Measuring Real Business Condition in China

C. James Huenga\textsuperscript{a, b}, Ping Liu\textsuperscript{c, *}

\textsuperscript{a} Department of Economics, Western Michigan University, Kalamazoo, MI 49008-5330.
\textsuperscript{b} School of Economics, Zhongnan University of Economics and Law, Wuhan, Hubei 430073, China.
\textsuperscript{c} Collaborative Innovation Center for the Cooperation and Development of Hong Kong, Macao and Mainland China, Sun Yat-Sen University, Guangzhou, Guangdong 510275, China.

Abstract

This paper constructs a monthly Chinese business condition index (CBCI) by using a mix-frequency state-space model to incorporate economic indicators from different frequencies. The modeling strategy is necessary to account for the Chinese labor market conditions. When choosing the components, we pay special attention to the reliability of Chinese data by avoiding the variables that are more likely subject to government manipulation or mismeasurement. Comparisons of the CBCI and official indicators show discrepancies before 2009 and consistency afterwards, supporting the argument that Chinese official data improve markedly after 2008. An out-of-sample prediction practice justifies the usefulness of the CBCI in forecasting the private sector’s perception of the business conditions.

JEL Classification: E32, E37, C01, C22

Keywords: Chinese Business Cycles; Latent Real Business Condition; Mixed-Frequency Model.

* Corresponding Author. The research was conducted when the author was a visiting scholar at Western Michigan University.

Email: C. James Hueng: James.Hueng@wmich.edu. Ping Liu: lp141308@163.com.
Highlights

- This paper constructs a real business condition index for China.
- We use a dynamic mixed-frequency state-space model to incorporate economic indicators from different frequencies.
- We pay special attention to the reliability of Chinese data by avoiding the variables that are likely subject to government manipulation or mismeasurement.
- We find discrepancies between our index and the official indicators before 2009 and consistency afterwards.
- An out-of-sample prediction justifies the usefulness of our index in forecasting the private sector’s perception of the business conditions.
1. **Introduction**

This paper assesses the state of the Chinese real economy at the monthly frequency. We use a dynamic mixed-frequency state-space model to incorporate quarterly labor market data as well as monthly economic indicators to build a monthly Chinese business condition index, denoted as the CBCI. The mixed-frequency model is needed because major Chinese labor market statistics are only available at the quarterly or the annual frequencies. When selecting the relevant indicators from different frequencies, special attention is paid to the reliability of Chinese data. We propose several selection criteria to exclude questionable indicators.

Extensive efforts have been put into replacing the quarterly Chinese GDP figures by monthly indices that can be used by policymakers and business practitioners for more timely decisions. These indices often incorporate multiple monthly indicators in a principle component model, and use the first principle component as the monthly business condition index. Examples include several popular indices listed on Table 1: the Conference Board index, the Chinese Academy of Science Index, the OECD index, and the National Bureau of Statistics (NBS) index. A close investigation of the listed components reveals that none of them is from the labor market. This is because major Chinese labor market statistics are not available at the monthly frequency and therefore, cannot be included in a monthly principle component model. However, any real business condition index ignoring labor market statistics is missing important information on the real economy. To take account for the labor market conditions, we need to use a model that can incorporate economic indicators from both the monthly and the quarterly frequencies.

*<Table 1 about here>*

In an attempt to incorporate economic indicators from different frequencies in a single U.S. business condition index, Aruoba, Diebold, and Scotti (2009) use a dynamic mixed-frequency factor model to construct the Aruoba-Diebold-Scotti Business Conditions Index (the ADS index), now maintained by the Federal Reserve Bank of Philadelphia. The ADS index measures the latent business conditions,
emphasizing that business cycle is not about any single variable, but about the dynamics and interactions
of many economic indicators from various frequencies. Currently the indicators included in the calculation
of the ADS index are weekly initial jobless claims; monthly payroll employment, industrial production,
personal income less transfer payments, and manufacturing and trade sales; and quarterly real GDP. These
indicators are related to a latent index designed to track real business conditions at the daily frequency. The
latent index is the optimal extraction of the state of real activities by using the Kalman filter and smoother.

The purpose of this paper is to adopt the ADS philosophy and methodology but cautiously select
the indicators to construct a business condition index to track the Chinese real economy. The ADS
methodology, however, can only incorporate a parsimonious set of indicators in the model. With dozens
of monthly and quarterly data series available, any combination of a few series is deemed arbitrarily chosen.
Without prior knowledge about which of the series are the most important ones, studies try to include as
much data as are available and use a principle component model directly [e.g., Mehrotra and Pääkkönen
(2011)] or in a factor-augmented vector autoregression (FAVAR) setting [e.g., Fernald, Spiegel, and
Swanson (2014)], to extract the latent business condition index. These statistical methods let the data speak
in terms of the goodness of fit. However, relying on statistical methods that consider all available variables
is not necessary a better strategy when it is known that some of the included variables are not reliable.
Therefore, to deal with the skepticism about the accuracy of the Chinese data, we opt to use the ADS
methodology and provide economic reasoning for choosing the parsimonious set of indicators.

We propose three criteria to narrow down the candidates for the set of indicators. First of all, the
purpose of our index is to track the Chinese real economy and focus on the production side of the economy.
Therefore, we exclude all nominal variables (e.g., money supply, bank loans, etc.) because they are subject
to fluctuations in the nominal factors. Secondly, due to the concerns on the accuracy and veracity of the
Chinese data, we exclude “flagship” variables such as the Value Added Industry (VAI), GDP, and
unemployment rates; and variables constructed from official surveys such as construction, investment, sales,
and revenue data. Finally, real variables that are constructed by using a deflator (e.g., real income, real
consumption, real exports, etc.) are not considered, either, because the deflator itself is a flagship variable.\(^1\) After narrowing down the candidate indicators, we take the suggestions in the literature and from Chinese government officials’ speeches to select the final indicators included in the model.

Unfortunately, unlike the U.S., where the weekly labor market data are available, there is no production or labor market data at such a high frequency in China. Therefore, the highest frequency of the variables that we use to construct the index is monthly. The indicators selected are: monthly Volume of Freight Handled in Main Coastal Ports, Freight Traffic of Railways, Passenger Turnover (Passenger-Kilometers), and Output of Electricity; and quarterly Ratio of Job-Offers-to-Seekers. All five indicators describe real production or labor market conditions, not distorted by nominal factors, within the corresponding frequency (a month or a quarter). This list of indicators is by no means the best combination of variables that reflects the Chinese real production. It is, however, a very reasonable parsimonious set of indicators.

