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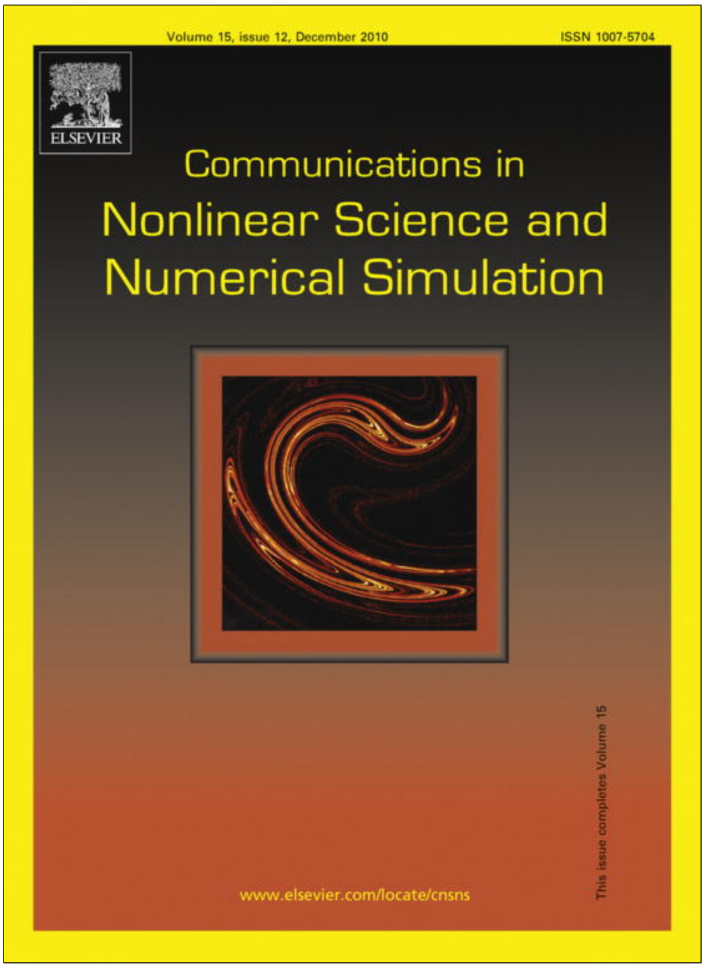

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Commun Nonlinear Sci Numer Simulat 15 (2010) 4020–4028

Contents lists available at ScienceDirect

Commun Nonlinear Sci Numer Simulat

journal homepage: www.elsevier.com/locate/cnsns

An evaluation of dynamic mutuality measurements and methods in cyclic time series

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ARTICLE INFO

Article history:
Received 17 November 2009
Received in revised form 2 February 2010
Accepted 2 February 2010
Available online 8 February 2010

Keywords:
Mutuality measurements
Method comparison
Cyclic time series

ABSTRACT

Several measurements and techniques have been developed to detect dynamic mutuality and synchronicity of time series in econometrics. This study aims to compare the performances of five methods, i.e., linear regression, dynamic correlation, Markov switching models, concordance index and recurrence quantification analysis, through numerical simulations. We evaluate the abilities of these methods to capture structure changing and cyclicity in time series and the findings of this paper would offer guidance to both academic and empirical researchers. Illustration examples are also provided to demonstrate the subtle differences of these techniques.

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1. Introduction

Measuring mutuality is a valuable field of time series study in econometrics and the problem become complicated when the effects of structure changing and cyclicity are mixed. Different methods are designed for measuring the synchronicity and relationship among economic variables. Besides the traditional linear regression (LR) using dummy to capture the structure changing, dynamic correlation (DC, [1,2]), Markov switching models (MS, [3–8]), concordance index (CI, [9–13]) and recurrence quantification analysis (RQA, [14–17]) are also prevalent dynamic mutuality models for time series analysis. A large amount of papers adopted these methods to study various empirical problems, but little literature analyzed the different performances of these models, especially when they are used in cyclic time series studies, which would provide guidance to both academic and empirical researchers.

