Journal of Asian Economics 20 (2009) 89–97

Contents lists available at ScienceDirect

Journal of Asian Economics

Measuring Chinese business cycles with dynamic factor models☆

Jin-ming Wang [a,1], Tie-mei Gao [b], Robert McNown [c,*]

[a] Center for Quantitative Economics of Jilin University, Changchun, China
[b] Department of Econometrics, Dongbei University of Finance and Economics, Dalian, China
[c] Department of Economics and Institute of Behavioral Science, University of Colorado at Boulder, USA

ARTICLE INFO

Article history:
Received 25 June 2008
Received in revised form 10 September 2008
Accepted 20 October 2008

JEL classification:
E32

Keywords:
Business cycles
Composite coincident index
State space model
Markov switching model
Dynamic factor model

ABSTRACT

The Stock–Watson method and the dynamic Markov switching factor (DMSF) model are employed to construct macroeconomic composite coincident indexes for the Chinese economy, January 1990–March 2008. Four coincident indicators, namely, industrial production, investment in fixed assets, sales revenues, and the money supply, M_1, are selected to compute the coincident index. Strong asymmetries are found with recent business cycles in China characterized by expansions of longer duration and smaller amplitude relative to the contraction stage. The two models produce similar composite index series, but the DMSF model shows frequent transitions that are difficult to interpret. A comparison of the composite coincident index and other measures of macroeconomic activity provides economic interpretations of the patterns in the index. There are notable differences between the index and GDP growth rates over this period, reflecting its more comprehensive measurement of economic activity. This more comprehensive view of macroeconomic activity increases understanding of changes in China's policies and economic fluctuations that are not shown by GDP growth rates alone.

1. Introduction

Burns and Mitchell (1946) developed methods for measuring business cycles and, based on them, the leading, coincident and lagging composite indexes were developed by the National Bureau of Economic Research (NBER) to depict macroeconomic activity and to anticipate future developments. Burns and Mitchell believed that business cycles are the results of the transmission and diffusion through the economy of a series of economic activities, and it is the general up and down movement of all parts of the economy that defines the business cycle. Although composite indexes are widely used by many governments, the classical methods used to compute indexes are sometimes criticized for lack of statistical foundation. Therefore, alternative mathematical models have been adopted to construct macroeconomic climate indexes. Among them the dynamic factor model adopted by Stock and Watson (1989, 1991, 2003) is an influential method for constructing macroeconomic climate indexes. They regard macroeconomic fluctuations as an unobserved common component of a set of macroeconomic variables, and this common component depicts the comovement of the major macroeconomic variables and embodies the essential features of macroeconomic activity. They put the dynamic factor model into state space representation and use the Kalman filter technique to estimate the unobserved component, which

☆ The authors thank the Editor of the *Journal of Asian Economics* and an anonymous referee for helpful suggestions on a previous draft of this paper. This research was sponsored by the Ministry of Education of China (project number: 197081290531) and project 985, "Analysis and Forecasting of Macroeconomy in China" at Jilin University.
* Corresponding author at: Department of Economics, 256 UCB, Boulder, CO 80309, USA. Tel.: +1 303 492 8295; fax: +1 303 492 8960.
E-mail address: mcnownr@colorado.edu (R. McNown).
1 Visiting Post-doctor in University of Colorado at Boulder.

1049-0078/$ – see front matter © 2008 Elsevier Inc. All rights reserved.
doi:10.1016/j.asieco.2008.10.003

is regarded as the new coincident composite index. In this study the dynamic factor model of Stock and Watson is applied to Chinese data, in order to characterize the essential features of economic fluctuations in China's economy since 1990.

Keynes (1936) argued that expansions and contractions were different from each other, with the former being long-lived while the latter were more violent. There is a growing interest in studying the nonlinear and asymmetric features of the business cycle in modern business cycle research and empirical analysis. Neftci (1984) and Sichel (1989) provided direct evidence on business cycle asymmetry, Quandt (1972), Goldfeld and Quandt (1973), and Ploberger, Kramer, and Kontrus (1989) considered models that allow structural change. Hamilton's (1989) seminal paper proposed the use of a Markov switching (MS) process to model expansions and recessions in U.S. GNP. Hamilton succeeded in reproducing the business cycle turning points established by the NBER. From then on, the Markov switching model has been widely used in the study of asymmetric features in business cycles and finance. This model is appropriate for the computation of a composite index to monitor business cycle activity. Diebold and Rudebusch (1996), by introducing the Markov switching mechanism to the dynamic factor model, proposed a multivariate dynamic factor model with regime switching that encompasses the comovement of key variables together with asymmetric features of the business cycles. The dynamic factor model with Markov switching expresses the idea that all observed coincident economic indicators depend on an autoregressive (AR) unobserved common factor known as the composite index of coincident indicators, plus a set of AR processes of idiosyncratic shocks to each indicator. The specific AR process governing the composite index depends on whether the economic condition is in recession or expansion states. Based on this model, Chauvet (1998) studied the characterization of business cycle dynamics in the U.S.; Kim and Nelson (1998) studied the business cycle turning points and tests of duration dependence; Kaufmann (2000) measured European countries' business cycles.