This paper is the first one to use a mixed-frequency model to construct a Chinese business condition index, but not the only one focusing on the reliability of Chinese data when constructing such an index. Fernald, Hsu, and Spiegel (2015) cleverly use trading-partner exports to China as an independent measure of Chinese economic activity. These data are reported by China’s major trading partners and therefore, are not subject to manipulation or mismeasurement by the Chinese authorities. Their index, however, is quarterly and only reflects one segment of the economy on the aggregate demand side. Our CBCI, on the other hand, is at a higher frequency and considers a broader aspect of the real economy. Henderson,

---

\(^1\) For example, the NBS does not disclose the weights of different components in the consumer price index (CPI), making it impossible to verify whether the movements in the index represent changes in prices or changes to the calculation method. Nakamura, Steinsson, and Liu (2016) use the Engel curves to construct alternative estimates of Chinese inflation and suggest that official statistics present a smoothed version of the reality.
Storeygard, and Weil (2012) use data on satellite-recorded nighttime lights to gauge economic growth for a group of countries including China. Clark, Pinkovskiy, and Sala-i-Martin (2017) use the same satellite data for China as an independent benchmark for comparing various published indicators in China. Although these data are out of the controls of the Chinese government, they are only available annually and therefore, not suitable for our purpose.

We construct the monthly CBCI for the period from January 2000 to December 2016. Compared to the real GDP growth rates and the VAI growth rates, the CBCI shows a better business condition from 2000 to 2005 than the reported official figures, but a much pessimistic condition leading to the great recession. Much better consistency between the CBCI and the official indicators is shown after 2008, confirming the arguments by Fernald, Hsu, and Spiegel (2015) and Holz (2014a) that the information content of Chinese GDP and VAI improves markedly after 2008.

To evaluate whether the CBCI better describes the actual business condition perceived by the private sector, we compare the out-of-sample prediction performances of the CBCI against the VAI, the NBS Macroeconomic Climate Coincident Index, the OECD Composite Leading Index, and the trading-partner exports to China. The CBCI produces the smallest mean squared prediction errors among the five indices and significantly outperforms the NBS index in predicting the CaiXin Purchasing Managers Index (PMI), which is completely independent from the controlling hand of the government and arguably very sensitive to the cyclical fluctuations of the real economy.

The rest of the paper is outlined as follows. The next section explains the selection the components, the model, and the estimation methodology. Section 3 shows the estimation results and the derived CBCI. Then the CBCI is compared to other Chinese economic indicators in Section 4. Section 5 offers further discussions and concludes the paper.
2. Model and Methodology

2.1 Selection of Components

Efforts have been put into increasing the transparency of the independent system for data collection from Chinese provinces since the 1990s. However, the quality of the data produced by local and provincial governments is still known to be questionable and biased towards government targets. For example, the NBS reported on its website on March 12, 2012 that local government officials had forced some hotels, coal miners, and aluminum makers to report false data. Another famous example is a State Department memo released by WikiLeaks, where the current Premier of China Mr. Li Keqiang, then the Party Committee Secretary of Liaoning Province, told a US ambassador in 2007 that the GDP figures in Liaoning were “man-made” and unreliable. He preferred to track Liaoning's economy by looking at three other indicators: the cargo volume on the province's railways, electricity consumption, and loans disbursed by banks, which led to the so called “Li Keqiang Index” maintained by the *Economists.*\(^2\) More recently, in a rare confession on January 17, 2017, the governor of Liaoning province admitted that the economic figures from 2011 to 2014, such as GDP, industrial output, fixed-asset investment, and exports were inflated.

Ironically, as shown in Table 1, those popular Chinese business condition indices all incorporate some of the inflated variables in their components. These indices are derived from the principle component model, which has the advantage of including many economic indicators. But at the same time, it also brings in noises when some of the indicators are not reliable. Among the components listed on Table 1, Value Added of Industry (VAI), which is often used to proxy for monthly production, is based on published data reported by the “directly reporting industrial enterprises” (DRIEs) plus unpublished data from non-DRIEs. As argued by Holz (2014b), data manipulation is easily accomplished when the data are composed of published and unpublished data sources. It is the unpublished data not reported directly to the statistics system that can be manipulated. In addition, Holz (2014a) points out that changes to the coverage of the

---

\(^2\) See the *Economists*, December 9, 2010.
industrial enterprises and changes to the sectoral classification system over the years together prevent a consistent time series analysis for the VAI. It is, however, the most popular variable being included as a component in constructing those indices.

The same problem applies to the data from official surveys. When abstracting information from the survey samples to all the units that do not report directly to the statistics system, the NBS can freely vary its standard on criteria such as sample sizes, the representativeness of the survey, and the appropriate method to translate the data. Examples include construction, investment, sales, and revenue data.

Our monthly Chinese economic condition index, the CBCI, is constructed differently from these business condition indices in that we pay special attention to the reliability of the data. Based on the observations mentioned above, we purposely exclude “flagship” variables such as the VAI, GDP, unemployment rates, fixed-asset investment, and exports; and variables constructed from official surveys (construction, investment, sales, and revenue data). In addition, since the CBCI focuses on the real production of the economy, we do not consider nominal variables (e.g., money supply, bank loans, etc.). Real variables that are constructed by using a deflator (e.g., real income, real consumption, etc.) are not considered, either, because the deflator itself is a flagship variable and subject to skepticism.

For variables representing production, we look for “non-flagship” variables that are closely related to real production. A specific source is the transportation data, which can be seen as a popular choice in Table 1. The first variable we include in our construction of the CBCI is the Volume of Freight Handled in Main Coastal Ports. China is the world’s largest exporter and second-largest importer, and has six of world’s ten busiest ports, controlling a fifth of the world’s container fleet. The growth of China’s coastal ports is closely connected to China’s economic development plan that emphasizes export-led growth [Zhu and Kotz (2011)].

The second variable is the Freight Traffic of Railways, which refers to the total amount of goods (tons) moved around the country by railways. It is one of the variables suggested by Li Keqiang, who
mentions that this indicator is fairly accurate because fees are charged for each unit of weight. China’s railway transportation carries about 30% of the total market share in transportation of goods. It is a good way to measure the amount of goods being produced and consumed, and seen by many as a proxy for the health of the real economy.