Structural instability often exists when the economic systems suffer a tremendous and exogenous shock such as the price shock of crude oil and war. Another feature of economic variables is cyclicity driven by business cycles. In this study, we explore the key points of different econometric methods in cyclic time series analysis through numerical simulation and illustrative example study.

Numerical simulation can evaluate the capabilities of capturing main features, which may exist in empirical study, in econometrics through predetermined artificial data. Ever since Kraft and Kraft [18] studied the link between energy and economic output, a vast body of research on different countries including the United States [19], the United Kingdom [20], Spain [21], Germany [22] and China [23–81] has contributed to this topic. The previous works as illustrative examples and empirical evidences provide us opportunity to compare the performance of different techniques in the present study.

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doi:10.1016/j.cnsns.2010.02.004

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The remainder of the paper is organized as follows: Section 2 outlines the concerned methods; Section 3 compares these methods via numerical simulation; Section 4 presents an illustrative example on energy topic; and finally, a range of concluding comments are provided in Section 5.

2. Methodology

2.1. Linear regression

Let $X = \{x_t\}$ and $Y = \{y_t\}$ $(t = 1, 2, \ldots)$ denote two sequences of stochastic processes which are unknown to the researchers. When the cyclicity between X and Y exists, a dummy variable is needed to capture the influence of cyclical regimes. The model is assumed as

$$Y = X\beta + D\beta_D + f(X') + \varepsilon, \tag{1}$$

where X' is a sequence of multiple dimensional random deterministic variables besides X, $\{\varepsilon\}$ is an innovation sequence, β is an estimation of the impact effects of one unit changing of X given X', $f(\cdot)$ is a function of X', D is a parameter defined by an indicator function $I_{\{X \in regime\}}$ in which the regime is previously assumed, β_D is a parameter distinguishing the difference among regimes. Estimations of the parameter set $\{\Phi\}$ are obtained by solving the optimization problem:

$$\min_{\{\Phi\}} \| Y - X\beta - D\beta_D - f(X') \|, \tag{2}$$

where $\|\cdot\|$ is a norm. If $f(\cdot)$ is a linear function of X', the estimation system becomes a standard multiple linear regression model.

2.2. Dynamic correlation

Traditional correlation measurements based on spectrum analysis do not allow researchers to separate the idiosyncratic characteristics and co-movements, hence are not able to capture the dynamic information from cyclicity. Croux et al. [1] proposed a cohesion index framework to quantify the degree of synchronization between cyclic time series. Formally, the *dynamic correlation* in frequency domain between series X and Y, with spectral density function $S_X(\lambda)$ and $S_Y(\lambda)$, and co-spectrum $C_{XY}(\lambda)$ at frequency λ $(-\pi \leqslant \lambda \leqslant \pi)$ is defined by:

$$\rho_{XY}(\lambda) = \frac{C_{XY}(\lambda)}{\sqrt{S_X(\lambda) S_Y(\lambda)}}. \tag{3}$$

The dynamic correlation or cohesion lies between -1 and 1, incorporating the sign of the nexus and permitting quantification of the correlation for frequency bands. For instance, when the frequency is relatively small, the dynamic correlation indicates relationship for longer time span.

2.3. Markov switching methods

Markov switching model was first proposed by Hamilton [8] to study the US output growth in a first-order Markov process form, which is capable to separate peaks and troughs of economic cyclical series. A general Markov switching vector auto-regression (MSVAR) Gaussian framework can be expressed as follows:

$$\begin{cases} Y_t = \Lambda_{tK} \cdot \mathrm{B}_{R_t} + \varepsilon_t, \\ \varepsilon_t | R_t \sim N(0, \Sigma_{R_t}), \end{cases} \tag{4}$$