This study augments the dynamic factor model of Stock and Watson to capture possible asymmetries in Chinese business cycles through the inclusion of Markov switching. This application of the dynamic factor model and its extension to incorporate Markov switching are driven by several objectives. First, this use of the dynamic factor Markov switching model is distinguished from others in its application to a rapidly growing economy that has not experienced negative growth during the period of this study. Therefore, the methodology is tested for its ability to distinguish between strong expansions and growth recessions, i.e., periods of slower but positive growth. Second, this application tests for and measures the asymmetric feature of the business cycles in China, providing information on the average amplitude and duration of the two phases of the business cycle. Third, movements in the constructed composite index are compared with other macroeconomic events to more fully understand the relation between the index and macroeconomic activity. Finally, the comprehensive nature of the composite index is compared with fluctuations in GDP growth rates to reveal important differences in these two alternative measures of economic activity.

The organization of the paper is as follows. Section 2 presents the dynamic factor model and the model with Markov switching. In Section 3, we select four coincident indicators in China and construct a new coincident composite index to analyze the features of the business cycle history in China from January 1990 until March 2008. Section 4 concludes the paper.

2. The dynamic Markov switching factor model

2.1. Dynamic factor model

Stock and Watson (1989, 1991, 2003) developed a linear econometric model of coincident indicators to represent US business cycles. All the coincident indicators are linear functions of the current and lagged values of the unobserved common factor, which is interpreted as the composite index, plus individual error terms. These indicators are assumed to be generated by an AR process. The dynamic factor model is written as:

$$\Delta y_{it} = \gamma_i(L)\Delta c_t + u_{it}, \quad i = 1, 2, \cdots, n \tag{1}$$

$$\phi(L)\Delta c_t = \varepsilon_t, \varepsilon_t \sim \text{i.i.d.}N(0, \sigma_\varepsilon^2) \tag{2}$$

$$\psi_i(L)u_{it} = \upsilon_{it}, \upsilon_{it} \sim \text{i.i.d.}N(0, \sigma_i^2), \quad i = 1, 2, \cdots, n \tag{3}$$

where Δy_{it} is the demeaned first difference of the ith coincident indicator which is decomposed into the AR process of Δc_t, the first difference of the common factor c_t, and the indicator specific component u_{it}. Both the first difference of the common factor and the individual errors are AR processes. The variance of the innovation for Δc_t, σ_ε^2, is set to 1 in order to normalize the common component; $\gamma_i(L)$, $\phi(L)$ and $\psi_i(L)$ are lag operator polynomials ordered p_i, q, r_i, respectively, with roots outside the unit circle; all the shocks are assumed to be independent.

In order to estimate a model with unobserved components, the state space model is applied. Once the dynamic factor model above is written in state space form, the Kalman filter technique allows maximum likelihood estimation as well as inference on the unobserved component Δc_t.

2.2. Dynamic factor model with Markov switching

This application allows changes in regimes between upward and downward phases of the business cycle, and also accommodates different features, such as duration and amplitude, for each phase. Considering that the growth of the index is dependent on whether the economy is in the growth recession state or the strong expansion state, the model given by Eq. (2) may be modified as:

$$\phi(L)(\Delta c_t - \mu_{s_t}) = \varepsilon_t \tag{4}$$

where s_t is 0 under regime 0, which represents the slow-growth phase of the business cycle, and 1 under regime 1, which represents the strong expansion phase of the business cycle. So, μ_0 and μ_1 are the different means of Δc_t under regime 0 and 1, respectively:

$$\mu_{s_t} = \mu_0(1 - s_t) + \mu_1 s_t, \quad \mu_0 < \mu_1 \tag{5}$$

If s_t is known, i.e., the dates of regime switching are known, the model is easy to estimate for s_t is just a dummy variable. When it is not observed, one assumes a stochastic behavior for s_t. The evolution of the discrete variable s_t is dependent upon past information according to a two-state, first-order Markov switching process with transition probabilities:

$$\begin{aligned} p(s_t = 0|s_{t-1} = 0) &= p_{00} \\ p(s_t = 1|s_{t-1} = 0) &= p_{01} \\ p(s_t = 0|s_{t-1} = 1) &= p_{10} \\ p(s_t = 1|s_{t-1} = 1) &= p_{11} \end{aligned} \tag{6}$$

These transition probabilities are restricted so that $p_{00} + p_{01} = p_{10} + p_{11} = 1$.