As the services sector now accounts for half of China’s GDP and keeps widening its lead over manufacturing, we adopt another variable from the transportation data - the Passenger Turnovers (passenger-kilometers), which is an indicator closely linked to the service sector [Mehrotra and Pääkkönen (2011)]. It represents the inland transport of a passenger for one kilometer through railways, highways, waterways and civil aviation. The NBS compiles the data by collecting detailed records from Ministry of Transport and the Civil Aviation Administration of China, and the road traffic data from highway tolls.

In addition to the transportation data, the fourth variable included is another industrial indicator suggested by Li Keqiang - Output of Electricity, which is widely used in constructing monthly business condition indices. For example, Mehrotra and Pääkkönen (2011) use a factor analysis to summarize information from 83 indicators to produce coincident indices for China. They find that the first principal component has a high factor loading on electricity production. Wallace (2016) argues that electricity production and consumption data are highly correlated with GDP but relatively unnoticed compared to the politically sensitive GDP data in China. He uses electricity growth as a benchmark measure of economic

---

3 The passenger turnovers by no means fully represent China’s service sector during the transition from an industrial to services-led economy. However, other than the transportation data, the NBS only provides annual indicators on China’s service sector, with significant lag times about two years. The most visible frequent indicator of service sector is the official nonmanufacturing PMI published by the NBS, which is a flagship variable and only available from 2007. The NBS started to publish an index measuring services output in March 2017. But even the NBS spokesman mentioned in a news conference that the new indicator does not cover some parts of the services industry due to a lack of data.
growth in China, and the difference between GDP growth and electricity growth to gauge the likelihood of data manipulation.4

Another source of information on the real economy is the labor market. The most popular indicator in the labor market - the unemployment rate, however, is infamously unreliable in China [e.g., Solinger (2001), Giles, Park, and Zhang (2005) and Liu (2012)]. The official unemployment rate in China appears abnormally low and stable, staying between 4% and 4.3% in every quarter since the end of 2002. This is against the conventional wisdom (e.g., Okun’s Law) of a tight relationship between unemployment rates and GDP growth rates, especially when the Chinese economy has been going through periods of a clear domestic boom, the global financial crisis, the subsequent strong recovery, and now the slowest growing pace in the past 25 years.

An important alternative indicator of the labor market conditions is the Ratio of Job-Offers-to-Seekers, which is an inverse measure of slackness in the labor market. The ratio is a measure of balance between labor supply and demand and a popular proxy for cyclical fluctuations in the labor market. If the ratio is greater than one, the labor market is loose with more job vacancies; if the ratio is less than one, the labor market is tight with more job applicants. It is a relatively more reliable labor market indicator than the unemployment rates in China’s urban labor market [Wang (2012)]. The Ministry of Labor and Social Security (now the Ministry of Human Resources and Social Security) established a national monitoring network in 2000, now with more than a hundred cities chosen to establish a monitoring center to collect information on labor supply and demand. The data are collected by local employment bureaus, based on information provided by job seekers who register with the bureau and recruiters who advertise for employees. We include it as our fifth variable in the construction of our business condition index.

4 La Porta and Shleifer (2008) use the difference between GDP as estimated from the electricity consumption and official GDP to measure the size of the informal sector (activities) of 57 economies.
Labor market data in China, including the ratio of job-offers-to-seekers, however, are not available at the monthly frequency. This is the reason why the popular indices on Table 1 do not incorporate any labor market data in their components. The principle component model used by those indices can only deal with data from a single frequency. To handle data from multiple frequencies (four monthly variables and one quarterly variable in our case), we use a mixed-frequency model to derive our index.

2.2 The State-Space Model and the Kalman Filter/Smoother

The CBCI is a latent variable that is related to the observed economic indicators from different frequencies, as described in a time-varying state-space model. The measurement equation describes the dynamics of the observable variables, which are assumed to follow an AR(1) process, and their relationships with the latent variable:

\[
\begin{bmatrix}
  y_t^1 \\
  \vdots \\
  y_t^p \\
  \vdots \\
  y_t^q \\
\end{bmatrix} = \begin{bmatrix}
  \alpha_l \\
  \vdots \\
  \alpha_p \\
  \vdots \\
  \alpha_q \\
\end{bmatrix} + \begin{bmatrix}
  \beta_l \\
  \vdots \\
  \beta_p \\
  \vdots \\
  \beta_q \\
\end{bmatrix} \begin{bmatrix}
  0 \\
  0 \\
  0 \\
  \vdots \\
  0 \\
\end{bmatrix} + \begin{bmatrix}
  \gamma_l \\
  0 \\
  \vdots \\
  0 \\
  \gamma_q \\
\end{bmatrix} \begin{bmatrix}
  0 \\
  \cdots \\
  0 \\
  \cdots \\
  0 \\
\end{bmatrix} \begin{bmatrix}
  y_{t-M}^1 \\
  \vdots \\
  y_{t-M}^p \\
  \vdots \\
  y_{t-Q}^q \\
\end{bmatrix} + \begin{bmatrix}
  u_t^1 \\
  \vdots \\
  u_t^p \\
  \vdots \\
  u_t^q \\
\end{bmatrix}, \quad (1)
\]

where \( y_t^1, \ldots, y_t^p \) are monthly observable variables, \( y_{t+1}^p, \ldots, y_t^q \) are quarterly observable variables, \( y_{t-M}^p \) is the lag of the monthly variable \( y_t^p \), \( y_{t-Q}^q \) is the lag of the quarterly variable \( y_t^q \), and \( \gamma_i \)'s are the AR(1) coefficients. The subscript \( t \) denotes month, and the quarterly variables are only observed in March, June, September, and December. The latent variable \( x_t \) is our monthly index, \( \beta_i \)'s are the relationships between the latent variables and the observable variables, and \( C_t \) is the accumulator defined by the following state equation:

\[
\begin{bmatrix}
  x_t \\
  C_t \\
\end{bmatrix} = \begin{bmatrix}
  \rho & 0 \\
  \rho & \xi_t^Q \\
\end{bmatrix} \begin{bmatrix}
  x_{t-1} \\
  C_{t-1} \\
\end{bmatrix} + \begin{bmatrix}
  1 \\
  1 \\
\end{bmatrix} \epsilon_t, \quad (2)
\]
where $\xi_{t}^{Q} = \begin{cases} 0 & \text{if } t \text{ is the first month of a quarter} \\ 1 & \text{otherwise} \end{cases}$.

and 

$$
\begin{bmatrix}
\xi_{t} \\
\epsilon_{t}
\end{bmatrix} \sim N\left(0, \begin{bmatrix} Q & 0 \\ 0 & R \end{bmatrix} \right),
$$

$$
Q = \begin{bmatrix}
\sigma_{1}^2 & \cdots & 0 \\
\vdots & \ddots & \vdots \\
0 & \cdots & \sigma_{q}^2
\end{bmatrix},
$$

$R = 1 - \rho^2$.

