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Lean Yu
Chinese Academy of Sciences/Beijing Univers...



Shouyang Wang
Chinese Academy of Sciences



Haibin Xie
University of International Business and Econ...

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RESEARCH ARTICLE

# Neural network methods for forecasting turning points in economic time series: an asymmetric verification to business cycles

**Dabin ZHANG[1,2], Lean YU (✉)[2], Shouyang WANG[2], Haibin XIE[2]**

1 Department of Information Management, Huazhong Normal University, Wuhan 430079, China
2 Institute of Systems Science, Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Beijing 100190, China



**Abstract** This paper examines the relevance of various financial and economic indicators in forecasting business cycle turning points using neural network (NN) models. A three-layer feed-forward neural network model is used to forecast turning points in the business cycle of China. The NN model uses 13 indicators of economic activity as inputs and produces the probability of a recession as its output. Different indicators are ranked in terms of their effectiveness of predicting recessions in China. Out-of-sample results show that some financial and economic indicators, such as steel output, M2, Pig iron yield, and the freight volume of the entire society are useful for predicting recession in China using neural networks. The asymmetry of business cycle can be verified using our NN method.

**Keywords** turning points, business cycle, leading indicators, neural networks (NNs)

## 1 Introduction

The forecasting of business cycle turning points is a challenging task with limited success in economic analysis. Although some new progress has emerged in the field of business cycles and economic indicators, none of the existing models are suitable for all circumstances [1]. The traditional regression methods have relied mainly on linear models with constant parameters, without considering the asymmetries and complexities of business cycle fluctuations. Usually, business cycle activity is measured by constructing the composite indexes of various economic and financial indicators. The indicators can be divided into the leading indicator, lagging indicator and coincident indicator, which can be used to measure the cycles. In the case of leading indicators, a quantitative estimation of the business cycle peak or turning points is presented.

In regression models, e.g., the dynamic factor model, these indicators or indices are used to estimate turning points, while in probabilistic models, these indictors or indices are used to estimate the probability of a recession [2,3]. Usually, regression models are linear in nature and cannot capture the complex mechanisms hidden in practical business cycle dynamics. For this reason, a nonlinear model is required. In this circumstance, neural networks (NNs), a class of flexible nonlinear models inspired by the way in which the human brain processes information, are proposed. Neural network can be seen as an event-oriented nonlinear regression approach that captures turning points in the business cycle [4].

For this purpose, this paper applies neural networks to Chinese data during the period 1998–2008. Accordingly the different indicators are ranked in terms of their effectiveness of predicting Chinese recessions. This method can solve the economic and financial indicators selection problem. This method can form a composite index of leading indicators and give a forecast in two subperiods to verify asymmetry of business cycle [5]. To test whether these indicators hold optimal persistently, these

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E-mail: yulean@amss.ac.cn

indicators are ranked by their effectiveness of recession prediction in two sub-periods. The great changes in the ranking results indicates evidence of the asymmetry of business cycle.

Section 2 provides a review of the current literature covering business cycle turning point forecasting. Section 3 describes the neural network forecasting model and business cycle forecasting method. Section 4 provides an empirical study of out-of-sample data forecasting. Concluding remarks and further discussions are provided in Section 5.

## 2 Literature review

In the theoretical research and empirical analysis of modern business cycle, forecasting the business cycle turning point mainly focuses on studying nonlinear and asymmetric features of the business cycle. Employing neural networks for predicting business cycle turning points forecasting is still in its infancy. In the existing literature, some linear models are used for business cycle analysis. Neftci [6] and Sichel [7] provided direct evidence indicating that business cycles are asymmetric. Quandt [8], Goldfeld and Quandt [9], and Ploberger, Kramer, and Kontrus [10] considered some linear models with structural changes. From then on, the Markov switching model has been widely used in the study of asymmetric features in business cycles and finance. Empirical analysis has shown the Markov switching model is appropriate for the computation of a composite index monitoring business cycle activity [11]. Diebold and Rudebusch [12] argue that the non-regression methods such as Markov switching models can be used to construct *expansion* and *contraction* leading indices for turning point prediction. Based on the Markov switching model, Chauvet [13] analyzed the features of business cycle dynamics in the USA, whilst Kim and Nelson [14] studied the business cycle turning points and investigated the duration dependence of business cycle.