where $\Lambda_{tK} = (1, X, Y_{t-1}, \ldots, Y_{t-K})'$ and $B_{R_t} = \left(\alpha^{R_t}, \beta^{R_t}, \beta_1^{R_t}, \ldots, \beta_K^{R_t}\right)'$ are the parameters conditioned on an unobservable discrete regime variable $R_t \in \{1, \ldots, M\}$, β^{R_t} measures the correlation between X and Y, ε_t is a Gaussian error term condition on S_t. The transition probabilities of discrete state Markov stochastic process are defined as follows:

$$p_{ij} = \Pr(R_{t+1} = j | R_t = i), \sum_{j=1}^{M} p_{ij} = 1, \qquad \text{for } \forall i, j \in \{1, \ldots, M\}. \tag{5}$$

The Kth lag, M-state MSVAR model is denoted as MS (M)-VAR (K). Under the generalized covariance assumption, the matrix of covariance is defined by $\Sigma_{R_t} = (\sigma_{ij}(R_t)), \forall i, j \in \{1 \ldots M\}$.

Hamilton [3] gave a comprehensive cover of filtering and smoothing methods for estimation of parameters. MS models need not assume stable behavior for variables during the discussed time span and have the capability to capture structure changes by allowing the switching between regimes or states.

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2.4. Concordance index

Based on nonparametric methods, Harding and Pagan [10,12] suggested a new measurement of mutuality or synchronization, which is called *concordance index*:

$$\mathrm{CI} = T^{-1}\sum_{t=1}^{T}[W_{xt}W_{yt} + (1 - W_{xt})(1 - W_{yt})], \tag{6}$$

where X and Y are two time series, T is the number of observations, and W_{xt} and W_{yt} are a dummy variable that takes 1 when the series is in regime 1 and takes 0 if not. If CI is bigger than its expect value, one can say there is a link between the cycles. The expectation of CI will be:

$$E(\mathrm{CI}) = 1 + 2u_{W_x}u_{W_y} - u_{W_x} - u_{W_y}, \tag{7}$$

where u_{W_x} and u_{W_y} are the means of W_{xt} and W_{yt}. Artis et al. [9,11] modified CI and transformed it to lie between zero and 100. The regression given by [10,12] for statistical testing is

$$\sigma_{W_y}^{-1}W_{yt} = \delta + \rho_W\sigma_{W_x}^{-1}W_{xt} + \mu_t, \tag{8}$$

where σ_{W_x} and σ_{W_y} are the standard errors of W_{xt} and W_{yt}. The hypothesis on ρ_W can be tested and the robust estimated standard errors can be obtained using HAC Newey–West method.

2.5. Recurrence quantification analysis

Eckmann et al. [14] introduced *recurrence quantification analysis* (RQA) to visualize the recurrence of states in a phase space based on nonlinear data science. Marwan and Kurths [15] extended the recurrence plots (RP) to multivariate revision known as cross-recurrence plots (CRP). Marwan et al. [16] gave a comprehensive literature review on RP. CRP of embedded series X and Y are defined as:

$$CR_{ij} = H(\tau - \|x_i - y_j\|), \tag{9}$$

where $i, j = 1, \ldots, N$, τ is a predefined threshold, $\|\cdot\|$ is a Euclidean norm and H is the Heaviside function. For short-term and non-stationary data, RQA shows advantages and provides useful information where other methods often fail.

3. Comparing and numerical simulation

Cyclicity driven by business cycles and structure changing derived from economic shocks often exist simultaneously in the evolution of economy. To evaluate and compare the performances of different methods, numerical simulation is well suited as minor distinctions can be explicitly detected. We demonstrate the aforementioned methods on three examples and compare their differences.