That is, the index $x_{t}$ is assumed to follow an AR(1) process and has zero mean and unit variance. The accumulator $C_{t}$ in March, June, September, and December can be interpreted as the quarterly CBCI.

The state-space model (1)-(2) is estimated by the Kalman filter, which sequentially updates the best linear forecast of $x_{t}$, denoted as $\hat{x}_{t-1}$. Specifically, rewrite the model in a compact form:

$$
y_{t} = A'X_{t} + H'\xi_{t} + w_{t},
$$

$$
\xi_{t+1} = F_{t}\hat{\xi}_{t} + v_{t+1},
$$

where $X_{t}$ contains a constant and the lag of $y_{t}$. Let $\xi_{t+1|t-1} = E(\xi_{t+1}|y_{t},X_{t})$ and $P_{t+1|t-1} = E[(\xi_{t+1} - \hat{\xi}_{t+1}) (\xi_{t+1} - \hat{\xi}_{t+1})']$ be the mean squared error of $\xi_{t+1}$. Then the Kalman filter updating and prediction equations are [see Hamilton (1994, ch.13) and Durbin and Koopman (2001)]:

$$
\hat{\xi}_{t+1|t} = \hat{\xi}_{t+1|t-1} + P_{t+1|t-1} H (H'P_{t+1|t-1}H + R)^{-1} (y_{t} - A'X_{t} - H'\hat{\xi}_{t+1|t-1}),
$$

$$
\hat{\xi}_{t+1|t} = F_{t}\hat{\xi}_{t|t},
$$

$$
P_{t+1|t} = P_{t+1|t-1} - P_{t+1|t-1} H (H'P_{t+1|t-1}H + R)^{-1} H' P_{t+1|t-1},
$$

and

$$
P_{t+1|t} = F_{t} P_{t|t} F_{t}' + Q.
$$
The Kalman filter remains valid with missing data. This is crucial because the quarterly variables are only observed in the last month of the quarter and are missing values in the other months. For the months where the quarterly data are not available, the measurement equation is replaced by

\[ \hat{y}_t = \tilde{A}'X_t + \tilde{H}'\xi_t + \tilde{w}_t, \]

where \( \tilde{y}_t = \omega y_t, \tilde{A} = \omega A, \tilde{H} = \omega H, \tilde{w}_t = \omega \omega_t \) and \( \omega \) is a \( pxq \) transformation matrix whose \( p \) rows are the rows of an identity matrix corresponding to the observed elements of \( y_t, (y_1, \ldots, y_p). \)

Replace \( y_t, A, \) and \( H \) with \( \tilde{y}_t, \tilde{A}, \) and \( \tilde{H} \) for these months and the Kalman filter works exactly as described above. As is standard for classical estimation, we initialize the Kalman filter using the unconditional mean and the covariance matrix of the state vector.

The conditional distribution of the observable vector is

\[ y_t | x_t, y_{t-1} \sim N(A'X_t + H'\hat{\xi}_{t-1}, H'P_{t-1}H + R) \]

and the log likelihood function is

\[ \frac{1}{\sqrt{(2\pi)^n | H'P_{t-1}H + R |}} \exp\{-\frac{1}{2} (y_t - A'X_t - H'\hat{\xi}_{t-1})(H'P_{t-1}H + R)^{-1}(y_t - A'X_t - H'\hat{\xi}_{t-1})\}. \]

We then use the maximum likelihood estimation to estimate the parameters \( (\gamma_i, \alpha_i, \beta_i, \rho, \text{ and } \sigma_i). \)

Since we are interested in the values of the latent variables in the state vector \( \xi_t, \) we use the Kalman smoother to derive our index \( \hat{\xi}_{tT}, \) which is an inference about the value of \( x_t \) based on all the data available \( (t=1, 2, 3, \ldots, T). \) Specifically, let \( \hat{\xi}_{Tt} \) be the last entry in \( \hat{\xi}_{tT}. \) Given the updating rules (3)-(6), we go backward and use

---

5 In cases where there are missing values in the monthly data, the number of rows of the transformation matrix \( \omega \) would be reduced by the number of missing values in that month.
\[
\hat{\xi}_{t|T} = \hat{\xi}_t + F_t^{-1} P_{t+1|T}^T (\hat{\xi}_{t+1|T} - \hat{\xi}_{t+1|T}) \text{ for } t = T-1, T-2, \ldots, 1
\] (7)

to obtain the smoothed estimates of the unobservable state vector, with the mean squared errors equal to

\[
P_{t|T} = P_t + F_t^{-1} P_{t+1|T} (P_{t+1|T} - P_{t+1|T}) (F_t^{-1} P_{t+1|T})'.
\] (8)

Using the same transformation as in the filter, the Kalman smoother remains valid with missing data.

For statistical inference about \( \hat{\xi}_{t|T} \), we use a Monte Carlo simulation. Let \( \hat{\theta} \) be the estimated model parameters and \( \sqrt{\text{var}(\hat{\theta})} \) be the standard errors. We randomly draw a large number of values of \( \theta \), say \( \theta^1, \theta^2, \theta^3, \ldots, \theta^n \) from a normal distribution, \( N(\hat{\theta}, \text{var}(\hat{\theta})) \). For each \( t \), the mean squared error of \( \hat{\xi}_{t|T}(\hat{\theta}) \) is

\[
\frac{1}{n} \sum_{j=1}^{n} \left[ (\hat{\xi}_{t|T}(\theta^j) - \hat{\xi}_{t|T}(\hat{\theta})) (\hat{\xi}_{t|T}(\theta^j) - \hat{\xi}_{t|T}(\hat{\theta})) + P_{t|T}(\theta^j)' \right],
\]

where the first term in the bracket represents the “parameter uncertainty” and the second term represents the “filter uncertainty.”

### 3. Data and Estimation

Our sample period starts in January 2000 and ends in December 2016.\(^6\) It is well known that Chinese monthly macro data are often distorted by the Chinese New Year, whose timing varies from year to year and may fall in different months on the Gregorian calendar. Especially, the January and the February figures of the monthly variables are clearly affected by this effect. Therefore, we use the United States Census Bureau X-13ARIMA-SEATS procedure to adjust the Chinese New Year effects for those four monthly variables.\(^7\) The Chinese New Year holiday is set to start from the New Year Eve and lasts for seven

\(^6\) We collect the final data in January 2017, when the ratio of job-offers-to-seekers of 2006Q4 is first released. All data are from Wind Datafeed Service and provided by the PRC Macro Advisors. The NBS website provides free access to the data, but many data are only available starting from 2005.