These linear models cannot, however, capture the complex mechanisms hidden in practical business cycle dynamics. For this reason, some nonlinear models such as NN models are used with the same forecasting goals. For example, Hoptoff et al. [15] applied neural networks to nonlinear multivariate forecasting. In their paper, they forecast the GDP of the UK economy one year ahead using 23 indicators. Their approach has been compared to the conventional forecasting approach using leading indicators and obtained good performance [15]. Similarly, Vishwakarma [16,17] applied the NN method to analyze multiple time series data. Soo [18] proposed a new forecasting model based on NN with weighted fuzzy membership functions (NEWFM) for turning points forecasting in business cycles using the composite index. The implementation of NEWFM demonstrates an excellent capability in the field of business cycle analysis. Qi [19] examines the relevance of various financial and economic indicators in predicting US recessions via neural network models. The out-of-sample results show that some indicators are useful in predicting US recessions via the NN model and the relevance of various leading indicators may change from time to time. George, Ghassan and Antoine [4] applied a NN based indicator ranking method to the prediction of business cycles in the Lebanese economy as a case study of information-poor economies. He goes on to use NN to forecast recursively the probability of a recession within six month period.

In our work we aim at predicting recession rather than quantitative values of future economic variables. We focus on out-of-sample performance rather than in-sample performance because the latter can always been improved by including more variables or employing more complex models [20].

## 3 Formulation of neural network forecasting model

### 3.1 Neural network models

NN models are a class of flexible nonlinear models inspired by the way in which the human brain processes information. NN can form a mapping from a vector of inputs to a vector of outputs. A number of applications have demonstrated the importance of neural network model [21–24]. Common applications include forecasting, character recognition, signal processing, robot control, and process monitoring. Bailey and Donna [25,26] have identified a number of criteria for defining if NN are appropriate for a particular application:

(1) Conventional computer technology is not adequate;

(2) Problem requires qualitative or complex quantitative reasoning;

(3) Solution is derived from highly-interdependent parameters with no precise quantification;

(4) Data are readily available but multivariate and noisy or error-prone;

(5) Project development time is short, but sufficient *training time* is needed.

Although there are a number of learning algorithms to train a neural network, the three-layer feed-forward network is the most widely used in the many studies [27]. A typical tree-layer feed-forward NN is shown in Fig. 1.

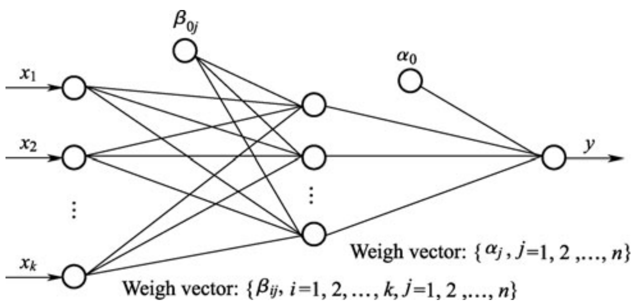


**Fig. 1** A three-layer feed-forward neural network, (assuming $k > 2$)

Given $X = (x_1, x_2, \ldots, x_k)'$ $(k > 2)$ is the input vector and $y$ the output, the NN mapping can be written as $y = f(X)$ where

$$f(X) = g\left(\alpha_0 + \sum_{j=1}^{n} \alpha_j g\left(\sum_{i=1}^{k} \beta_{ij} x_i + \beta_{0j}\right)\right) + \varepsilon, \quad (1)$$

where $n$ is the number of units in the hidden layer, $k$ is the number of input nodes (explanatory variables), $\alpha_j$ is the parameter from the hidden layer to the output layers, $\beta_{ij}$ is the parameter from the input to the hidden layers, and $g$ is a logistic transfer function defined as $g(a) = 1/(1 + \mathrm{e}^{-a})$, $\varepsilon$ is the error term. The error term $\varepsilon$ can be made arbitrarily small if sufficiently many explanatory variables are included, and if $n$ is chosen to be large enough. However, if $n$ is too large, the model may overfit in which case the in-sample errors can be very small but the out-of-sample errors can be very large. The choice of $n$ depends on the number of explanatory variables and the nature of the underlying relationship between $y$ and $X$. Because the number of explanatory variables in each of our NN models is never greater than 2, we fix $n$ to be 3.