Example 1. The time series, X and Y, are cyclical, and the nexus between them is determinate. The random shock $\varepsilon \sim N(0, 1)$. The equations can be written as

$$\begin{cases} x_t = \sin t + 0.1\varepsilon, \\ y_t = 0.5x_t + 0.1\varepsilon. \end{cases} \tag{10}$$

Example 2. The time series, X and Y, are generated by step function, and the relationship between them is stepped jumping. The random shock $\varepsilon \sim N(0, 1)$. The equations can be written as

$$\begin{cases} x_t = 0.8 + 0.1\varepsilon & 0 \leqslant t \leqslant 2\pi/3, \\ x_t = -0.4 + 0.1\varepsilon & 2\pi/3 \leqslant t \leqslant 4\pi/3, \\ x_t = 0.4 + 0.1\varepsilon & 4\pi/3 \leqslant t \leqslant 2\pi. \end{cases} \tag{11}$$

$$\begin{cases} y_t = 0.9x_t + 0.1\varepsilon & 0 \leqslant t \leqslant 2\pi/3, \\ y_t = 0.6x_t + 0.1\varepsilon & 2\pi/3 \leqslant t \leqslant 4\pi/3, \\ y_t = -0.7x_t + 0.1\varepsilon & 4\pi/3 \leqslant t \leqslant 2\pi. \end{cases} \tag{12}$$

Example 3. The time series, X and Y, are generated by periodic function, and structure changing exists. The random shock $\varepsilon \sim N(0, 1)$. The equations can be written as

$$\begin{cases} x_t = 0.8\sin t + 0.1\varepsilon & 0 \leqslant t \leqslant 2\pi/3, \\ x_t = -0.4\sin t + 0.1\varepsilon & 2\pi/3 \leqslant t \leqslant 4\pi/3, \\ x_t = 0.4\sin t + 0.1\varepsilon & 4\pi/3 \leqslant t \leqslant 2\pi. \end{cases} \tag{13}$$

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$$\begin{cases} y_t = 0.9x_t + 0.1\varepsilon & 0 \leqslant t \leqslant 2\pi/3, \\ y_t = 0.6x_t + 0.1\varepsilon & 2\pi/3 \leqslant t \leqslant 4\pi/3, \\ y_t = -0.7x_t + 0.1\varepsilon & 4\pi/3 \leqslant t \leqslant 2\pi. \end{cases} \tag{14}$$

All the random shocks ε in above examples are different, but generated by a same distribution function as commonly assumed in other studies.

3.1. Linear regression results

No structure jumping exists in Example 1 and no dummy is needed. The structure changes have taken place at the points when the values of X in Examples 2 and 3 equal $2\pi/3$ and $4\pi/3$, respectively. Two dummies are needed to capture the changing: Dummy 1 equals 1 when $0 \leqslant t \leqslant 2\pi/3$, and 0 if not; Dummy 2 equals 1 when $2\pi/3 \leqslant t \leqslant 4\pi/3$, and 0 if not. The results reported in Table 1 show that the dummy free regression fits Example 1 without structure change well but performs very poor for Examples 2 and 3 while structure changes exist. Even when the dummy is added properly, the multivariable regression only estimates Example 2 well, but still performs badly in Example 3 where cyclicity and structure change exist simultaneously.

3.2. Dynamic correlation results

The estimated dynamic correlation is traced out in Fig. 1. According to Croux et al. [1], when the frequency shown on horizontal axis is close to the right side, the dynamic correlation reflects a long term relationship between the variables and the left side denotes a short-term relationship. In Example 1, a stable relationship exists between variables. In Examples 2 and 3, only long term relationship exists and the short-term relationship is swinging. As shown in Fig. 1, the chart tallies with the relationship of Examples 2 and 3, but is inconsistent with nexus of Example 1 in the short and middle terms. The dynamic correlation captures the relationship of cyclic series better when the structure transform exist. As a nonparametric measurement, estimation significant levels cannot be obtained for the dynamic correlation method.

3.3. Markov switching results

Estimations of the examples using MSVAR method are shown in Table 2. P_{ii} denotes the diagonal elements in transition probabilities matrix. The models are determined by information criteria such as AIC and BIC. For Example 1, the value of P_{ii}

Table 1
Linear regression estimation results.