\(^7\) This is done by using the comment “genhol” of the “seasonal” package in the \( R \) language.
days. Following Lin and Liu (2003) and Findley and Soukup (2000), we also adjust the pre- and post-holiday effects, with the lengths of the pre- and post-holiday periods chosen by minimizing the Akaike information criterion corrected for finite sample sizes, i.e., the AICc of Hurvich and Tsai (1989). Figures 1(a)-(d) plot the year-on-year growth rates of these four seasonally adjusted monthly variables. Figure 2 plots the year-on-year changes of the quarterly job-offers-to-seekers ratio. These five variables are used to estimate the state space model.8

<Figures 1(a)-(d) and 2 about here>

Table 2 reports the estimation results. Most of the estimated coefficients are statistically significant at the traditional level. Most importantly, our latent business condition is positively related to all five observable variables and the relationships are statistically significant. That is, all the estimated $\beta$’s are highly significant. The CBCI estimated from the Kalman smoother and its ± one-mean-squared-error band are plotted in Figure 3. The narrow band around the index shows that the point estimates of the latent variables are very robust.

<Table 2 about here>

<Figure 3 about here>

Since the CBCI is assumed to have zero mean and unit variance, the absolute values on the Y-axis have no specific meanings. Progressively bigger positive values indicate progressively better-than-average conditions, whereas progressively more negative values indicate progressively worse-than-average

---

8 We remove the April and May, 2003, observations of the passenger turnovers due to the outbreak of the SARS epidemic, when air passenger volumes fell to around a quarter of the level for the same month in the previous year. Including these numbers would massively overestimate the impact of the disease on the economy.
conditions. Thus, the CBCI is used to compare business conditions at different times. For example, a value of -1.784 in October 2015, in the midst of the 2015-2016 stock market turbulence, would indicate that the business conditions were significantly worse than any time since the global financial crisis, when the index hit the lowest value in the sample (-1.890) in February 2009.

The accumulator $C_t$ in March, June, September, and December is the quarterly index of the CBCI. Figure 4 plots the quarterly CBCI along with the year-on-year real GDP growth rates. Both are standardized to have zero mean and unit variance for comparison purposes. Our quarterly index and the GDP growth rates have a correlation coefficient of 0.642. Compared to the real GDP growth rates, the quarterly CBCI shows a better business condition from 2000 to 2005 than the reported GDP growth. Then it indicates a much pessimistic condition than the official GDP growth leading to the great recession. This pattern is also found in Nakamura, Steinsson, and Liu (2016), who compare the official Chinese urban consumption growth with their own estimates based on the Engel curve.

The CBCI and the reported GDP growth match well between 2009 and 2012 (with a correlation coefficient of 0.938), which is consistent with Fernald, Hsu, and Spiegel (2013), who find that the information content of Chinese GDP improves markedly after 2008. After the strong recovery from the great recession, the reported “soft landings” are actually harder during the period 2013-2015. The recession in 2015 is worse than reported, but the recovery in 2016 is stronger than reported. This concurs with the argument by Nakamura, Steinsson, and Liu (2016) that the Chinese authority tends to slightly understate growth when growth is strong and more significantly overstate growth when growth is weak.

---

9 In particular, the consistency between the CBCI and GDP in 2012 also supports the finding of Fernald, Malkin, and Spiegel (2013) that China’s economy was not slowed more than what the official GDP figures indicate, as argued by some market observers.
Table 3 shows the correlation between the CBCI and the five components across different episodes mentioned above. The CBCI and the volume of freight handled in main coastal ports are consistently highly correlated across different sample periods. This is consistent with the fact that China started its export-oriented economy in December 2001 when it became a member of the WTO. The passenger turnovers (passenger-kilometers) has the lowest correlation with the CBCI with a correlation coefficient of 0.409. The jagged pattern shows in Figure 1(c) contributes to this relatively low correlation.

Other than the volume of freight handled in main coastal ports, the correlations of the other four series with the CBCI are relatively low during the 2000M1-2005M9 period compared to the other periods. Therefore, the volume of freight handled in main coastal ports is the dominant factor during this early period. On the other hand, the quarterly ratio of job-offers-to-seekers is relatively irrelevant during this period because this series only starts in 2002. However, it has a high correlation with the CBCI (0.883) in the subsequent period (2005Q3-2009Q1). As can be seen from Figures 1(a) and 2, the declines of the volume of freight handled in main coastal ports and the ratio of job-offers-to-seekers, i.e., the deteriorations in the foreign sector and the labor market, during 2005M10-2009M3 contribute to the downward trend in the CBCI. This period sees China’s foreign exchange reform that imposes restrictions on exports and thus the economy growth. To see the contribution of the ratio of job-offers-to-seekers to the CBCI, Figure 5 plots a business cycle index constructed by using only those four monthly indicators and excluding the ratio of job-offers-to-seekers, along with the CBCI.

4. Comparisons with Other Indicators

In Figure 6, we plot the CBCI and the VAI growth rates (standardized to zero mean and unit variance), which is arguably the most popular monthly indicator of output. These two series have a correlation coefficient of 0.811. The CBCI matches the VAI very well after 2008, but discrepancies exist
in the earlier sample. This concurs with the improvement of the VAI data collection process after 2008 and the problems existing before then [see Holz (2014a)].

<Figure 6 about here>

Figures 7 and 8 plot the CBCI against two publicly available monthly business condition indices: the NBS Macroeconomic Climate Coincident Index and the OECD Composite Leading Index.10 Not surprisingly, the NBS index follows a similar pattern with the official GDP and VAI data. The OECD index shows a much different pattern from both the CBCI and the official data.

<Figures 7 and 8 about here>

Fernald, Hsu, and Spiegel (2015) use trading-partner exports to China as an independent measure of Chinese economic activity. These data are reported by China’s major trading partners and therefore, are not subject to manipulation or mismeasurement by the Chinese authorities. The purpose of their paper is to investigate, compared to other alternative non-GDP indicators, how informative Chinese GDP is on their externally-reported exports measure. Therefore, they construct a quarterly index. To compare with the CBCI, we use monthly data to construct monthly trading-partner exports to China, denoted as the TPE index.