### 3.2 Neural network forecasting and performance measurement

For a given data set with $T$ observations, the out-of-sample forecasts for a given horizon $h$ are constructed by first estimating the NN model (1) with data up through date $t_0 < T$, so that the last observation used is $(y_{t_0}, X_{t_0-h})$. Let $\left(\hat{\alpha}_{t_0}^h, \hat{\beta}_{t_0}^h\right)$ be the parameters estimated with these observations. The first $h$-horizon forecast is computed with the following form:

$$\hat{y}_{t_0+h} = g\left[\hat{\alpha}_{0,t_0}^h + \sum_{j=1}^{3} \hat{\alpha}_{j,t_0}^h g\left(\sum_{i=1}^{k} \hat{\beta}_{ij,t_0}^h x_{i,t_0} + \hat{\beta}_{0j,t_0}^h\right)\right]. \quad (2)$$

This procedure is repeated for $t_0 + 1, t_0 + 2, \ldots, T - h$, thus yielding $N$ forecasts, where $N = T - t_0 - h + 1$.

To evaluate the prediction performance in this model, we use a mean squared forecast errors (*MSFE*) proposed in Hamilton and Perez-Quiros [28], which is defined as

$$MSFE = N^{-1} \sum_{t=t_0+h}^{T} (y_t - \hat{y}_t)^2. \quad (3)$$

A simple benchmark prediction of the recession probability can be easily constructed by letting $\hat{y}$ be a constant equal to the historical fraction of quarters for which the economy was in a recession: $\hat{y}_t = N^{-1} \sum_{t=t_0+h}^{T} y_t$. A forecasting model can be considered to be successful at identifying turning points if its *MSFE* beats the benchmark prediction.

In this paper, out-of-sample forecasts are performed in a recursive fashion to capture possible structural changes in the economy. First, a NN model is produced using data from the beginning of the sample up to a particular month, say, August 1999. Then the parameters are used for 1-month ahead forecasting, i.e., September 1999, or 2-month-ahead prediction, i.e., October 1999 and so on. Next, one more observation is added to the sample, i.e., the data up to September 1999 are used to refine the NN model. Subsequently the parameters are used to make prediction from October 1999 for the 1-month horizon prediction, from November 1999 for the 2-month horizon prediction, and so forth. Although whilst this is an automated computing process it is time consuming, this recursive procedure can generate predictions in a real time fashion.

## 4 Data and empirical results

### 4.1 Data

The inputs to the NN are 13 economic indicators which are used to effectively formulate a leading composite index. The whole sample of these indicators consists of monthly data from January 1998 to December 2008.

These indicators are published monthly by National Information Center (NIC) and National Statistics Bureau (NSB) of China [29]. Such timely publication allows, once the leading composite index is formed, to update the value of the leading composite index in real-time, for an economic time scale. Hence the leading composite index becomes a valuable tool for the business cycle forecasting [30–33]. The indicators are pig iron yield, steel output, cargo throughput of coastal port, new start operation area of commercial housing, financial expenditure budget, capital occupying volume of finished goods (reversal), M2, sales rate of industrial products, Hang Seng Index, new developed area of land, consumer index, plan projects of new start operation and freight volume of whole society [29,34], and are shown in Table 1.

To predict the business cycle, we first must determine the benchmark of recession for comparison. However, the benchmark of recession is not released in China. For this purpose, this paper uses industrial added value (IAV) to represent recession in China. The step of determining certain recession benchmark is shown below.

First, the seasonal factors must be adjusted for IAV before conducting economic analysis. In this paper, the method of seasonal-adjusting used is X12 ARIMA.

Subsequently, the Bry-Boschan method [35] is used to find the peak and trough curve. Usually, the distance between peak and trough is larger than 6 months, the distance between peak and peak is usually larger than 15 months.

Using the above data, the peak and trough curve is shown in Fig. 2. The peaks and troughs are marked with P and T respectively and the shading represents the recession period. We see there are five recession periods on the curve, as represented by the shaded areas.