Variable	Example 1	Example 2		Example 3	
	No dummy	No dummy	Dummy	No dummy	Dummy
X	0.52604*** (29.1443)	0.5903*** (0.0776)	−0.4587*** (0.1096)	0.3799*** (0.1411)	0.1694 (0.1472)
Dummy 1			1.0969*** (0.0893)		0.5947*** (0.1835)
Dummy 2			−0.3826*** (0.0594)		−0.1459 (0.0929)
R^2	0.7987	0.4831	0.8737	0.2325	0.4059
Adjusted R^2	0.7987	0.4831	0.8734	0.2324	0.3999

Note: Standard errors are in parenthesis. ***indicates 1% significance levels.

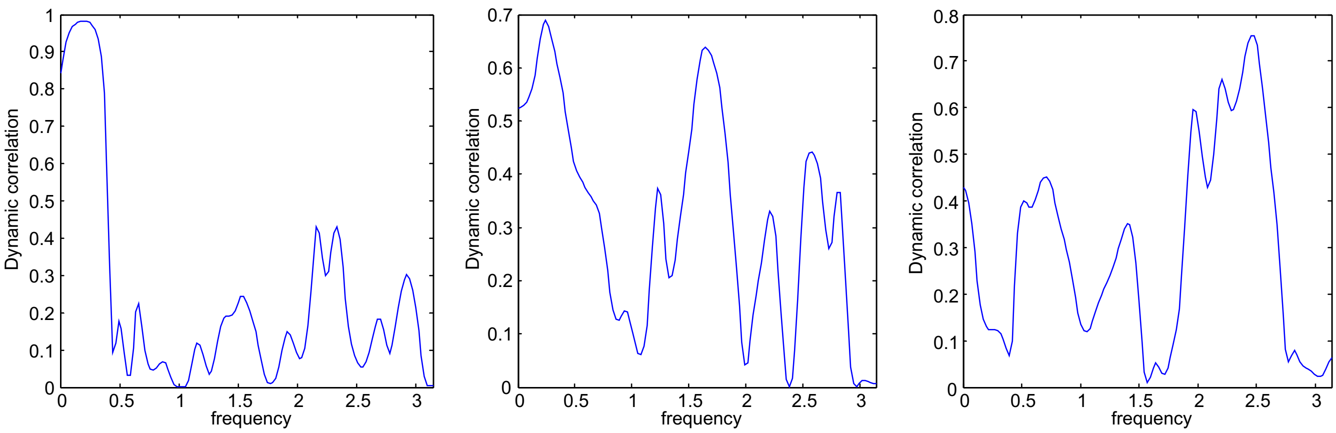

Fig. 1. The estimated *dynamic correlation* between X and Y, which are generated by the functions according to Example 1 (left), Example 2 (center), and Example 3 (right).

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Table 2
Estimated results based on MS methods.

	Example 1			Example 2			Example 3		
	Coefficient	*p*-Value	P_{ii}	Coefficient	*p*-Value	P_{ii}	Coefficient	*p*-Value	P_{ii}
Regime 1	0.5257	0.0000	1.00	0.8833	0.0000	0.99	0.3799	0.8100	0.80
Regime 2	9.4485	0.9200	0.00	0.5629	0.0000	0.98	0.3799	0.0900	0.80
Regime 3				−0.6768	0.0000	1.00	−0.3799	0.2900	0.80
Likelihood	52.4112			125.3192			162.321		

shows the estimation discerns only one regime in Example 1 correctly. The estimated coefficient is closed to true value significantly. The same thing happens to Example 2. For Example 3, the technique discriminates the positive or negative relationship between variables properly, but gaps exist between true values and estimated coefficients. MS distinguishes the regimes of cyclic time series and estimates the coefficient fairly well, but the capabilities are relatively weak when structure changing and cyclicity exist contemporarily.

