



Does the Great Moderation of China's Macroeconomic Exist During the Reform Era?

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Abstract. This paper documents the Great Moderation of China's macroeconomic volatilities during the reform period. Using the conditional Markov chain model, it is found that with the break date at 1995Q1, China's business cycle has changed from the "Boom-bust Cycle" to the "Great Moderation". Evidence from the multiresolution wavelet analysis reveals that a decline in output volatility appears to be evenly distributed across frequencies. These results provide some striking evidence consistent with the potential explanations of good institution, good luck and good policy, but weaker evidence for the good practice hypothesis.

1. Introduction

China has experienced remarkably high growth since its economic reform started in 1978. The annual real GDP growth rate has averaged nearly 10% (Dai and Wen, 2014). Other than the persistently high growth rate, some studies have also noted that China's business cycles appear to have become more benign in the second half of the reform period. That is to say, the phenomenon, which is known as "the Great Moderation", may also exist in China.

However, the start time of the Great Moderation of China's business cycle is still controversial. Xu (2007) chooses 1992 as the start time point for the reasons that Deng Xiaoping's Southern Tour and the 14th Committee of the Communist Party (CCP) marked this year as the start of a new phase of China's reform process. Tao (2006) notes that, in 1993, Vice Premier Zhu Rongji succeeded Yao Yilin to be in charge of economic affairs and that the Third Plenary Session of the 14th CCP was held at the end of the year, which had passed a resolution to accelerate the transition of the economic system from a planned economy to a market economy. Wu (2004) argues that the reforms implemented after 1994 in China show a watershed in

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the evolution of economic reform. The implementation of a series of reforms in financial market, foreign exchange system, fiscal decentralization and some other fields means that the government has begun to push the economic reform from an "incremental reform" track to a comprehensive promotion stage. These reforms established the fundamental institutions for the stability of macroeconomy. Some other economists have put forward different views about the break, such as the soft landing in 1996 (Wang and Ai, 2010), the reform of monetary policy in 1997 (Sun, 2007), and even the entry into the WTO in 2001 (Yin, 2010), etc.

While the existing views above almost dominate in the 1990s and the beginning of the 21st century, no attempt has been made to analyze the timing of the Great Moderation in China using the formal econometric model and statistical inference. Efforts have been devoted to determine the timing of the Great Moderation in the US (see, among others, Kim and Nelson, 1999; McConnell and Perez-Quiros, 2000; Stock and Watson, 2002). A recent work by Bai and Wang (2011) formulates the changing volatilities as a recurrent structure change problem through a conditional Markov chain. The proposed model admits rich features while keeping a reasonably parsimonious model structure. It includes the unknown change point Markov switching model (Kim and Nelson, 1999) and the independent Markov switching model (McConnell and Perez-Quiros, 2000) as special cases.

Another issue, which is the sources of China's Great Moderation, arises naturally. The decline of macroeconomic volatilities is evident in most of the developed economies, particularly the United States. A vast amount of empirical literature has investigated the sources of the Great Moderation in an attempt to disentangle the relative contribution of three broad categories: good policy, good luck, and good practice. Ahmed et al. (2004) first utilize frequency-domain method to distinguish among the explanations. In the frequency domain, the basic versions of each explanation can be associated with different patterns for the shift: (1) improved monetary policy would be expected to shift the spectrum primarily at business-cycle frequencies (periodicity of 4-32 quarters); (2) improved inventory management and other relevant changes in business practices¹ would tend to be manifested more at relatively high frequencies (periodicity less than 6 quarters); and (3) reduced innovation variance would generate a proportional decline in the spectrum at all frequencies.

Based on the ideas of Ahmed et al. (2004), this paper investigates the sources of China's Great Moderation in two extended directions.

Firstly, from a methodological point of view, instead of the spectral analysis, we will use the wavelet analysis. Compared to the frequency-based method, wavelet analysis provides better resolution in the time domain since wavelet basis functions are time-localized (in addition to being scale-localized), which is useful for capturing the changing volatility of the business cycle. The fact that the wavelets are localized in both time and scale, contrary to what happens with trigonometric functions, makes them ideal candidates for analyzing non-stationary signals and those with transient phenomena or singularities. The first application of wavelets to economic growth was by Gallegati and Gallegati (2005) and in the form of GDP in Yogo (2008) and then more recently in a working paper by Crowley and Hallett (2011).

Secondly, from an economic point of view, China's economy is still in the transitional period, in which the institutional reforms would play an important role in the macroeconomic volatility. As shown in the spectral analysis on the China's macroeconomic series (Laurenceson and Rodgers, 2010), a clear spectral peak occurs at lower than business cycle frequencies (around 32-64 quarters), which suggests that, other than the good policy, good luck, and good practice, there may exist another potential explanation - "good institution". Generally, the institutional reforms such as the household responsibility system, open door policy, market-oriented banking system, and partially privatization of SOEs, are related to the supply side and plausibly generate cycles in output and productivity growth that display high persistence, i.e., volatility at lower than business cycle frequencies.

In an attempt to shed light on the above issues, this paper uses the conditional Markov chain model to identify the timing of China's Great Moderation. The results show that: with the break date at 1995Q1, China's business cycle has changed from the "Boom-bust Cycle" to the "Great Moderation". The wavelet-filtered series reveal that a decline in output volatility appears to be evenly distributed across frequencies.