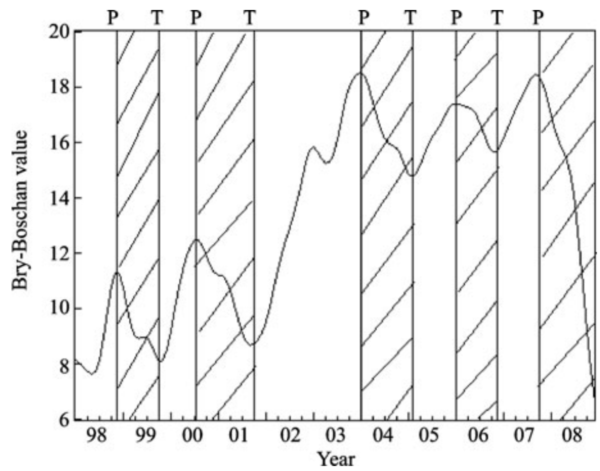


**Fig. 2** Peaks and troughs of industrial added value (P: peak; T: tough)

Using such a procedure, the recession benchmark can be determined.

In the above data set, the whole sample consists of monthly data from January 1998 to December 2008 with a total of 132 monthly observations ($T = 132$). In the 132 observations, there are 59 observations that fall in the recession periods. These data are divided into two parts: in-sample data and out-of-sample data. In this study, the in-sample data are used as training sample, starting from January 1998 to December 1999, the out-of-sample

**Table 1** Economic indicators

| Indicator | Code | Description | Publishing mechanism |
|---|---|---|---|
| PIY | 1 | pig iron yield | NIC |
| SO | 2 | steel output | NIC |
| CTCP | 3 | cargo throughput of coastal port | NIC, NSB |
| NSOACH | 4 | new start operation area of commercial housing | NIC, NSB |
| FEB | 5 | financial expenditure budget | NIC |
| COVFG | 6 | capital occupying volume of finished goods (reversal) | NIC |
| M2 | 7 | M2 | NSB |
| SRIP | 8 | sales rate of industrial products | NSB |
| HSI | 9 | Hang Seng Index | NSB |
| NDAL | 10 | new developed area of land | NSB |
| CI | 11 | consumer index | NSB |
| PPNSO | 12 | plan projects of new start operation | NSB |
| FVWS | 13 | freight volume of whole society | NSB |

forecasts start from January 2000 and end in December 2008. In the out-of-sample data, there are a total of 108 observations ($N = 108$) including 48 observations that fall in recession periods. The recession periods are used to determine the values of $y$, the recession dummy is equal to 1 in a recession or 0 otherwise. A simple benchmark prediction of the recession probability can be constructed as follows.

Let $\hat{y}$ be a constant equal to the historical fraction of months. In this case, $\hat{y} = 48/108 = 0.44$. Using Eq. (3), the *MSFE* of benchmark is 0.247. Now we can use the above 13 indicators to predict whether the Chinese economy is going to enter a recession period within 1 to 8 months in the future ($h = 1,2,3,...,8$). The criteria for choosing the best indicators for the Chinese recession prediction are that the *MSFE* of the proposed model can beat that of the benchmark.

### 4.2 Out-of-sample results over the entire forecasting period

Table 2 reports the out-of-sample *MSFE* for each of individual indicators listed in Table 1 within 1-8 months in the future. The first column gives the ranking, and the second and third columns represent the codes of the indicators and their corresponding *MSFE*s (sorted in ascending order) for the 1-month-ahead prediction. Columns 4 and 5 show the codes of the indicators and their corresponding 2-month-ahead prediction and so on. From Table 2, there are a number of interesting findings in terms of the *MSFE*s reported in this table.

First, across all eight forecast horizons, steel output (SO) is the best indicator, indicating that steel output is a good candidate for beating the benchmark prediction.

Second, from 1 to 8-month horizons, the number of indicators that can beat the benchmark prediction gradually declines. The number of greatest change is occurred from the 4-month horizon to the 5-month horizon, the number of indicator declines from 9 to 4.

Third, from 1-month to 4-month prediction horizons, 9 indicators are often used. Most of these 9 indicators are published by NSB. This implies the data of NSB might be a better choice of indicators than those of NIC.

However, it is not clear whether these indicators can also compose good leading index. For this issue, we perform an indicator selection experiment in Section 4.3.

