying (6), one has to use the following test statistic to test for the nonlinear Granger causality:

$$\sqrt{n}\left(\frac{C_1(M_x+L_x,L_y,e,n)}{C_2(L_x,L_y,e,n)}-\frac{C_3(M_x+L_x,e,n)}{C_4(L_x,e,n)}\right) \qquad (7)$$

Readers may refer to Bai, et al. (2010, 2011, 2018) and Chow, et al. (2018) for the details of the equation (7). Under this setting, Bai, et al. (2010, 2011) prove that to test the null hypothesis, H_0, that $\{Y_{1,t}, \ldots, Y_{n2,t}\}$ does not strictly Granger cause $\{X_{1,t}, \ldots, X_{n1,t}\}$, under the assumptions that the time series $\{X_{1,t}, \ldots, X_{n1,t}\}$ and $\{Y_{1,t}, \ldots, Y_{n2,t}\}$ are strictly stationary, weakly dependent, and satisfy the mixing conditions stated in Denker and Keller (1983), if the null hypothesis, H_0, is true,

the test statistic defined in (7) is distributed as $N\left(0, \sigma^2\left(M_x, L_x, L_y, e\right)\right)$.

(8)

When the test statistic in (7) is too far away from zero, we reject the null hypothesis. Readers may refer to Bai, et al. (2010, 2011, 2018) and Chow, et al. (2018) for the details of the consistent estimator of the covariance matrix.

The nonlinear causality test has the ability to detect a nonlinear deterministic process which originally "looks" random. The nonlinear causality test is a complementary test for the linear causality test as linear causality tests could not detect nonlinear causal relationship while the nonparametric approach adopted in this paper can capture the nonlinear nature of the relationship among variables.

From literature we note an interest in analyzing the cross-correlation relationship. Podobnik and Stanley (2008) propose a detrended cross-correlation analysis (DXA) to investigate power-law cross-correlations between different simultaneously-recorded time series in the presence of non-stationarity. Podobnik, et al. (2009) introduce a joint stochastic process to model cross-correlations. In addition, using stock market returns from two stock exchanges in China, Ruan, et al. (2018) employ the MF-DCCA to investigate the non-linear cross-correlation between individual investor sentiment and Chinese stock market return. Zhang, et al. (2018) study the cross-correlations between Chinese stock markets and the other three stock markets. Xiong, et al. (2018) use a new policy uncertainty index to investigate the time-varying correlation between economic policy uncertainty and Chinese stock market returns. Wan and Wong (2001) develop a model to study the contagion effect. Cerqueti, et al. (2018) develop a model based on Mixed Poisson Processes to deal with the theme of contagion in financial markets. Wang, et al. (2018) propose a non-Markovian social contagion model in multiplex networks with inter-layer degree correlations to delineate the behavior of spreading, and develop an edge-based compartmental theory to describe the model. The nonlinear causality used in this paper could also be used to measure nonlinear cross-correlation to handle the nonlinear contagion effect. One could easily use or modify Equation (6) to deal with the nonlinear cross-correlation and the nonlinear contagion effect.

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