3.4. Concordance index

CI focuses on the bi-variable relationship and is not able to detect mutuality among time series where there are three or more regimes, thus comparing CI with other models in this case is meaningless. Intuitionally, the main advantage of CI is that when the regimes have been identified correctly, the researchers could establish the nexus between the variables quickly relying on a little information.

3.5. Recurrence quantification analysis

RP shows the times at which a state recurs in the dynamic system, and gives illustrations of mutuality intuitively. In Fig. 2(a), the stable mutuality of two cyclical time series generated from equations of Example 1 is correctly mirrored by regular marked black zones. Fig. 2(b) can be divided into three parts. The different color shows that strongest synchronicity appears in the left-hand series while the weakest in the right-hand ones. Fig. 2(c) also indicates that the time series in three areas have different stable relationships, which are not captured by previous methods. RQA can detect main stylized features of time series, even when the series have the properties of cyclicity and structure changing. But RQA cannot obtain the numerical parameters to quantify the degrees of correlation and its forecasting capability is also poor.

3.6. Summary of comparison

Based on theory studying and numerical simulations, several notable features of the different methods can be found in Table 3, which summarizes the major differences in six layers. LR and MS belong to parametric methods, DC is a spectrum analysis and CI is the nonparametric method. RQA and DC have strong capabilities in detecting nonlinear relationship and capturing the cyclicity. MS has the best forecasting capability amongst the five models. RQA cannot get the coefficient and significant levels. CI can only be used in two regime switching. Different methods may be suitable for discrepant data generating processes according to the purpose of study. For instance, when cyclicity and structure changing exist in time series, LR could not be adopted.

4. Empirical illustration

4.1. Data

We measure mutuality between electricity consumption and output in China using the concerned econometric methods and demonstrate the different information obtained. The growth rates of GDP, electricity consumption and real GDP are used to depict the output cycles. We use logarithmic transformation of real GDP. The annual data for the period 1961–2007 are extracted from [82,83]. Through Augmented Dickey-Fuller (ADF) unit root-testing procedures, we found that the real GDP is integrated at order one, i.e., $I(1)$, and the growth rates of electricity consumption are stationary, i.e., $I(0)$. We use the first-order difference of real GDP variables in this analysis.

4.2. Estimation and results

Table 4 presents estimations of GDP and electricity consumption in China using LR, MS and CI. The structure of Chinese economy was changed in 1978 because of *reform and openness*. In linear regression Dummy_1978 is used to capture this fact. The dummy is set as 0 before 1978, and 1 after that year. LR results show that positive relationship exists between GDP and electricity consumption in long term, but after 1978 these relationship was weakened. Synchronicity and non-synchronicity can be detected in MS results according to different states. The phenomenon has also been proven by CI and ρ_W. In Fig. 3 the

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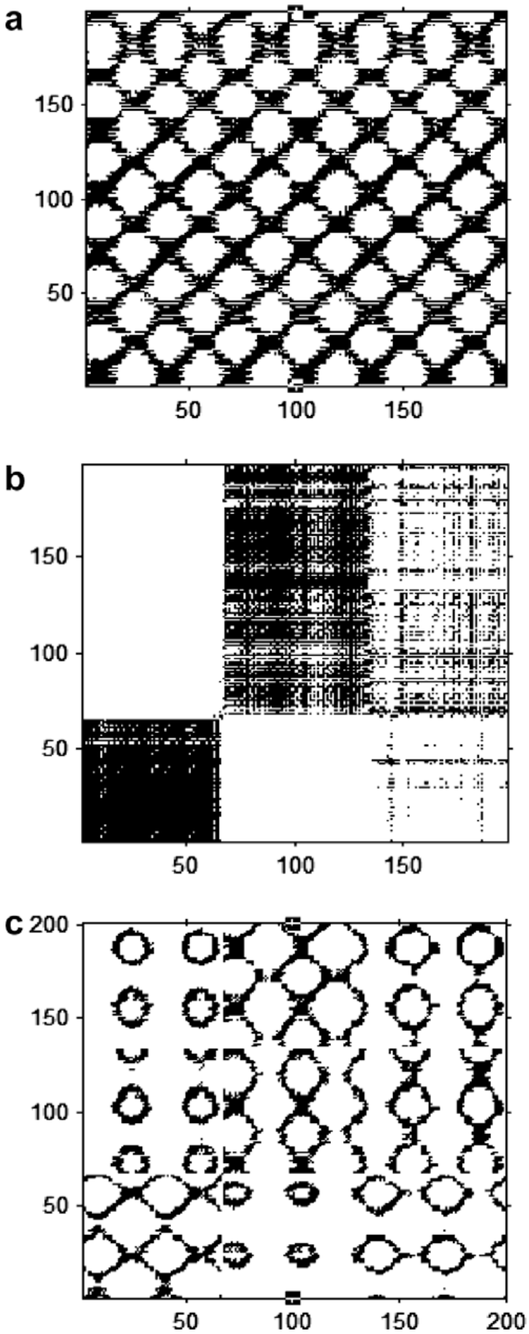