¹) Potentially relevant changes in practice also include financial innovation and better risk sharing, and reduction of trade barriers.

These results provide some striking evidence consistent with the potential explanations of good luck, good policy and good institution, but weaker though nontrivial evidence for better practices.

The remainder of this paper is organized as follows. Section 2 briefly introduces the methodologies, including the conditional Markov chain model and multiresolution wavelet analysis. Section 3 is empirical analysis, in this section, we first describe the data, report the empirical results for the timing of China’s Great Moderation, and then examine the economic rationale behind each of potential explanations, and implement the multiresolution wavelet analysis on the real GDP series to investigate the links between the frequency-domain properties and the potential explanations. Section 4 concludes the paper.

2. Methodology

2.1. Conditional Markov Chain Model

A few different powerful methods can be used to describe the modern characteristics of business cycle. The idea of using Markov switching model in econometrics was first introduced by Goldfeld and Quandt (1973) for serially uncorrelated data. Hamilton (1989, 1990) used this concept for serially correlate data by modeling booms and recessions as regime switches in the growth rate of the output. A novel feature of the Markov switching model is that the switching mechanism is controlled by an unobservable (latent or imbedded or hidden) state variable that follows a first-order Markov chain. However, at that time the changing volatility was not a noteworthy feature of the data. Kim and Nelson (1999) propose a modified model to estimate the date of a structural break in the output growth process to investigate whether there has been a structural break in postwar US and real GDP growth towards stabilization. McConnell and Perez-Quiros (2000) allow the mean and the variance to follow independent switching processes. The empirical evidence in support of this extension is based on the existence of a structural break in the volatility of the US growth rate in 1984. Bai and Wang (2011) formulate the regime switching problem through a conditional Markov chain. They model the long-run volatility change as a recurrent structure change, while short-run changes in mean growth rate as regime switches. Despite allowance for rich data features, this proposed model maintains a reasonably parsimonious model structure. It includes Kim and Nelson’s (1999) model and t McConnell and Perez-Quiros’s (2000) model as special cases. According to Bai and Wang (2011), the DGP of growth rate series $\{y_t\}_{t=1}^T$ is specified as:

$$y_t = \mu(A_t, s_t) + \sigma(A_t)\varepsilon_t \tag{1}$$

where $\varepsilon_t \sim N(0, 1)$ is independent with (A_t, s_t) , the two types of hidden state variables. The exogenous state, or structure A_t , is designed to characterize long-run structure changes and evolves according to homogenous Markov chain, while the endogenous state, or regime s_t is used to describe short-run business cycles. Given structure, the regime also follows a homogenous Markov chain. These assumptions can be formulated as follows.

$$Pr(A_{t+1}|A_t, s_t, A_{t-1}, s_{t-1}, \dots, A_0, s_0) = Pr(A_{t+1}|A_t) \tag{2}$$

$$Pr(s_{t+1}|A_t, s_t, A_{t-1}, s_{t-1}, \dots, A_0, s_0) = Pr(s_{t+1}|A_t, s_t) \tag{3}$$

The assumption (2) implies that A_t forms a sufficient statistic for the entire history of (A, s) to predict A_{t+1} . The assumption (3) means conditional on historical structure states, the regime s is Markovian. Following Wang and Bai (2011), we use a conditional Markov chain model with two mean states $\{s_H, s_L\}$, and two variance states $\{A_H, A_L\}$, where ‘H’ and ‘L’ denote high and low respectively. Let $\sigma(A_i) = \sigma_i, \mu(A_i, s_j) = \mu_j^i, i, j = H, L$. The structure state is first-order Markovian, with transition matrix $P^A = \begin{pmatrix} p & 1 - q \\ 1 - p & q \end{pmatrix}$.

Given $A_t = \sigma_H^2$, the regimes are driven by $P^H = \begin{pmatrix} p_1 & 1 - q_1 \\ 1 - p_1 & q_1 \end{pmatrix}$. Accordingly, regimes will be driven by $P^L = \begin{pmatrix} p_2 & 1 - q_2 \\ 1 - p_2 & q_2 \end{pmatrix}$. under $A_t = \sigma_L^2$. With the above specification, there are 6 mean and variance parameters $\{\mu_L^H, \mu_H^H, \mu_L^L, \mu_H^L, \sigma_H^2, \sigma_L^2\}$ and 6 transition probability parameters $\{p, q, p_1, q_1, p_2, q_2\}$ to be estimated.

The specified model provides certain restrictions on the conventional Hamilton Markov regime switching framework which involves 12 probability parameters concerning the transition matrix of the four regime states. More generally, the number of parameters increases with the same magnitude as the squared number of states in the conventional setup, making MLE numerically inoperable. Instead, this conditional Markov chain implies a grand transition matrix with only 6 parameters, which greatly reduces the computational burden.