### 4.3 Selection of indicators

In Table 2 we present the results of the NN estimation, in terms of ranking, which economic indicators were successful in predicting a recession. Because there are at least 9 indicators that beat the benchmark predication within the 1st-4th horizons, we select the 9 indicators (SO, CI, M2, PIY, SRIP, FVWS, NSOACH, CTCP and COVFG) as optimization indicators. To compare performance of optimization indicators, we compute the leading composite index (LCI) of leading indicators published by NIC and NSB. The results are shown in Figs. 3(a)–(d). Note that CCI in Fig. 3 represents the coincident composite index.

As can be observed from Figs. 3(a)–(d), it is easy to find that LCI curves of Figs. 3(b)–(d) are very similar.

**Table 2** Out-of-sample forecasts, *MSFE* and rank of economic indicators ($h$ = 1–8)

| Rank | $h$ = 1 | | $h$ = 2 | | $h$ = 3 | | $h$ = 4 | | $h$ = 5 | | $h$ = 6 | | $h$ = 7 | | $h$ = 8 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *i* | *MSFE* | *i* | *MSFE* | *i* | *MSFE* | *i* | *MSFE* | *i* | *MSFE* | *i* | *MSFE* | *i* | *MSFE* | *i* | *MSFE* |
| 1 | 2 | **0.141** | 2 | **0.139** | 2 | **0.157** | 2 | **0.150** | 2 | **0.183** | 2 | **0.204** | 2 | **0.213** | 2 | **0.200** |
| 2 | 1 | **0.141** | 11 | **0.162** | 7 | **0.191** | 11 | **0.209** | 7 | **0.239** | 7 | 0.258 | 13 | 0.252 | 13 | 0.263 |
| 3 | 11 | **0.142** | 1 | **0.170** | 11 | **0.198** | 7 | **0.216** | 13 | **0.244** | 8 | 0.262 | 8 | 0.267 | 6 | 0.283 |
| 4 | 8 | **0.164** | 7 | **0.178** | 6 | **0.203** | 1 | **0.221** | 1 | **0.245** | 11 | 0.267 | 7 | 0.276 | 8 | 0.291 |
| 5 | 6 | **0.165** | 8 | **0.183** | 13 | **0.219** | 8 | **0.232** | 11 | 0.249 | 13 | 0.270 | 11 | 0.283 | 11 | 0.293 |
| 6 | 13 | **0.172** | 6 | **0.188** | 1 | **0.219** | 13 | **0.236** | 8 | 0.254 | 6 | 0.285 | 6 | 0.291 | 1 | 0.296 |
| 7 | 7 | **0.178** | 13 | **0.196** | 3 | **0.229** | 4 | **0.237** | 6 | 0.257 | 1 | 0.288 | 1 | 0.312 | 7 | 0.327 |
| 8 | 3 | **0.190** | 3 | **0.200** | 8 | **0.229** | 3 | **0.240** | 3 | 0.278 | 3 | 0.299 | 4 | 0.329 | 4 | 0.329 |
| 9 | 9 | **0.193** | 4 | **0.222** | 4 | **0.232** | 6 | **0.242** | 4 | 0.285 | 4 | 0.317 | 3 | 0.337 | 3 | 0.355 |
| 10 | 4 | **0.193** | 9 | **0.237** | 12 | **0.237** | 12 | 0.308 | 10 | 0.342 | 9 | 0.360 | 10 | 0.388 | 9 | 0.383 |
| 11 | 12 | **0.209** | 10 | 0.249 | 9 | 0.285 | 9 | 0.311 | 12 | 0.350 | 10 | 0.381 | 9 | 0.394 | 10 | 0.406 |
| 12 | 5 | **0.214** | 12 | 0.255 | 10 | 0.309 | 10 | 0.335 | 9 | 0.352 | 12 | 0.394 | 12 | 0.412 | 12 | 0.414 |
| 13 | 10 | **0.236** | 5 | 0.262 | 5 | 0.309 | 5 | 0.388 | 5 | 0.435 | 5 | 0.471 | 5 | 0.492 | 5 | 0.487 |

Note: bold numbers are lower than the *MSFE* of the benchmark prediction made based on ex post probability of the recession (0.247).