Exports to China or Hong Kong from the United States, the Euro area, and Japan are from original sources in these trading partner regions. We convert all data to nominal U.S. dollars using the bilateral exchange rates, sum up these three series, and convert it to real values using the U.S. export price index for all commodities. The same procedure for adjusting the Chinese New Year effect mentioned in Section 3 is applied before the year-on-year growth rates are calculated. Figure 9 plots this monthly TPE index,

10 The Conference Board Leading Economic Index is not publicly available. The Chinese Academy of Science has stopped publishing its coincident index. Another available business condition index published by Baidu is only available from 2011 and is too short for our analysis.
standardized to mean zero and unit variance, along with the CBCI. Consistent with the CBCI, the over-optimistic situation before the financial crisis seen in the official indices does not show on the TPE index. In addition, it also indicates a strong rebound in 2016 like the CBCI does. The match with the CBCI after 2008, however, is not as good as the VAI and GDP. It displays a deeper recession and a stronger recovery in the great recession.

The immediate question is, how can we evaluate the CBCI against these alternative indices? Evaluations of a business condition indicator are often conducted by comparing it with the dynamics of the GDP data or by assessing how well it forecasts the future path of the GDP growth. This is, however, against the motivation of this paper because we start with doubting the reliability of the GDP data. It is meaningless to use our index to forecast any flagship variables that we believe to be unreliable. Therefore, we propose to evaluate the CBCI in an alternative way. The evaluation is based on the out-of-sample prediction performance of the competing indices in reflecting the true historical business conditions that the private sectors perceive, i.e., whether the indices can predict the private sector’s assessment of the business condition out of sample.¹¹

The CaiXin Purchasing Managers Index (PMI), compiled and summarized through the results of the monthly survey of enterprises purchasing managers by a private international franchise – the IHS Markit, is completely independent from the controlling hands of the Chinese government. Compared to the official PMI published by the NBS, the CaiXin PMI has more exposure to small and medium-sized enterprises.

¹¹ We use all the data available to estimate the CBCI in order to see whether the index describes the “true” economic conditions historically. This is different from the evaluation of policies where the real-time data are needed. Therefore, we do not re-estimate the state-space model and the index in each regression. Please refer to the last section (Discussions and Conclusions) for the real-time data issues.
SMEs have a relatively tough time securing credit when the economy is slowing and therefore, are very sensitive to the cyclical fluctuations of the real economy. The PMI is one of the leading indices commonly adopted by international societies to monitor macroeconomic trends, and has been shown to be highly correlated with GDP in other countries.\textsuperscript{12}

Figure 10 plots the Caixin PMI, along with the CBCI for references. The Caixin PMI is only available starting in September 2005. Results are given between 0 and 100, with the 50 line separating improvement from deterioration in the state of the manufacturing sector. The index is mostly above the 50 line up to August 2008, about the same time when the CBCI drops below its mean. It indicates that the perception of business condition turns from deteriorate to improvement in April 2009, about the same time when the CBCI comes back to the mean. The perception turns negative in July 2010, the same time when the CBCI drops below its mean again. After 2011, the Caixin PMI hovers around the 50 line, while the CBCI is mostly below the mean. However, it shows the same strong rebound in 2016 as the CBCI does.

We compare the out-of-sample prediction performances of the CBCI against four Chinese business condition indices - the VAI, the NBS Index, the OECD Index, and the TPE index. The competing models are:

\begin{equation}
PMI_t = \alpha_1 + \beta_{11} PMI_{t-1} + \beta_{12} CBCI_{t-1} + \epsilon_{t_1},
\end{equation}

\begin{equation}
PMI_t = \alpha_2 + \beta_{21} PMI_{t-1} + \beta_{22} Z_{t-1} + \epsilon_{2t},
\end{equation}

\textsuperscript{12} For instance, Banerjee and Marcellino (2006) and Lahiri and Monokroussos (2013) show that the PMI can be useful in forecasting U.S. GDP. For the euro area, see Lombardi and Maier (2011) and Kilinc and Yucel (2016).
where $Z_t = VAI_t, NBS_t, OECD_t$, or $TPE_t$. The reason why we use the lagged predictors on the right-hand-side is that the surveys of the CaiXin PMI are collected in the middle of a month (but are released on the first day of the month after the survey month). The information available to the managers taking surveys is only up to the first half of the month. Therefore, the indicator in the survey month cannot be used to forecast the CaiXin PMI in that month.

We investigate the forecast results by conducting a battery of statistical tests based on West (1996) and West and McCracken (1998). Specifically, let $y_{1t}$ and $y_{2t}$ be the out-of-sample predictions of $y_t$ from the two competing forecasts. The one-step-ahead forecast errors are $v_{it} = y_t - y_{it}, i=1,2$. We consider four tests: (1) The test of zero mean prediction errors is to test the null of $\alpha = 0$ in a simple OLS regression $v_{it} = \alpha + \text{disturbance}$. (2) The efficiency test, or the bias test, is to test the null of $(\alpha_0, \alpha_1) = (0, 0)$ in the regression $v_{it} = \alpha_0 + \alpha_1 y_{it} + \text{disturbance}$. (3) The test of zero first-order serial correlation is to test the null of $(\alpha_0, \alpha_1) = (0, 0)$ in the regression $v_{it+1} = \alpha_0 + \alpha_1 v_{it} + \text{disturbance}$. (4) The equality of mean squared prediction errors (MSPE) from the two competing forecasts.

The analysis is limited to the period from September 2005 to December 2016, with a total of 136 observations. We use the first five years of data as the first regression period to start the one-step ahead prediction. Then one observation is added in each successive regression. That is, the regression sample size is increasing as prediction progresses.

The first row of Table 4 shows the MSPE of each model. The model with the CBCI yields the smallest MSPE, while the model with the NBS index yields the highest MSPE. The MSPE of the model with the NBS index is significantly higher than that of the model with the CBCI at the traditional significance level. On the other hand, the differences of the MSPEs between the model with the CBCI and the models with the VAI, the OECD index, and the TPE index are not statistically significant.

<Table 4 about here>
The models with the CBCI, the VAI, and the TPE pass those three individual tests (zero mean prediction errors, model efficiency, zero first-order serial correlation) at the traditional significance level. The model with the NBS index fails all three tests, while the one with the OECD index fails the zero mean and auto-correlation tests, and the model efficiency is marginally rejected at the 5.3% significance level. Clearly the CBCI outperforms the NBS index and the OECD index.