When Eq. (2) incorporates Eqs. (4)–(6), the new model combined with Eq. (1) and Eq. (3) becomes the dynamic factor model with Markov switching. This framework allows business cycle phases to display asymmetries with respect to their duration and amplitude. In this model, there are two unobserved variables: Δc_t and s_t. When the model is put into a state space form, the former can be estimated by the Kalman filter algorithm. For the latter, Hamilton (1989) provided a filtering algorithm. This complex model is very difficult to estimate and rarely achieves convergent solutions. Kim (1994) simplified the model by modifying Eq. (4) as:

$$\phi(L)\Delta c_t = \mu_{s_t} + \varepsilon_t \tag{7}$$

resulting in a state space form in which the conditional density of the vector of observed series, y_t, depends only on s_t and not on lagged values of s_t, which greatly simplifies the iterative solution. For each time period, the conditional density of y_t is the weighted average of the conditional densities given $s_t = 0$ and $s_t = 1$, respectively, for straightforward representation of the log likelihood function. Through maximum likelihood estimation, we can both estimate the parameters in the model and, most importantly, calculate the coincident composite index from the dynamic factor model with Markov switching. We can also estimate the smoothed probability function, which shows whether the economy is in the recession phase or not. If $p(s_t = 0) > 0.5$, we infer that the business cycle is in the growth recession phase in time t.

3. Coincident composite index and business cycles in China

3.1. Growth rate cycles and data

Studies of business cycle monitoring techniques include two types, namely classical cycles and growth-type cycles. The study of classical cycles considers fluctuations in the original macroeconomic indicators, distinguishing between positive growth periods (expansions) and negative growth episodes (contractions). In China, since the reform and opening to the outside world, most of the macroeconomic indicators show persistent upward movements and only fluctuate in their growth rates, so that research on business cycles in China is mainly about growth-type cycles. Studies of growth-type cycles include growth rate cycles and deviation (growth) cycles. The former focus on the fluctuations of growth rates of the original macroeconomic indicators while the latter are based on fluctuations of the de-trended macroeconomic indicators. This paper presents an investigation of grow rate cycles in China.

Viewing the business cycle as the result of a series of economic activities' transmission and diffusion, no single economic variable can represent the entire macroeconomy. Therefore, monitoring the business cycle and analyzing its features cannot be based exclusively on the indicator of Gross Domestic Product (GDP). Instead, one should consider the major sectors such as production, domestic demand, trade, fiscal policy, finance, employment, etc. We choose industrial production to be the reference indicator and select three additional coincident indicators, namely total investment in fixed assets in the whole country, sales revenue of wholesale and retail sectors, and money supply M_1. This selection is based on their maximum pairwise correlations with industrial production from a set of over 100 macroeconomic indicators. Industrial production and total sales revenues are also components of the coincident index produced by the Conference Board for United States data. The data for this study are monthly, spanning January 1990 to March 2008, from the *Economic Statistical Monthly* of the National Bureau of Statistics of China, the *Statistical Quarterly* of the People's Bank of China and http://www.cei.gov.cn. The growth rates are computed as year-over-year changes; line graphs of these growth rates are displayed in Fig. 1.