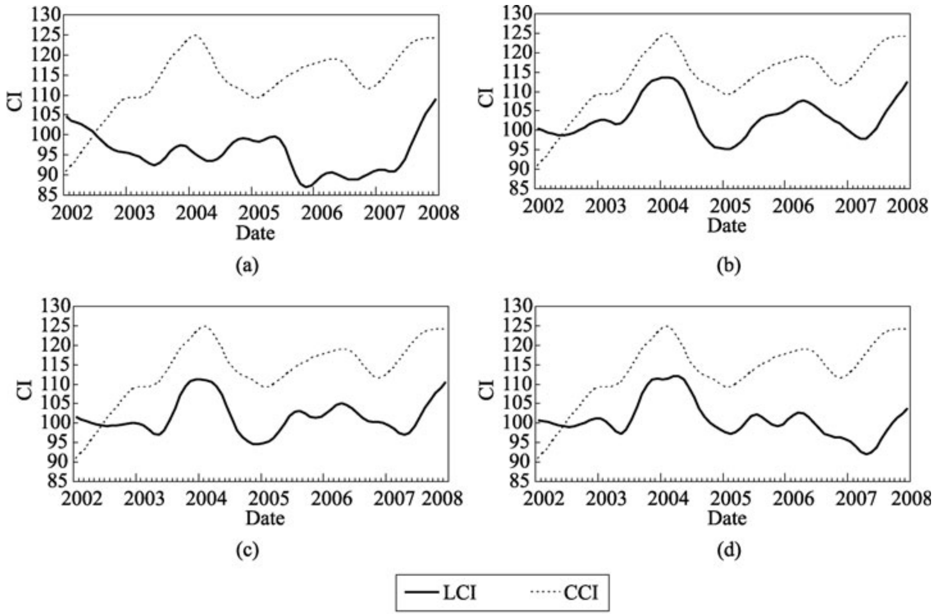


**Fig. 3** Composite index of different indicators. (a) Composite index of NIC; (b) composite index of NSB; (c) composite index of all indicators; (d) composite index of optimization indicators

Furthermore, LCI curve in Figs. 3(b)–(d) have a similar trend with CCI, but the LCI curve of Fig. 3(a) is not consistent with CCI curve of Fig. 3(a). The CCI released by the NSB is used as the benchmark, since it is consistent with China's Macro-economic fluctuation. It is obvious that the LCI given by the NIC works poorly since it is inconsistent with the fluctuation of CCI. For Figs. 3(c)–(d), though the LCI performs similarly, Fig. 3(c) is obtained using all the 13 indicators in Table 2, while Fig. 3(d) is obtained by NN using only 9 indicators, which means similar results are obtained using fewer indicators. Therefore the indicators selected by indicator prediction ranking via the NN model are more effective.

## 4.4 Out-of-sample forecasting results in the two sub-periods

Although the results reported in the previous subsections may indicate the relevance of various indicators in the entire forecasting periods, it does not provide direct information on whether the importance of various indicators changes over time. Therefore, all periods are divided into two-sub periods: January 1998 to December 2002, and January 2002 to December 2008. The corresponding results of *MSFE* and the rankings of various predictors are reported in Tables 3 and 4. The *MSFE* of the simple benchmark prediction in the two sub-periods are 0.234 and 0.248, respectively.

From Tables 3 and 4, we observe the following interesting results. First, the out-of-sample forecasting accuracy of various indicators tends to change from sub-period to sub-period. For example, at the 1-month forecast horizon, SRIP ranked No.1 in the 2nd sub-period, but it ranked the 9th in the 1st sub-period. The ranking changes dramatically for steel output (SO). At all 1–8 month horizons, though SO indicator is the best in the entire out-of-sample forecast period, it does not rank No.1 at the 1st and 2nd sub-periods.

Second, even at the same forecasting horizon, the best predictors in the two sub-periods are rarely the same. For example, CI is the best indicator in the 1st sub-period, but it is replaced by SRIP in the 2nd sub-period.

Third, although certain indicators can beat the benchmark prediction at all eight horizons in certain sub-periods or at certain horizons in all two sub-periods, none of them beats the benchmark in all two sub-periods. For example, CI beats the benchmark prediction at all eight horizons but it is only limited in the 1st sub-period. In addition, all indicators beat the benchmark at the 1-month ahead forecasting only in the entire forecasting period, which is reported in Table 2.