Fig. 2. The *recurrence plots* of Example 1 (a), Example 2 (b), and Example 3 (c).

coefficients of mutuality reach 0.9 in long term but stay around 0.3 in short term. In case of RP, in Fig. 4 there is a clear line of synchronicity before 1978, but the non-synchronicity presents because of time lags as shown in the color[1] line, which has been plotted using the algorithm from [15].

As far as the mutuality between electricity consumption and GDP growth in China is concerned, we can obtain some key conclusions. First, the synchronicity between those variables is not significant in short term, but strong in long term. Second, there is a great structure change in 1978 because of economic reform. Finally, the lagging effects between the growth rates of electricity consumption and GDP exist.

5. Concluding remarks

In this paper, we summarize five dynamic mutuality models in econometrics and compare their performances via numerical simulations. We focus on structure changing and cyclicity of time series, which are the two key characteristics of

[1] The small distances between the color line and diagonal line mean strong synchronicity according to [16].

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Table 3
Comparison of performance using different methods.

Methods	Category	Nonlinear detecting	Cyclicity detecting	Forecasting capability	Worse performance	Main weakness
LR	Parametric	Weak	Weak	Common	Example 3	No nonlinear
MS	Parametric	Common	Common	Strong	Example 3	–
DC	Spectrum	Strong	Strong	Weak	Example 1	No coefficient
CI	Nonparametric	Common	Common	Weak	–	Only two regimes
RQA	Graphics	Strong	Strong	Weak	None	No coefficient

Table 4
Estimated Mutuality between GDP and electricity consumption in China using LR, MS and CI.

Variables	LR		MS		CI
Constant	0.06384^{***} (0.0242)	-0.0290^{*} (0.0154)	0.5407^{***} (0.0951)	CI	0.4565
GDP	0.0090^{***} (0.00142)	0.0094^{**} (0.0015)	-0.0229^{***} (0.0079)	E(CI)	0.5189
GDP(−1)		0.3142 (0.1615)	−1.2930 (0.1374)		
GDP(−2)		0.0817 (0.1160)	−1.2403(0.1425)	ρ_W	
Dummy_1978	-0.00547^{**} (0.00234)			−0.1601 (0.2314)	
R^2	0.3376	Likelihood	75.1287		
Adjusted R^2	0.3082				

Note: Standard errors are in parenthesis. *, ** and *** indicate 10%, 5% and 1% significance levels, respectively. The critical values of null hypothesis are obtained by using HAC Newey–West method.