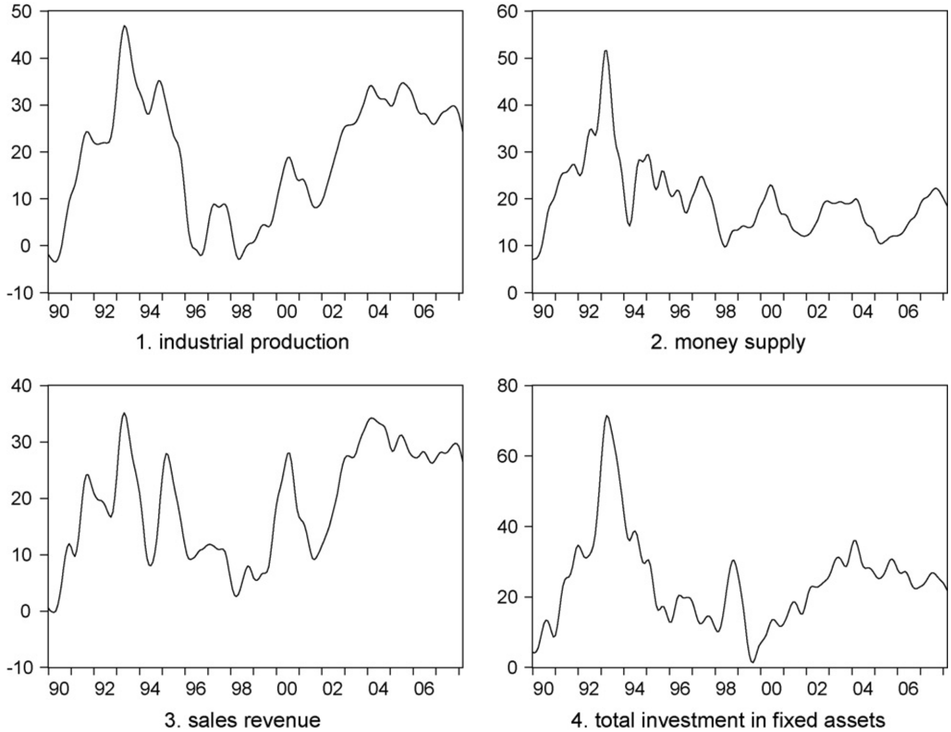

Fig. 1. Growth rates of the four coincident indicators.

Table 1
Augmented Dickey–Fuller test of the coincident indicators.

Variables	Test equation specification			ADF statistics	Test critical values (1% level)
	Intercept	Trend	Lag length		
ΔM_1	No	No	3	−5.00	−2.58
Δip	No	No	3	−5.17	−2.58
Δsr	No	No	3	−5.14	−2.58
Δinv	No	No	4	−6.13	−2.58

Note: 1. The lag length of the test equations are chosen based on Schwarz Information Criteria. 2. Tests were also conducted with constant terms included, and the results were the same and all constant terms were statistically insignificant.

As the dynamic factor model requires the variables to be stationary, we test for unit roots with the Augmented Dickey–Fuller test. As shown in Table 1, the first difference series of the four coincident indicators are all stationary and can be used in the dynamic factor model.

3.2. The comovement and asymmetric features of business cycles in China

First, we calculate the Stock–Watson index with the dynamic factor model. A specification search led to second-order autoregressive specifications for both the common component and the four idiosyncratic components in Eq. (2) and Eq. (3): $\phi(L) = 1 - \phi_1 L - \phi_2 L^2$ and $\psi_i(L) = 1 - \psi_{i1} L - \psi_{i2} L^2$, $i = 1, 2, 3, 4$. For $\gamma_i(L)$ in (1), we adopt $\gamma_i(L) = \gamma_{i1} + \gamma_{i2} L$, $i = 1, 2, 3, 4$. Table 2 presents parameter estimates of the model. Column 2 of the table lists the parameter estimates and column 3 displays the standard error of each estimator. The Stock–Watson index c_t from this dynamic factor model is shown in Fig. 2. In order to show the asymmetric feature of the business cycles in China, we also calculate the index c_t^* from the dynamic Markov switching factor model, and this index is also displayed in Fig. 2. The two composite indexes are nearly identical since they are both grounded in the dynamic factor model.

The estimates of the dynamic factor model are augmented by additional parameters that capture the asymmetries and transition probabilities in the dynamic Markov switching factor model. The estimator of μ_1, 0.46, is smaller than the absolute value of estimator of μ_0, 1.40, which shows the asymmetric feature of quick decline and slow rise. The estimators of transition probabilities are significant, with p_{11} (0.88) larger than p_{00} (0.67). This indicates that the duration of the strong expansion phase is longer than that of the growth recession phase. Therefore, during the transition to the socialist market

Table 2
Parameter estimation of the dynamic factor model of coincident indicators.

Parameters	Dynamic factor model		Dynamic Markov switching factor model	
	Estimates	Standard errors	Estimates	Standard errors
ϕ_1	1.73	0.04	1.58	0.05
ϕ_2	−0.85	0.03	−0.62	0.04
γ_{11}	0.07	0.03	0.10	0.02
γ_{12}	0.02	0.02	−0.01	0.02
ψ_{11}	1.51	0.03	1.40	0.06
ψ_{12}	−0.83	0.03	−0.49	0.04
γ_{21}	0.09	0.01	0.08	0.01
γ_{22}	0.09	0.01	0.10	0.02
ψ_{21}	1.54	0.02	1.62	0.79
ψ_{22}	−0.98	0.02	−0.65	0.64
γ_{31}	0.08	0.02	0.08	0.01
γ_{32}	0.08	0.02	0.07	0.01
ψ_{31}	1.69	0.03	1.59	0.05
ψ_{32}	−0.86	0.03	−0.63	0.04
γ_{41}	0.09	0.03	0.09	0.02
γ_{42}	−0.04	0.03	−0.06	0.02
ψ_{41}	1.64	0.04	1.56	0.05
ψ_{42}	−0.84	0.04	−0.61	0.04
μ_0	–	–	−1.40	0.25
μ_1	–	–	0.46	0.14
p_{00}	–	–	0.67	0.07
p_{11}	–	–	0.88	0.04
Log likelihood	302.60		929.07	