The implication of these findings is that the best predictor of the Chinese recessions at one time period or at one forecasting horizon may not necessarily be the best at other time periods or at other forecasting horizons. These empirical results verify the asymmetry of business cycles.

**Table 3** Out-of-sample *MSFE* and rankings of individual indicators, 1–8 months ahead, in first sub-period (January 1998 to December 2002)

| Rank | $h$ = 1 | | $h$ = 2 | | $h$ = 3 | | $h$ = 4 | | $h$ = 5 | | $h$ = 6 | | $h$ = 7 | | $h$ = 8 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *i* | *MSFE* | *i* | *MSFE* | *i* | *MSFE* | *i* | *MSFE* | *i* | *MSFE* | *i* | *MSFE* | *i* | *MSFE* | *i* | *MSFE* |
| 1 | 11 | **0.138** | 11 | **0.147** | 11 | **0.147** | 11 | **0.114** | 11 | **0.114** | 11 | **0.114** | 11 | **0.106** | 11 | **0.106** |
| 2 | 13 | **0.163** | 13 | **0.171** | 13 | **0.179** | 13 | **0.171** | 6 | **0.201** | 10 | **0.237** | 3 | **0.169** | 3 | **0.206** |
| 3 | 5 | **0.191** | 8 | **0.180** | 8 | **0.180** | 10 | **0.212** | 13 | **0.212** | 6 | **0.237** | 10 | **0.262** | 2 | **0.229** |
| 4 | 12 | **0.192** | 3 | **0.182** | 6 | **0.183** | 8 | **0.221** | 3 | **0.214** | 3 | 0.238 | 2 | **0.262** | 10 | 0.262 |
| 5 | 6 | **0.193** | 6 | **0.199** | 10 | **0.237** | 3 | **0.232** | 10 | **0.224** | 13 | 0.253 | 13 | 0.277 | 6 | 0.290 |
| 6 | 1 | **0.199** | 5 | **0.199** | 3 | 0.240 | 5 | **0.232** | 2 | 0.245 | 2 | 0.262 | 6 | 0.301 | 4 | 0.291 |
| 7 | 10 | **0.212** | 10 | **0.212** | 5 | 0.241 | 6 | **0.237** | 8 | 0.246 | 12 | 0.290 | 12 | 0.315 | 12 | 0.307 |
| 8 | 3 | **0.212** | 7 | **0.213** | 2 | 0.277 | 2 | 0.245 | 5 | 0.266 | 5 | 0.291 | 4 | 0.316 | 5 | 0.307 |
| 9 | 8 | **0.221** | 12 | 0.247 | 7 | 0.288 | 12 | 0.248 | 12 | 0.266 | 1 | 0.299 | 5 | 0.316 | 13 | 0.310 |
| 10 | 2 | **0.228** | 1 | 0.249 | 12 | 0.290 | 7 | 0.271 | 7 | 0.296 | 4 | 0.307 | 1 | 0.332 | 1 | 0.340 |
| 11 | 7 | **0.230** | 2 | 0.278 | 1 | 0.291 | 1 | 0.274 | 1 | 0.307 | 8 | 0.320 | 8 | 0.353 | 7 | 0.386 |
| 12 | 4 | 0.257 | 4 | 0.282 | 4 | 0.291 | 4 | 0.291 | 4 | 0.324 | 7 | 0.320 | 7 | 0.361 | 9 | 0.386 |
| 13 | 9 | 0.287 | 9 | 0.385 | 9 | 0.386 | 9 | 0.427 | 9 | 0.435 | 9 | 0.468 | 9 | 0.443 | 8 | 0.386 |

**Table 4** Out-of-sample *MSFE* and rankings of individual indicators, 1–8 months ahead, in second sub-period (January 2003 to December 2008)