2.2. Multiresolution Wavelet Analysis

Multiresolution wavelet analysis is a useful tool for studying the time and frequency properties of an economic time series (Huang et al., 2011, 2013). The scale of resolution with which we look at the data plays an important role in wavelet analysis. Analyzing a data at a low-resolution scale gives us information about its long-run behavior with gross distinguishing features of the data; on the other hand looking at higher resolution scale gives information about minute and detailed features of the same data. Wavelets thus are intrinsically connected to the notion of ‘multiresolution analysis’, namely, signal or data can be examined and analyzed at widely varying levels of focus using wavelets. It is this feature of wavelet decomposition that is useful for econometric analysis. Multiresolution wavelet analysis is a natural way to decompose an economic time series into trend, cycle, and noise (Yogo, 2008). Using a wavelet filter, a time series $x(t)$ can be decomposed as

$$x(t) = x_0(t) + \sum_{j=0}^{J-1} y_j(t) \tag{4}$$

where $x_0(t)$ denotes cycles with periodicity greater than 2^J periods and $y_j(t)$ denotes cycles with periodicity between 2^{J-1-j} and 2^{J-j} periods. If $J = 4$ and sampling frequency is quarterly, $x_0(t)$ is the long-run trend (periodicity greater than 32 quarters). $y_0(t)$, $y_1(t)$ and $y_2(t)$ are the business-cycle components (periodicity of 16-32, 8-16, and 4-8 quarters, respectively). $y_3(t)$ is high frequency noise (periodicity less than 4 quarters).

The technical details of the multiresolution wavelet analysis are as follows.

Any series $x(t)$ can be built up as a sequence of projections onto two different sets of wavelet functions, one used to capture trend movements and cycles beyond the scale limit chosen by the researcher (the “father” wavelet, or scaling function); and another used to capture deviations from trend for cycles at different frequencies (the “mother” wavelet, or wavelet function). Scaling function and wavelet function are therefore indexed by both j , the scale ²⁾, and k , the number of translations ³⁾ of the wavelet, where k is often assumed to be dyadic ⁴⁾. The scaling and wavelet functions at scale j and location k are given by:

$$\tilde{\phi}_{j,k}(t) = 2^{j/2} \tilde{\phi}(2^j t - k) \tag{5}$$

$$\tilde{\psi}_{j,k}(t) = 2^{j/2} \tilde{\psi}(2^j t - k) \tag{6}$$

where the analysis scaling function is defined by the analysis dilation equation

$$\tilde{\phi}(t) = \sum_k 2h_0(k) \tilde{\phi}(2t - k) \tag{7}$$

and the analysis mother wavelet $\tilde{\psi}(t)$ can be expressed in terms of $\tilde{\phi}$ in the following way:

$$\tilde{\psi}(t) = \sum_k 2h_1(k) \tilde{\phi}(2t - k) \tag{8}$$

²⁾ Scale refers to the range of frequencies which the wavelet function encompasses.

³⁾ Translation refers to the location in the series.

⁴⁾ A dyadic series has length 2^n where n is an integer.

$\{h_0(k)\}_{k=0}^{N_1}$ and $\{h_1(k)\}_{k=0}^{N_2}$ are the so called low-pass and high-pass analysis filters used for computation discrete wavelet transform.

In order to be efficient and useful, a method designed for analysis also has to be able to perform synthesis (reconstruction). The analysis starts from $x(t)$ and results in the wavelet coefficients. The synthesis starts from the wavelet coefficients and reconstructs $x(t)$. Synthesis is the reciprocal operation of analysis. The corresponding low-pass and high-pass synthesis filters are $\{f_0(k)\}_{k=0}^{N_2}$ and $\{f_1(k)\}_{k=0}^{N_1}$. The synthesis dilation and wavelet equations are $\phi(t) = \sum_k 2f_0(k)\phi(2t - k)$ and $\psi(t) = \sum_k 2f_1(k)\phi(2t - k)$. The synthesis scaling and wavelet functions at scale j and location k are denoted by $\phi_{j,k}(t)$ and $\psi_{j,k}(t)$.

Finally, the J-level decomposition of a signal $x(t)$ is

$$x(t) = \sum_k \tilde{a}_{0,k}\phi_{0,k}(t) + \sum_{j=0}^{J-1} \sum_k \tilde{b}_{j,k}\psi_{j,k}(t) \tag{9}$$

where the coefficients are given by $\tilde{a}_{0,k} = \int_{-\infty}^{+\infty} x(t)\tilde{\phi}_{0,k}(t)dt$ and $\tilde{b}_{j,k} = \int_{-\infty}^{+\infty} x(t)\tilde{\psi}_{j,k}(t)dt$.

Wavelet decomposition produces a family of hierarchically organized decompositions. The selection of a suitable level for the hierarchy will depend on the signal and experience. At each level j , we build the j -level approximation A_j , or approximation at level j , and a deviation signal called the j -level detail D_j . For a detailed discussion of the relationship between approximation/detail and the coefficients given in (9), one may refer to Crowley (2007) or Strange and Nguyen (2007).

Let $H_0(\omega)$ and $H_1(\omega)$ be the frequency responses of the low-pass and high-pass analysis filters. The filter relating the scaling coefficients $\tilde{a}_{0,k}$ to the original signal has a frequency response

$$A_0(\omega) = \prod_{l=0}^{J-1} H_0(2^l\omega) \tag{10}$$

In other words, the filter is a low-pass filter with an approximate passband $|\omega| \in [0, \pi/2^J]$. The filter relating the wavelet coefficients $\tilde{b}_{j,k}$ at level J to the original signal has a frequency response

$$B_j(\omega) = H_1(2^{J-j-1}\omega) \prod_{l=0}^{J-j-2} H_0(2^l\omega) \tag{11}$$

which is a bandpass filter with an approximate passband $|\omega| \in [\pi/2^{J-j}, \pi/2^{J-j-1}]$.