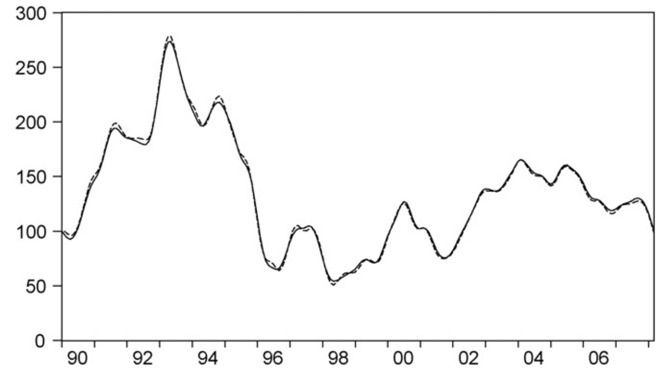

Fig. 2. c_t from dynamic factor model and c_t^* from the dynamic factor model with Markov switching (dashed line) (c_1 = 100).

economy, business cycles in China are asymmetric, with periods of long, gradual expansions and short, sharp growth recessions.

Fig. 3 depicts the smoothed probability function that the economy is in the growth recession state ($p(s_t = 0)$). Following Hamilton (1989), the growth recession state is characterized by this probability exceeding 0.5, and this can identify the turning points of the business cycle. Based on Fig. 3 it is difficult to judge the turning points of the business cycles due to the frequent movement of this probability across the 0.5 boundary. This is a result of the construction of the coincident index from monthly growth rate data that are highly volatile in China. This illustrates a weakness of including Markov switching in the dynamic factor model to calculate the comovement factor of the variables expressed as growth rates in China. On the other hand, the use of Markov switching does provide information on asymmetries between the expansion and slow growth phases of the business cycle. In any case, the following analysis is based on the Stock–Watson index computed from the dynamic factor model, even though the two indexes have very similar implications.

The Stock–Watson index, which is the common component of the four coincident indicators, shows the pattern of business cycles in China since 1990. The index initially rises steadily from 92.63 (April 1990) to 194.33 (September 1991) followed by a 10-month slight slowdown (179.6 in July 1992), then ascends again to 273.89 (May 1993). After that, the index goes down to its lowest value (54.15) in May 1998 with short-term increases twice during this interval. The amplitude of fluctuations in the 1990s is very large in comparison with that of the following cycles. The index rises from May 1998 to July 2000 (127.04) and then declines until October 2001 (75.49), which is a short-term fluctuation with smaller amplitude. After that, the index continues increasing to 165.63 (February 2004) and, roughly speaking, falls off until the last observation.

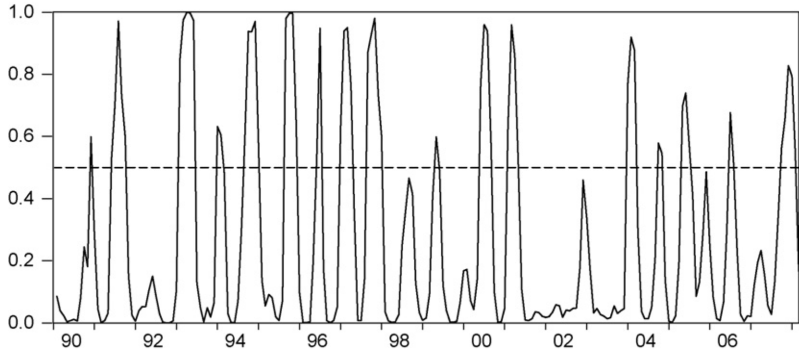

Fig. 3. Smoothed probability that the economy is in contraction state of business cycles ($p(s_t = 0)$).

Thus, the business cycles that emerged in the late-1990s and early-2000s have smaller amplitudes in comparison with those in the early-1990s.

The dramatic fluctuations in the index reflect the very large movements in the growth rates of the underlying series. The large drop in the composite index in the mid-1990s, for example, is the result of a sharp reduction in monetary growth rates from 50% in 1993 to approximately 25% in 1995, a decline in investment growth from 70% in 1993 to less than 20% by 1995, and the precipitous fall in industrial production from 47% to nearly zero by 1996.

Sample truncation at both ends of the period precludes determination of whether there is a trough at the beginning or the end of the sample. Based on the "peak to peak" method, only one complete business cycle exists in China during this sample period (May 1993 to February 2004) with a trough in May 1998. The duration of the contraction state is 60 months and the index falls by 219.74, while the duration of the expansion state is 69 months and the index rises by 111.48. This confirms that the business cycle has the property of longer duration and smaller amplitude in expansion state and shorter duration and larger amplitude in contraction state.