5. Discussions and Conclusions

Unlike popular monthly Chinese business condition indices that are created by using the principle component model, this paper uses a dynamic mixed-frequency model to incorporate several economic indicators from multiple frequencies to construct the Chinese Business Condition Index (CBCI). The mixed-frequency model is particularly useful because the labor market data are not available at the monthly frequency in China. Since the principle component model can only handle variables from a single frequency, the indices constructed by the model ignore an important source of information on the Chinese real economy. This paper pioneers a new approach for future research dealing with the Chinese data.

The mixed-frequency model, however, has its limitation in that only a parsimonious set of variables can be incorporated into the model. With dozens of variables available, any combination of a few variables will be deemed arbitrary. Without prior knowledge on the reliability of the variables, statistical methods such as the principle component model and the FAVAR model can incorporate as many variables as are available. However, there is a trade-off between arbitrarily selecting the components and relying on statistical methods that consider all available variables, including some unreliable ones. To deal with skepticism over the accuracy of the Chinese data, this paper opts to use the mixed-frequency model and provide economics reasoning for choosing the parsimonious set of indicators. We avoid the “flagship” variables that are more likely subject to government manipulations, and seek relevant economic indicators from academic literature and the Li Keqiang Index. We are not, however, arguing that this method is better
than the statistical methods. Instead, we advocate that this alternative way of thinking should have its value when dealing with the Chinese data.

Evaluating the indices is a major difficulty. It is not reasonable to compare the dynamics of the CBCI with the flagship variables, or use the CBCI to forecast them because we cast doubt on the reliability of those flagship variables. Rather, we propose to test whether our index reflects the true business conditions that are perceived by the private sector historically, with the assumption that the private sector does not totally trust the information published by the government, but utilizes the information about the economic conditions that it observes. A simple out-of-sample-prediction practice shows that our index has the best results compared to other indices. Rather than claiming a victory, however, we would call for more research to find other clever ways to access the usefulness of our CBCI.

One of the major advantages of our dynamic mixed-frequency model is that it can provide a timely update on the real economic conditions whenever a release of a new data point or a revision of a historical data point of any of the components becomes available. The model would be re-estimated, the index would be regenerated, and the forecasts would be updated. It will be interesting to compare the accuracy of the forecasts generated by the model over different vintages in real time. This is feasible for the ADS index because the Philadelphia Fed has been keeping the vintage data since December 2008. Our CBCI is brand new and cannot be traced back because the real time data of the components are not available in China. Therefore, we have to leave this task to future studies when the vintage data are accumulated.

Furthermore, the current CBCI does not take full advantage of the mixed-frequency model’s ability to update business conditions at a higher frequency, because we do not have relevant daily or weekly variables in China. It only updates the real business conditions up to the previous month. To actually access the business condition in real time at the daily frequency, we need to obtain higher frequency data from the labor market, such as the weekly initial jobless claims in the United States. All hopes point to the
improvement of the transparency on the methodology underpinning data and the technology of data collection processes in China in the near future.

Acknowledgment

This research is supported by the Sun Yat-Sen University under Grant No. 02300-18827001 and by the PRC Macro Advisors (PRC Macro Limited Ltd).
Reference


Table 1: Components of Different China Business Condition Indices

<table>
<thead>
<tr>
<th>NBS (CEMAC) Coincident Index</th>
<th>OECD Composite Leading Index</th>
<th>Conference Board Leading Economic Index</th>
<th>Chinese Academy of Science Coincident Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Index of industrial output</td>
<td>M2</td>
<td>Value-Added of Industrial Production</td>
<td>Industrial production</td>
</tr>
<tr>
<td>Industrial workers index</td>
<td>Volume of cargo handled at ports</td>
<td>Retail Sales of Consumer Goods</td>
<td>Investment in fixed assets</td>
</tr>
<tr>
<td>Tax revenue</td>
<td>Volume of chemical fertilizer production</td>
<td>Electricity Production</td>
<td>Consumer goods</td>
</tr>
<tr>
<td>Industrial corporate profits</td>
<td>Corporate internal reserves</td>
<td>Railway Freight Traffic</td>
<td>M1 (money supply)</td>
</tr>
<tr>
<td>Disposal income of urban residents</td>
<td>Value of imports from Asia</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed asset investment</td>
<td>Volume of nonferrous metal production</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total sales of retail goods</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value of exports and imports</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Parameter Estimation

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constants:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volume of Freight Handled in Main Coastal Ports</td>
<td>11.070</td>
<td>0.000</td>
</tr>
<tr>
<td>Freight Traffic of Railways</td>
<td>5.546</td>
<td>0.000</td>
</tr>
<tr>
<td>Passenger Turnover (Passenger-Kilometers)</td>
<td>0.999</td>
<td>0.287</td>
</tr>
<tr>
<td>Output of Electricity</td>
<td>2.750</td>
<td>0.016</td>
</tr>
<tr>
<td>Ratio of Job-Offers-to-Seekers</td>
<td>0.008</td>
<td>0.391</td>
</tr>
<tr>
<td>Coefficients on the State Variables</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>6.157</td>
<td>0.000</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>3.099</td>
<td>0.001</td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>1.976</td>
<td>0.002</td>
</tr>
<tr>
<td>$\beta_4$</td>
<td>1.572</td>
<td>0.013</td>
</tr>
<tr>
<td>$\beta_5$</td>
<td>0.006</td>
<td>0.003</td>
</tr>
<tr>
<td>Observable Variables AR(1) Coefficients:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volume of Freight Handled in Main Coastal Ports</td>
<td>0.003</td>
<td>0.921</td>
</tr>
<tr>
<td>Freight Traffic of Railways</td>
<td>0.375</td>
<td>0.000</td>
</tr>
<tr>
<td>Passenger Turnover (Passenger-Kilometers)</td>
<td>0.705</td>
<td>0.000</td>
</tr>
<tr>
<td>Output of Electricity</td>
<td>0.518</td>
<td>0.000</td>
</tr>
<tr>
<td>Ratio of Job-Offers-to-Seekers</td>
<td>0.533</td>
<td>0.000</td>
</tr>
<tr>
<td>State Variable AR(1) Coefficient</td>
<td>$\rho$</td>
<td>0.936</td>
</tr>
<tr>
<td>Measurement Equation Residual Standard Deviation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_1$</td>
<td>2.962</td>
<td>0.000</td>
</tr>
<tr>
<td>$\sigma_2$</td>
<td>4.437</td>
<td>0.000</td>
</tr>
<tr>
<td>$\sigma_3$</td>
<td>4.072</td>
<td>0.000</td>
</tr>
<tr>
<td>$\sigma_4$</td>
<td>6.227</td>
<td>0.000</td>
</tr>
<tr>
<td>$\sigma_5$</td>
<td>0.038</td>
<td>0.000</td>
</tr>
</tbody>
</table>