Let $F_0(\omega)$ be the frequency response of the low-pass synthesis filter. When $F_0(\omega)$ has p zeros at π , the analysis wavelet has p vanishing moments. Consequently, polynomials of degree $p - 1$ can be expressed as a linear combination of the synthesis scaling functions $\phi_{0,k}(t)$. In order to filter out the linear trend in nonstationary economic time series such as real GDP, $p \geq 2$ is a necessary criteria in choosing wavelet filters.

3. Empirical Analysis

3.1. Data

In this study, we employ the real GDP data, spanning from the first quarter of 1978 to the second quarter of 2011. There are 134 observations in total. Official statistical data provides quarterly GDP at current prices and cumulative GDP growth rate over the same period last year since 1992. To get the quarterly data before 1992, we decompose Chinas annual real GDP data from 1978 to 1991 into quarterly data by using the method of Abeyasinghe and Gulasekaran (2004). This method is essentially the Chow-Lin estimation method in the spirit of Chow and Lin (1971). The estimated quarterly real GDP series based on this method seem to match the officially published annual data by the Chinas National Bureau of Statistics quite convincingly and so that be employed widely in the studies of Chinas business cycle (see Laurenceson and Rodgers, 2010; Zheng et al., 2012; Zhang and Marasawa, 2012; Wen et al., 2014).

In order to get real quarterly GDP, we first re-calculate real value at comparable price (with 1992 as the base year) based on cumulative GDP growth rate, and then compute the seasonally adjusted GDP series via Tramo/Seats seasonal adjustment method executed by the software Eviews. The growth rate is measured as the log-difference of the seasonally adjusted real quarterly GDP multiplied by 100, i.e., $y_t = 100\log(GDP_t/GDP_{t-1})$.

Figure 1 plots the real GDP growth rate series in the period 1978Q2-2011Q2. In comparison of the two periods before and after the mid-1990s, the business cycles in China have obviously changed from a path of violent fluctuations to a path of gentle ups and downs, with a remarkable feature as narrowing mean growth rate gap.

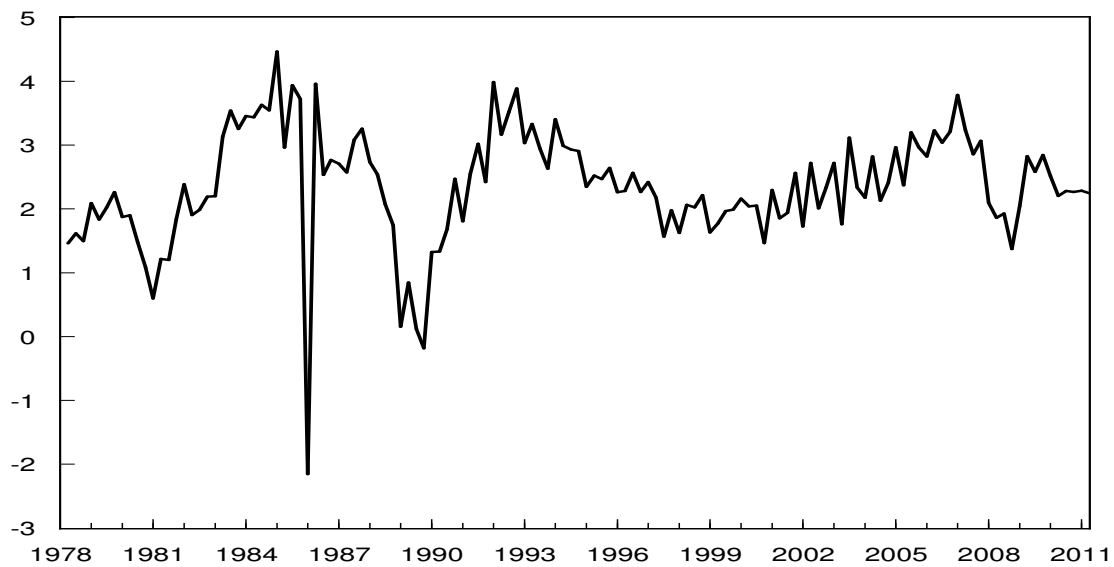


Figure 1: China's real GDP growth rate (1978Q2-2011Q2)

For further exploration of the decline of macroeconomic fluctuations, we use the rolling standard deviation of real GDP growth rate as a simple measure of volatility. To check the robustness, we use the 12-, 16- and 20-quarter rolling windows to calculate the standard deviations which are presented in Figure 2 respectively.