3.3. The comparison between the composite index and macroeconomic activity in China

In this section we outline the economic growth path of China during these years, and relate this descriptive information on macroeconomic activity to the results from the model.

3.3.1. The expansion stage pulled by the consumption and investment in the early years of the 1990s

In the early years of the 1990s, deep reforms occurred in China, as the economic system changed from the traditional planned economy into a market-based system. These transformations promoted macroeconomic growth, increasing the GDP growth rate from 3.8% in 1990 to 9.2% in 1991. After Deng Xiao-ping's inspection in South China, the nonstate-owned enterprises developed very quickly, and the growth rate of investment in fixed assets throughout the country was much higher than before (see Fig. 1_4). With the quick growth of residents' disposal income, consumption also grew rapidly. Therefore, the growth rate of GDP in 1992 reached a very high rate of 14.2%. Thus, the expansion stage of these years was driven by the increase of investment and consumption demands resulting from the system's transition (Wang, Liu, Gao, & Zhang, 2004). The composite coincident index composed of four coincident indicators fits this description of macroeconomic activity in this expansion stage of the 1990s. The index rose from 92.63 in April 1990, continuing to increase until May 1993 when it reached a high of 273.89.

3.3.2. Contraction stage accompanied by "soft-landing" and deflation

Because of the over-heated economy in the early-1990s, the Chinese government adopted contractive monetary and fiscal policies to keep the economy stable. To avoid possible sharp economic declines, which occurred in the late-1980s after severely contractive policies, subsequent policies were not overly strict. As a result the inflation rate decreased from 17.1% in 1995 to 8.3% in 1996 while the growth rate of GDP was sustained at a high level of 9.6%, indicating that China's economy achieved a "soft-landing". However, the composite index tells another story. After May 1993, the index went down from its highest value of 273.89 to the lowest value (54.15) in May 1998. Two of the four component series (growth in industrial production and investment) account for this sharp decline in the composite index, while money and sales revenues growth rates showed more moderate decreases over this period. This episode emphasizes the difference between a composite index versus a single variable (GDP) as alternative measures of economic activity.

Under the influences of the Asian financial crisis in 1997 and the shortage of domestic demand, China's economic growth moderated further in the following years, with the composite index fluctuating around the low level reached in 1996. Given the lack of government programs in medical care, education and old age pensions, the citizens tend to have high rates of saving for possible expenditures in the future. The saving rate in China is higher than both the developed countries and most of the developing countries. In 2000, for example, the saving rate in China was 37.7% while India's saving rate was 24.4%.

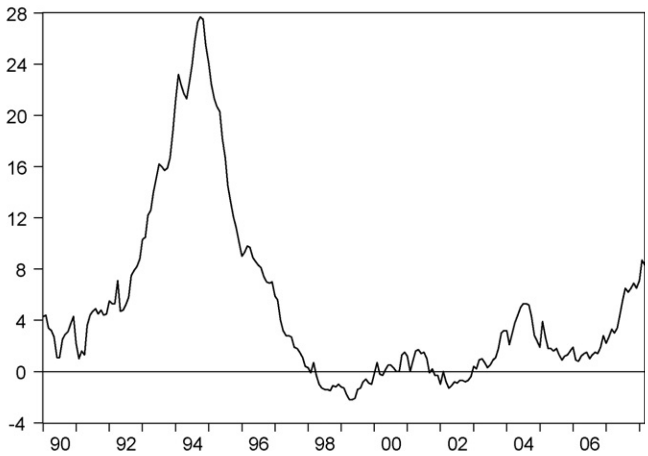

Fig. 4. Inflation rate (CPI-100).

Therefore, the domestic demand growth rate is suppressed. At the same time, with the adoption of modern foreign technologies and management techniques, productivity of China's industry improved greatly, thereby increasing aggregate supply. This disequilibrium between aggregate demand and aggregate supply brought about a slowing of economic growth rates and, in particular, price deflation. The GDP growth rate decreased to 7% in the first quarter of 1998, and the inflation rate remained below zero during the period between April 1998 and January 2000 (see Fig. 4).