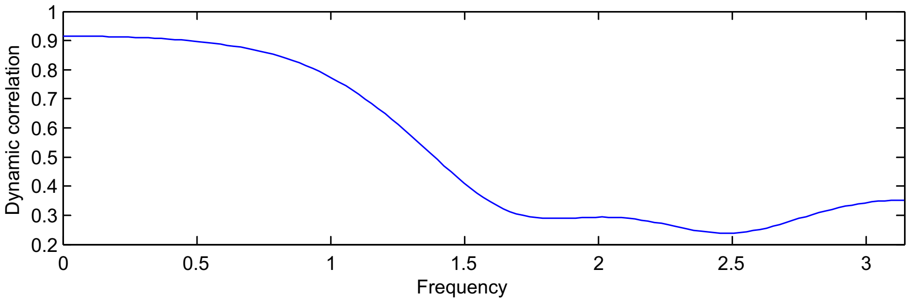

Fig. 3. The estimated *dynamic correlation* between GDP and electricity consumption in China.

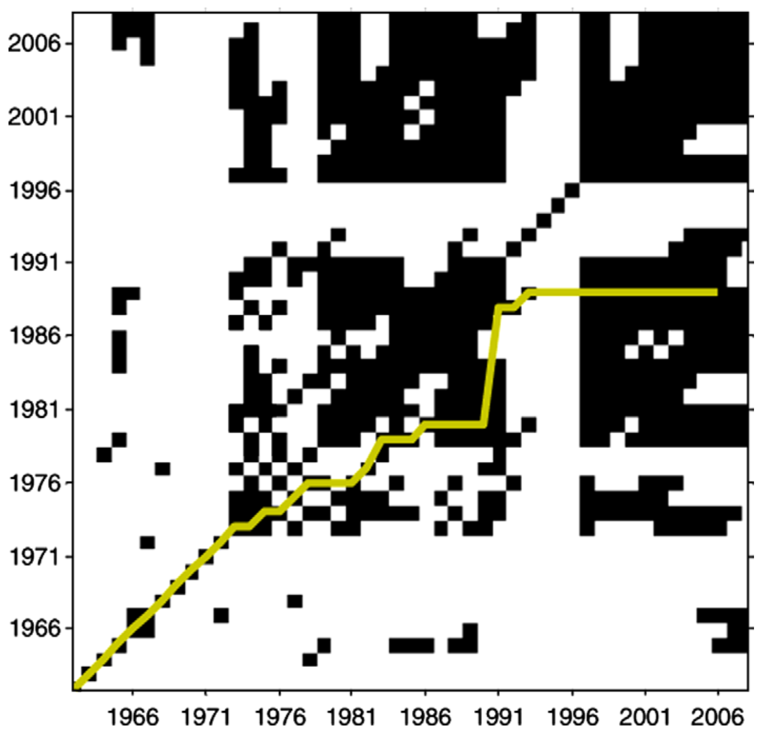

Fig. 4. The *recurrence plots* of GDP (horizon axis) and electricity consumption (vertical axis) in China.

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economic time series. Several notable features have been dug out. First, even the dummy added properly, the performance of multivariable regression is poor when cyclicity and structure changing exist simultaneously. Second, dynamic correlation may capture the relationship of cyclic series well when structure changing exists. Third, the main advantage of CI is that when the regimes have been identified correctly, the researchers could establish the nexus between the variables quickly based on only a little information. Finally, RQA can detect main stylized features of time series, even when the series have the properties of cyclicity and structure changing. But RQA cannot obtain the numerical parameters to quantify the degrees of correlation and its forecasting capability is poor. Different methods may be suitable for discrepant data generating processes according to the purpose of study. In the last part of this paper, we give an illustration in economics study. All of the methods are used to obtain different information from the statistics data. In terms of studies in mutuality measurements of time series, ample scope can be founded for further study: first, improving the forecasting ability of the methods is of important; second, offering more precise measurement is another key topic in this field. We leave further consideration of these topics to future work.

Acknowledgements

This study has been supported by the National Natural Science Foundation (Grant No. 50676105) and in part by the National Key Program for Basic Research (973 Program, Grant No. 2005CB724204). The authors are very grateful to Zhang Bo and Chen Zhan-Ming for the helpful suggestions.

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