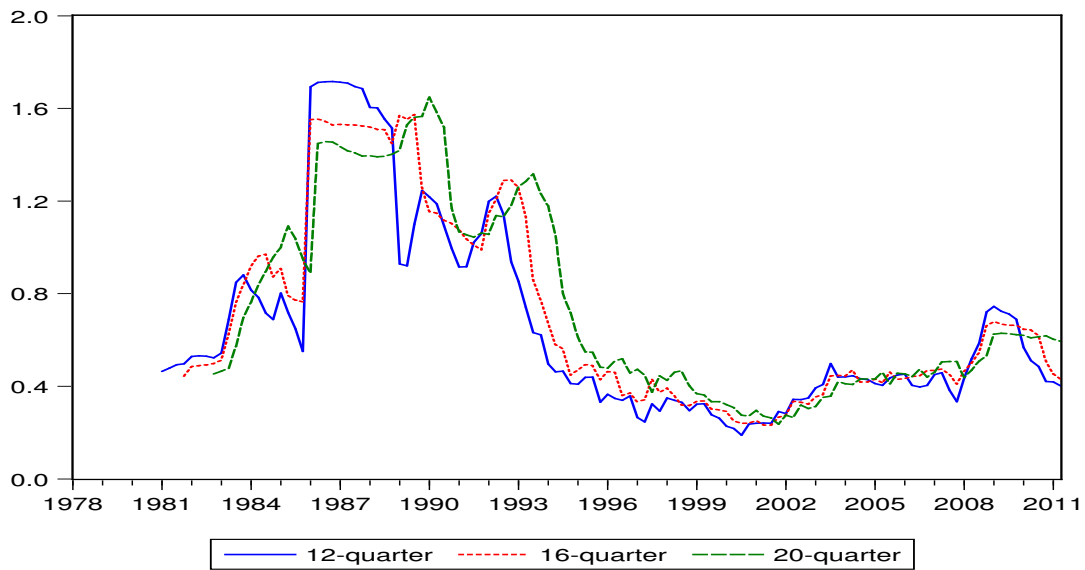


Figure 2: Rolling standard deviation

It turns out that our results are robust across different windows. The volatility is relatively low in the early 1980s, but trends upward in the mid-1980s. From the mid-1990s the volatility drops sharply and remains relatively low and stable. Since 2007, the onset of the recent financial crisis, this stability has been shaken. Overall, the rolling deviation pattern shows that the variance state is recurrent and not a mere deterministic break at some unknown time. Changing volatility is one of the most striking features of China's business cycle and should be captured in the model specification for the dating of Great Moderation.

3.2. The Timing of Great Moderation

In this section, we use examine the timing of China's Great Moderation using conditional Markov chain model. Because both A_t and s_t are hidden, we can treat them as missing data and apply the EM algorithm⁵⁾ to estimate the model. The EM algorithm will iterate between expectation and maximization steps until some convergence criterion is met. Robustness of the estimation results can be checked by trying different initial values. One favorable feature of EM algorithm is that each iteration increases the likelihood value. As shown in Figure 3, the update likelihood values are increasing gradually. As a refinement, we also use the EM algorithm to obtain initial estimates for parameters, and then directly maximize the likelihood function to obtain the standard errors.

⁵⁾ For a detailed description, one may refer to the appendix of Bai and Wang (2011).

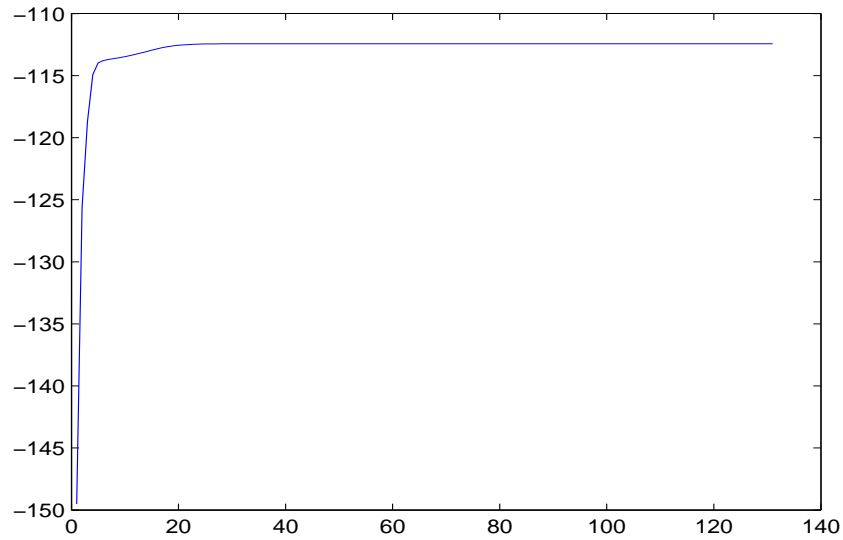


Figure 3: Update likelihood value

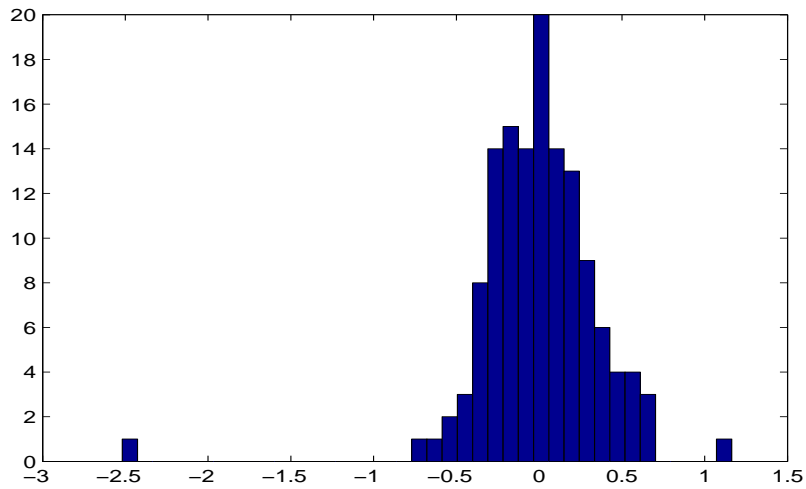


Figure 4: The empirical distribution of residuals

Table 1 reports parameter estimates and standard errors. As shown in the table, all parameters are significant under 5% significant level, except for μ_L^H . We calculate the residuals, of which the corresponding empirical distribution appears to be shaped like that in Figure 4. It seems that the conditional Markov chain model can well describe the behavior of mean regime switching and variance structure change.