* The state space model is:

$$
\begin{bmatrix}
  y_t^1 \\
  \vdots \\
  y_t^p \\
  y_{t+1}^p \\
  \vdots \\
  y_t^q
\end{bmatrix} =
\begin{bmatrix}
  \alpha_1 \\
  \vdots \\
  \alpha_p \\
  \alpha_{p+1} \\
  \vdots \\
  \alpha_q
\end{bmatrix} +
\begin{bmatrix}
  \beta_1 \\
  \vdots \\
  \beta_p \\
  \beta_{p+1} \\
  \vdots \\
  \beta_q
\end{bmatrix} \begin{bmatrix}
  x_t \\
  \vdots \\
  x_{t-1} \\
  \vdots \\
  x_{t-q}
\end{bmatrix} +
\begin{bmatrix}
  \gamma_1 \\
  \vdots \\
  \gamma_p \\
  \gamma_{p+1} \\
  \vdots \\
  \gamma_q
\end{bmatrix} +
\begin{bmatrix}
  \gamma_{1-M} \\
  \vdots \\
  \gamma_{p-M} \\
  \gamma_{n-1} \\
  \vdots \\
  \gamma_{n-Q}
\end{bmatrix} +
\begin{bmatrix}
  \gamma_{n} \\
  \gamma_{n+1} \\
  \gamma_{n+2} \\
  \gamma_{n+3} \\
  \gamma_{n+4} \\
  \gamma_{n+5}
\end{bmatrix}
$$

$$
\begin{bmatrix}
  x_t \\
  \vdots \\
  x_{t-1} \\
  \vdots \\
  x_{t-q}
\end{bmatrix} =
\begin{bmatrix}
  \rho & 0 \\
  \vdots & \vdots \\
  \rho & 0 \\
  \xi_0 & \xi_{-1} \\
  \vdots & \vdots \\
  \xi_0 & \xi_{-1}
\end{bmatrix} +
\begin{bmatrix}
  \epsilon_t \\
  \vdots \\
  \epsilon_t \\
  \epsilon_{t-1} \\
  \vdots \\
  \epsilon_{t-1}
\end{bmatrix}
\sim N\left(0, \begin{bmatrix} q & 0 \\
  0 & 1 - \rho^2 \end{bmatrix}\right),
\begin{bmatrix}
  \sigma_1^2 & \cdots & 0 \\
  \vdots & \ddots & \vdots \\
  0 & \cdots & \sigma_q^2
\end{bmatrix}
$$

** A $p$-value of 0.000 indicates that the $p$-value is nonzero, but smaller than 0.0005.
Table 3: Correlations between the CBCI and the Components

<table>
<thead>
<tr>
<th>Period</th>
<th>Volume of Freight Handled in Main Coastal Ports</th>
<th>Output of Electricity</th>
<th>Freight Traffic of Railways</th>
<th>Passenger Turnover (Passenger-Kilometers)</th>
<th>Period</th>
<th>Ratio of Job-Offers-to-Seekers</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000M1-2016M12</td>
<td>0.936</td>
<td>0.710</td>
<td>0.713</td>
<td>0.409</td>
<td>2002Q1-2016Q3</td>
<td>0.581</td>
</tr>
<tr>
<td>2000M1-2005M9</td>
<td>0.854</td>
<td>0.463</td>
<td>0.139</td>
<td>0.323</td>
<td>2002Q1-2005Q3</td>
<td>-0.212</td>
</tr>
<tr>
<td>2005M10-2009M3</td>
<td>0.925</td>
<td>0.764</td>
<td>0.705</td>
<td>0.401</td>
<td>2005Q4-2009Q1</td>
<td>0.883</td>
</tr>
<tr>
<td>2009M4-2016M12</td>
<td>0.929</td>
<td>0.794</td>
<td>0.807</td>
<td>0.428</td>
<td>2009Q2-2016Q4</td>
<td>0.683</td>
</tr>
</tbody>
</table>
Table 4: Out-of-Sample Prediction Results

<table>
<thead>
<tr>
<th>Test</th>
<th>CBCI</th>
<th>VAI</th>
<th>NBS</th>
<th>OECD</th>
<th>EXT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Squared Prediction Errors (MSPE)</td>
<td>1.070</td>
<td>1.093</td>
<td>1.317</td>
<td>1.144</td>
<td>1.126</td>
</tr>
<tr>
<td>Hypothesis Tests (P-values)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Zero mean prediction error</td>
<td>0.928</td>
<td>0.480</td>
<td>0.004</td>
<td>0.012</td>
<td>0.111</td>
</tr>
<tr>
<td>Model efficiency</td>
<td>0.167</td>
<td>0.140</td>
<td>0.030</td>
<td>0.053</td>
<td>0.161</td>
</tr>
<tr>
<td>Zero first order serial correlation</td>
<td>0.665</td>
<td>0.462</td>
<td>0.004</td>
<td>0.016</td>
<td>0.144</td>
</tr>
<tr>
<td>MSPE significantly different from the model with CBCI</td>
<td>0.402</td>
<td>0.042</td>
<td>0.392</td>
<td>0.216</td>
<td></td>
</tr>
</tbody>
</table>

* Except for the MSPE, all entries are P-values.
Figure 1: Monthly Components

(a) Volume of Freight Handled in Main Coastal Ports

(b) Freight Traffic of Railways

(c) Passenger Turnover (Passenger-Kilometers)

(d) Output of Electricity
Figure 2: Ratio of Job-Offers-to-Seekers

Figure 3: Chinese Business Condition Index (CBCI) and its One-Standard-Deviation Bands
Figure 4: Quarterly CBCI vs GDP Growth (Both are standardized to zero mean and unit variance)

Figure 5: CBCI without the Ratio of Job-Offers-to-Seekers and the CBCI
Figure 6: CBCI vs. VAI (Standardized to zero mean and unit variance)

Figure 7: CBCI vs. NBS Index (Standardized to zero mean and unit variance)
Figure 8: CBCI vs. OECD Index (Standardized to zero mean and unit variance)

Figure 9: CBCI vs. Trading-Partner Exports (TPE) Index (Standardized to zero mean and unit variance)
Figure 10: Caixin Purchasing Managers’ Index (PMI) and the CBCI (secondary vertical axis on the right)