3.3.3. The new expansion stage of recent years

In order to eliminate deflation and step up to a high growth rate development stage, the Chinese government began to adopt active fiscal and monetary policies to stimulate domestic demand. The central bank decreased interest rates eight times between 1996 and 2002, e.g., from 10.98% in 1996 to 1.98% in 2002 for the interest rate on 1-year time deposits. At the same time, the Chinese government raised the level of national debt and fiscal expenditures to stimulate domestic demand. As a result of these policies, a new expansion stage emerged in the early-2000s. The composite coincident index rose from May 1998 to July 2000 and, after a short pause, continued going up to 165.63 by February 2004. This was mimicked by the performance of the growth rate of GDP, which experienced a brief pause in 2000 but otherwise increased steadily throughout this same period (see Fig. 5). The fluctuations in economic activity over this period exhibit the features of longer expansion duration and smaller amplitude in comparison with the previous period.

Beginning in early-2004 the growth rate of GDP and the composite index moved in opposite directions (compare c_t in Fig. 2 and the GDP growth rate in Fig. 5). According to c_t there has been a contractive phase from March 2004 until now while GDP growth remained at a high and ever increasing rate. This difference reflects the more comprehensive nature of the composite index, which is derived from several monthly coincident indicators of economic activity—not just output alone. Fig. 1 shows that three of the four component series declined over the period after March 2004, the exception being the money supply.

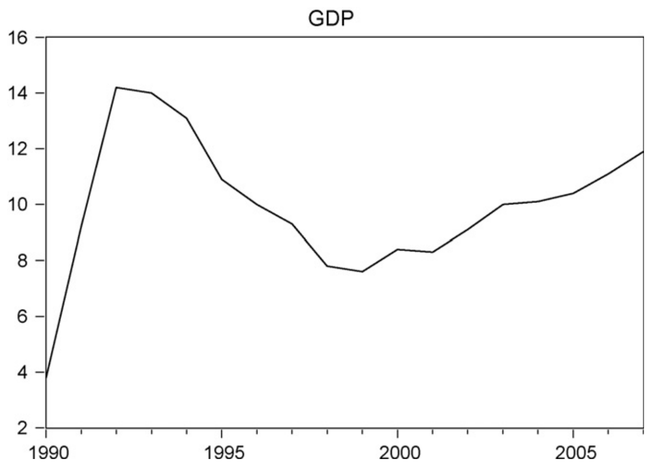

Fig. 5. GDP annual growth rate.

The emergence of this contraction in the composite index is the result of the tightening of policies, adopted from 2004, aimed to lower the growth rate of the investment in fixed assets. In particular, the People's Bank of China frequently raised benchmark interest rates for loans and deposits of financial institutions throughout this period, so as to achieve a moderate growth of financial and real investment. Fig. 1_4 shows that these contractive policies were effective in a producing a decline in fixed investment growth over this period.

Despite the People's Bank of China (PBC) attempts to tighten monetary policy over this period, money supply growth remained strong due to an inability to sterilize large balance of payments surpluses (Fig. 1_2). Thin financial markets preclude the reliance on open market operations that are the primary tool of monetary control in industrialized countries. Although steps have been taken to develop short-term capital markets to facilitate open market operations, these markets remain small relative to the size of the required sterilization (Jingu, 2008). Consequently, large balance of payments surpluses have contributed to continued strong growth in the monetary base and thus the money supply.

In the face of the increasing monetary base, the PBC has had to rely on interest rate increases and hikes in reserve requirements, to curb the growth in loans and investments. Illiquidity conditions of some commercial banks has limited the extent to which the PBC can raise required reserves that puts further pressure on bank profits (Jingu, 2008). Therefore, China has continued to experience strong money supply growth over the post-2004 period, despite PBC attempts to offset the expansionary pressures of China's large BOP surpluses.

The observation that GDP growth has continued to rise during the post-2004 period, while industrial production and sales revenue growth rates have declined can be explained by the strong growth in construction activity. Construction activity is not a component of industrial production, and it is included in sales revenue only in this sector's use of raw materials and intermediate goods. The value added in construction itself is not counted in the total revenues of wholesale and retail trade. Output growth rates in the construction section surged during the 3 years after 2004 to an average annual rate of 13%, compared with a 7% growth rate during the first 3 years of this decade. Its inclusion as a part of GDP accounts for the higher GDP growth rates after 2004, while the composite index shows a moderate slackening of the economy.

4. Conclusion

This paper presents the composite coincident index using the Stock–Watson model and the dynamic Markov switching factor model in order to examine business cycles in China since 1990. Four coincident indicators, namely, industrial production, investment in fixed assets in the whole country, sales revenues, and the money supply, M_1 are selected to compute the coincident index. In China, most of the macroeconomic indicators show persistent upward movements and only fluctuate in their growth rates, so in this study all variables are expressed in terms of growth rates relative to the same month of the prior year. The coincident indexes from the two models are very similar. The dynamic Markov switching factor model provides additional information on the asymmetries of the business cycle, but the transition probabilities from this model as applied to growth rates are highly unstable. Therefore, the Stock–Watson method seems more appropriate for the Chinese case and is emphasized in this study.