Table 1: Parameter estimates of the conditional Markov chain model.

mean & variance parameters	μ_L^H 0.3614 (0.3230)	μ_H^H 3.3025 (0.1476)	μ_L^L 1.8949 (0.0700)	μ_H^L 2.5113 (0.1044)	σ_H^2 0.3787 (0.0937)	σ_L^2 0.1021 (0.0219)
transition probability parameters	p_1 0.8486 (0.1369)	q_1 0.9694 (0.0309)	p_2 0.9080 (0.0523)	q_2 0.9177 (0.0490)	p 0.8679 (0.0589)	q 0.9360 (0.0292)

Note: Figures in parentheses are corresponding standard errors.

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Based on the specification, the joint state $Z_t \equiv (A_t, s_t)$ is proved to be first-order Markovian with respect to itself, whose transition matrix is given by P^Z . If we order the joint state Z_t as $\{(A_H, s_L), (A_H, s_H), (A_L, s_L), (A_L, s_H)\}$, then the corresponding transition matrix takes the form $P^Z = \begin{pmatrix} p \cdot P^H & (1 - q) \cdot P^H \\ (1 - p) \cdot P^L & q \cdot P^L \end{pmatrix}$, whose estimate is presented in Table 2.

Table 2: Parameter estimates of P^Z .

	HV-LM	HV-HM	LV-LM	LV-HM
HV-LM	0.7365	0.0265	0.0543	0.0019
HV-HM	0.1314	0.8413	0.0096	0.0620
LV-LM	0.1199	0.0108	0.8498	0.0770
LV-HM	0.0121	0.1211	0.0860	0.8589

Note: H-high, L-low, V-variance, M-mean

Probabilities for low growth regimes and high variances structure are shown in Figure 5. Although the results of filtered and smoothed probabilities are slightly different in some periods, we prefer to the latter which contains full-sample information (i.e., I_T) in formulating the prediction. The shaded areas are the dated recessions where the smoothed low-mean probabilities $Pr(s_t = L|I_T)$ are computed by $Pr(A_t = H, s_t = L|I_T) + Pr(A_t = L, s_t = L|I_T)$. If the smoothed probability is close to 1, the economy is in recession. As showed in in Figure 5, we can identify 5 business cycles during 1978Q2-2011Q2, where the recessions are 1978Q2-1982Q4⁶⁾, 1986Q1, 1988Q3-1991Q1, 1997Q2-2002Q3 and 2008Q1-2009Q1. These identified business cycles are highly consistent with the process of China’s economy. Some similar results are reported in Zheng et al. (2012) and Wang and Ai (2010).

High volatility and low volatility alternate over the period 1978Q2-1994Q4, followed by an 11-year sustained low-volatility period. That is to say, with the break date at 1995Q1, China’s business cycle changed from the “Boom-bust Cycle” to the “Great Moderation”. The results also show that, while the Great Moderation was interrupted in 2006-2007 due to the economic overheating, it came back soon during the Global Financial Crisis. Furthermore, in the post-financial-crisis era, China’s economy appears neither overheating nor ‘double dip’.

⁶⁾ The recession periods 1978Q2-1982Q4 include two types of low-mean probabilities, $Pr(A_t = H, s_t = L|I_T)$ and $Pr(A_t = L, s_t = L|I_T)$. In the “Boom-bust Cycle” period, 1978Q2-1994Q4, the state (A_H, s_L) is the recession indeed, which covers 1981Q4-1982Q4.