| Rank | $h$ = 1 | | $h$ = 2 | | $h$ = 3 | | $h$ = 4 | | $h$ = 5 | | $h$ = 6 | | $h$ = 7 | | $h$ = 8 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *i* | *MSFE* | *i* | *MSFE* | *i* | *MSFE* | *i* | *MSFE* | *i* | *MSFE* | *i* | *MSFE* | *i* | *MSFE* | *i* | *MSFE* |
| 1 | 8 | **0.129** | 11 | **0.169** | 11 | **0.161** | 8 | **0.177** | 8 | **0.234** | 8 | **0.242** | 9 | 0.250 | 7 | **0.185** |
| 2 | 11 | **0.145** | 8 | **0.201** | 2 | **0.193** | 11 | **0.201** | 11 | 0.258 | 11 | 0.250 | 7 | 0.258 | 8 | **0.201** |
| 3 | 6 | **0.169** | 9 | **0.201** | 8 | **0.210** | 5 | **0.226** | 5 | 0.258 | 9 | 0.274 | 8 | 0.266 | 2 | 0.258 |
| 4 | 13 | **0.185** | 6 | **0.210** | 7 | **0.218** | 7 | **0.242** | 7 | 0.274 | 7 | 0.282 | 2 | 0.266 | 9 | 0.266 |
| 5 | 9 | **0.193** | 7 | **0.218** | 9 | **0.226** | 9 | **0.242** | 2 | 0.290 | 2 | 0.298 | 11 | 0.322 | 11 | 0.290 |
| 6 | 1 | **0.210** | 1 | **0.226** | 5 | **0.242** | 2 | 0.266 | 9 | 0.306 | 5 | 0.338 | 3 | 0.330 | 5 | 0.314 |
| 7 | 2 | **0.210** | 13 | **0.234** | 1 | 0.250 | 1 | 0.274 | 1 | 0.338 | 6 | 0.338 | 5 | 0.338 | 3 | 0.314 |
| 8 | 7 | **0.210** | 2 | **0.242** | 10 | 0.266 | 6 | 0.290 | 10 | 0.355 | 10 | 0.355 | 10 | 0.379 | 1 | 0.355 |
| 9 | 5 | **0.218** | 5 | 0.258 | 6 | 0.282 | 10 | 0.290 | 6 | 0.355 | 3 | 0.355 | 1 | 0.387 | 10 | 0.371 |
| 10 | 3 | **0.218** | 3 | 0.266 | 13 | 0.290 | 3 | 0.322 | 12 | 0.355 | 1 | 0.371 | 4 | 0.395 | 6 | 0.371 |
| 11 | 10 | 0.258 | 10 | 0.274 | 3 | 0.290 | 13 | 0.338 | 3 | 0.379 | 12 | 0.387 | 6 | 0.411 | 12 | 0.419 |
| 12 | 4 | 0.266 | 12 | 0.314 | 4 | 0.306 | 12 | 0.355 | 4 | 0.403 | 4 | 0.427 | 12 | 0.443 | 4 | 0.427 |
| 13 | 12 | 0.266 | 4 | 0.330 | 12 | 0.355 | 4 | 0.363 | 13 | 0.427 | 13 | 0.467 | 13 | 0.492 | 13 | 0.500 |

It may be unrealistic for people to believe the existence of a single model that will work the best at all time periods and at all forecasting horizons. Researchers should always take the efforts to investigate the possible structural changes in the economy.

## 5 Conclusions

In this paper, a NN model is employed to investigate the predictability of the Chinese recessions using a set of candidate input variables including all 13 leading indicators published on a monthly basis by NIC and NSB. The different indicators are ranked in terms of their effectiveness of predicting Chinese recessions. Based on the mean squared forecast errors, the out-of-sample results indicate that among the 13 investigated indicators, the iron output is the best indicator of the China recession for a horizon of 1–8 months ahead. Meanwhile, we can acquire a set of optimal leading indicators based on above method.

When the entire out-of-sample forecast period is divided into two sub-periods, we find that the relevance of optimal leading indicators tends to change from time to time. The best predictor of the Chinese recessions at one time period or at one forecasting horizon may not necessarily be the best at other time periods or at other forecasting horizons. Therefore, we consider business cycles to be asymmetric and cannot be adequately accommodated by the single-index models with linear constant parameters.

Although our results are encouraging, the present study is still limited in many ways and will be extended in future work. Currently, we use only 13 indicators as input of NN; more indicators will be investigated in the future. It is particularly important if we want to investigate whether NN could be an alternative to the dynamic factor models that typically rely on more than two variables. In the present study, the number of hidden neurons in NN is fixed at 3; overfitting may not be a serious problem because the number of indicators used in each model is either one or two. In future work, if more indicators are included in an NN model, cross validation procedures can be used to select the best model with the optimal number of hidden neurons and the best set of indicators.

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