The resulting index summarizes the business cycle activity emerging in China since 1990. Based on the "peak to peak" method, only one complete business cycle, lasting from May 1993 to February 2004, is identified over the period since 1990. The duration of the contraction state is 60 months, when the index falls by 219.74 units, while the length of the expansion state is 69 months, with the index rising by 111.48 points. Therefore, the business cycle has the property of longer duration and smaller amplitude in the expansion state and shorter duration and larger amplitude in contraction state. The dramatic fluctuations in the index reflect the very large movements in the growth rates of the underlying series.

A comparison of the composite coincident index and other measures of macroeconomic activity provides economic interpretations of the patterns in the index. There are notable differences between the index and GDP growth rates during this period, reflecting its more comprehensive measurement of economic activity—not just output alone. Based on GDP growth rate, China's economy achieved "soft-landing" in the late-1990s, while the coincident index indicates a substantial decline from its highest value of 273.89 to the lowest value (54.15) in May 1998. In addition, the GDP growth rate maintained a high level over the most recent 3 years, while the coincident index showed a gradual decline since March 2004. These differences can be understood in terms of the contractive policies of these periods that restrained the growth in investment, sales revenues, and industrial output, three of the four variables used to construct the coincident index. The continued strong growth in GDP reflects the sustained increase in construction activity, which is not included in the sales revenue and industrial production components of the index. Monetary growth, the fourth component of the composite index, could not be restrained by the central bank in the face of large balance of payments surpluses. Instead the People's Bank of China relied on interest rate increases to temper the growth in loans and investments. The more balanced view of macroeconomic activity provided by the composite index enhances the understanding of China's policies and economic fluctuations beyond what is shown by GDP growth rates alone.

References

Burns, A. F., & Mitchell, W. C. (1946). *Measuring business cycles*. New York: NBER.
Chauvet, M. (1998). An econometric characterization of business cycle dynamics with factor structure and regime switches. *International Economic Review, 39*(4), 969–996.
Diebold, F. X., & Rudebusch, G. D. (1996). Measuring business cycles: A modern perspective. *Review of Economics and Statistics, 78*(1), 67–77.

Goldfeld, S. M., & Quandt, R. E. (1973). A Markov model for switching regression. *Journal of Econometrics, 1*(1), 3–16.
Hamilton, J. D. (1989). A new approach to the economic analysis of the nonstationary time series and the business cycle. *Econometrica, 57*(2), 357–384.
Jingu, T. (2008). China's monetary policy challenges. *Nomura Capital Market Review, 10*(4), 31–45.
Kaufmann, S. (2000). Measuring business cycle with a dynamic Markov switching factor model: An assessment using Bayesian simulation methods. *Econometrics Journal, 3*(1), 39–65.
Keynes, J. M. (1936). *The general theory of employment, interest, and money*. NJ: Macmillan.
Kim, C. J. (1994). Dynamic linear models with Markov-switching. *Journal of Econometrics, 60*, 1–22.
Kim, C.-J., & Nelson, C. R. (1998). Business cycle turning points, a new coincident index, and tests of duration dependence based on a dynamic factor model with regime switching. *Review of Economics and Statistics, 80*(2), 188–201.
Neftci, S. N. (1984). Are economic time series asymmetric over the business cycle? *Journal of Political Economy, 92*(April (2)), 306–328.
Ploberger, W., Kramer, W., & Kontrus, K. (1989). A new test for structural stability in the linear regression model. *Journal of Econometrics, 40*(2), 307–318.
Quandt, R. E. (1972). A new approach to estimate switching regressions. *Journal of the American Statistical Association, 67*(338), 306–310.
Sichel, D. E. (1989). Are business cycles asymmetric? A correction. *Journal of Political Economy, 97*(5), 1255–1260.
Stock, J. H., & Watson, M. W. (1989). In O. Blanchard & S. Fischer (Eds.), *New indexes of coincident and leading economic indicators in NBER macroeconomics annual* (pp. 351–394). NJ: MIT Press.
Stock, J. H., & Watson, M. W. (1991). In K. Lahiri & G. H. Moore (Eds.), *A probability model of the coincident economic indicators in leading economic indicators: New approaches and forecasting records* (pp. 63–89). NJ: Cambridge University Press.
Stock, J. H., and M. W. Watson (2003), *Understanding changes in international business cycle dynamics*, NBER Working Paper, 9859.
Wang, J. M., Liu, Y. H., Gao, T. M., & Zhang, G. L. (2004). The empirical analysis of the characters of business cycles in China. *Jilin University Journal Social Science Edition, 5*, 93–97 (in Chinese).