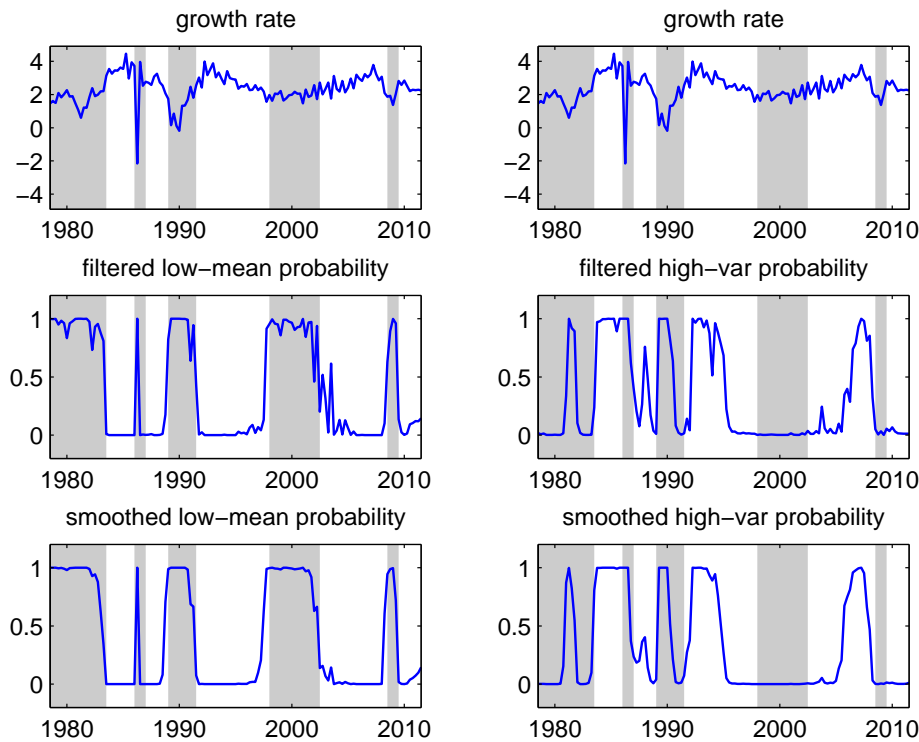


Figure 5: GDP growth and estimated state probabilities, 1978Q2-2011Q2.

3.3. Potential Explanations Using Wavelet Analysis

In this section, we will examine the economic rationale behind each of the potential explanations and the links to the frequency-domain properties of the economic time series.

Good Institutions. China's economy is still in the transitional period, where the institutional reforms should play an important role in the macroeconomic volatility. Generally, the institutional reforms are related to the supply side and plausibly generate cycles in output and productivity growth that display high persistence, i.e., volatility at lower than business cycle frequencies.

Good Policies. If improved monetary and fiscal policies act to dampen business cycle fluctuations, as is likely, then we should find that the post-1995 decline in volatilities occurred disproportionately at business cycle frequencies.

Good Practices. Improved business practices (such as better inventory management techniques, more sophisticated financial markets, or expanding international trade flows) seem likely to smooth output on a quarter-by-quarter basis. Thus, if the reduction in variance reflected better business practices, we would expect the decline in variance to occur primarily at relatively high frequencies.

In any case, these three explanations (good institutions, good policies and good practices) would likely work, partly at least, by changing the structure of the economy rather than changing the nature of the shocks hitting the economy⁷⁾.

⁷⁾ In some economists' view, the good policy and good practice hypotheses are mixed as the changes in the economy's structure (Gali and Gambetti, 2009; Benati and Surico, 2009).

Good Luck. Under the good luck hypothesis, the fall in output volatility is due to exclusively to a reduction in the volatility of shocks hitting the economy. Ahmed et al. (2004) find the links between this hypothesis and the spectrum. Assuming that cycles are covariance-stationary, Wold’s theorem indicates that they can be represented as $MA(\infty)$ processes. The good luck hypothesis can be interpreted as a decline in innovation variance with no change in the MA coefficients. Because the spectrum of any $MA(\infty)$ process is proportional to the innovation variance, this hypothesis implies a parallel downward shift in spectrum. In the framework of wavelet analysis, this link can be interpreted as a proportional decline in the wavelet-filtered series at all frequencies.

In analyzing economic time series, the timing of events at various frequencies is important. This motivates the use of biorthogonal, rather than orthogonal, wavelet filters, which have linear phase (zero phase when centered). Within the family of biorthogonal filters, the filter must be sufficiently long to avoid undesirable artifacts in the filtered series. Through experimentation, starting with shorter filters, Yogo (2008) found that the 17/11 filter works well in practice. Figure 6 shows the impulse response if the analysis and synthesis filters in the biorthogonal 17/11 filter bank. The filters are symmetric, resulting in zero phase. The high-pass analysis (synthesis) filter is the alternating flip of the low-pass synthesis (analysis) filter, which assures perfect reconstruction.

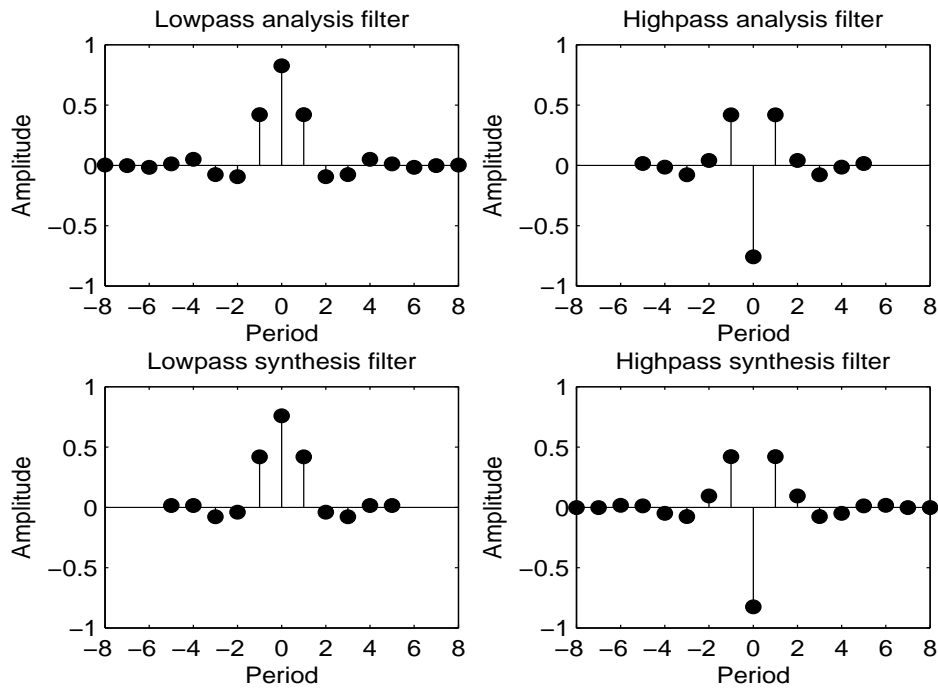


Figure 6: Impulse response of the analysis and synthesis filters in the biorthogonal 17/11 filter bank.

By the most generous definition, business cycles are cycles in real output that are of between 6 and 32 quarters in length (Baxter and King, 1999)⁸⁾. According to this generous definition, Yogo (2008) takes the 4-level wavelet decomposition as a natural way to filter an economic time series into trend (periodicity greater than 32 quarters)⁹⁾, cycle (periodicity of 4-32 quarters), and noise (periodicity less than 4 quarters).

⁸⁾ Others prominent macroeconomicists, such as Sargent (1979), prefer to confine them to a much narrower range for the business cycle frequency, corresponding to cycles of 8 to 16 quarters.

⁹⁾ We can also use 8 instead of 6 quarters. The difference is obscured in practice because these finite impulse response filters are only approximations to ideal brick wall filters.

Since the scales in wavelet filters are dyadic, we use 4 instead of 6 quarters in the definition.

To further investigate the cycles of lower than business cycle frequencies, i.e., cycles greater than 32 quarters, we use a 5-level wavelet decomposition rather than the 4-level one. An economic time series is decomposed into long-run trend (periodicity greater than 64 quarters), 8-16 year cycle, business cycles, and noise.

Figure 7 shows the frequency response of the biorthogonal wavelet filter. Frequency is in units of cycles per period, which is radian frequency normalized by 2π . Then periodicity is simply the inverse of frequency. At level 0 approximation, the wavelet filter is a low-pass filter with a stopband of approximately 64 quarters (see Eq.(10)). The level 0, 1, 2, and 3 details correspond to bandpass filters of approximately 32-64, 16-32, 8-16 and 4-8 quarters, respectively (see Eq.(11)). The level 4 detail corresponds to a high-pass filter with a stopband of approximately 4 quarters.

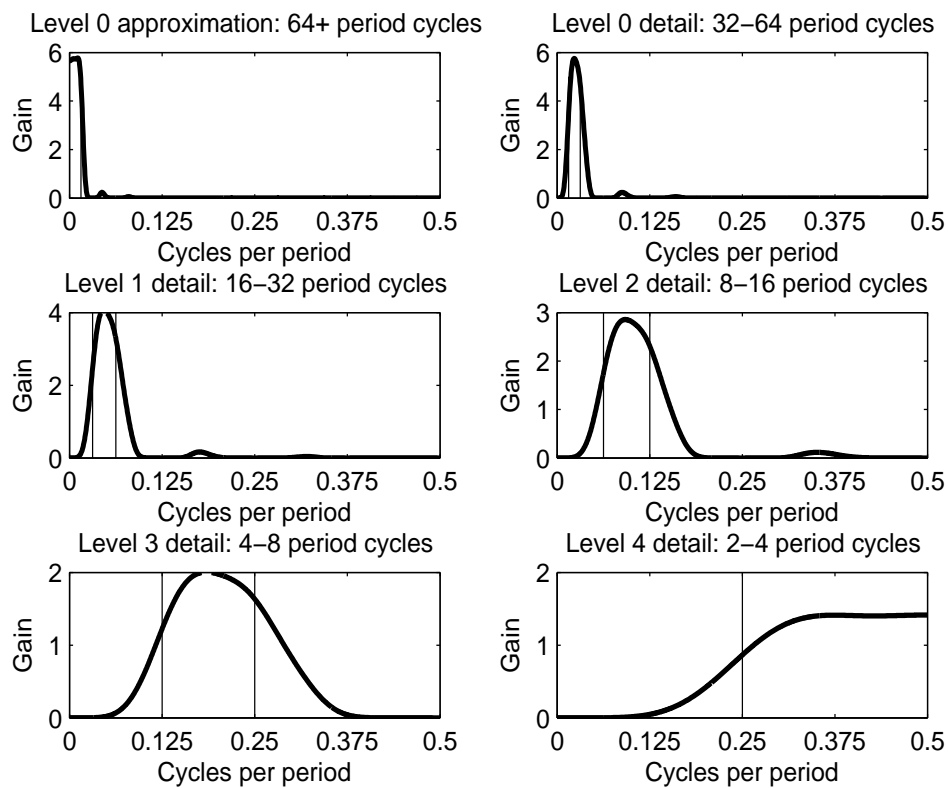


Figure 7: Frequency response of the biorthogonal 17/11 wavelet filter with 5-level.

Figure 8 plots quarterly log real GDP and its long-run trend. When calculating the long-run trend, we use the level 0 approximation of the 5-level wavelet decomposition instead of the one of the 4-level wavelet decomposition, corresponding to cycles with periodicity greater than 64 quarters.

Figure 9 shows the 5 levels of detail in the wavelet decomposition. Level 0 contains the cycles lower than business cycle frequencies, i.e., cycles corresponding to 32-64 quarters. Levels 1 through 3 contain the business cycle components of GDP. Level-4 detail, which corresponds to high frequency noise with cycles less than 4 quarters, is reported in the bottom panel.

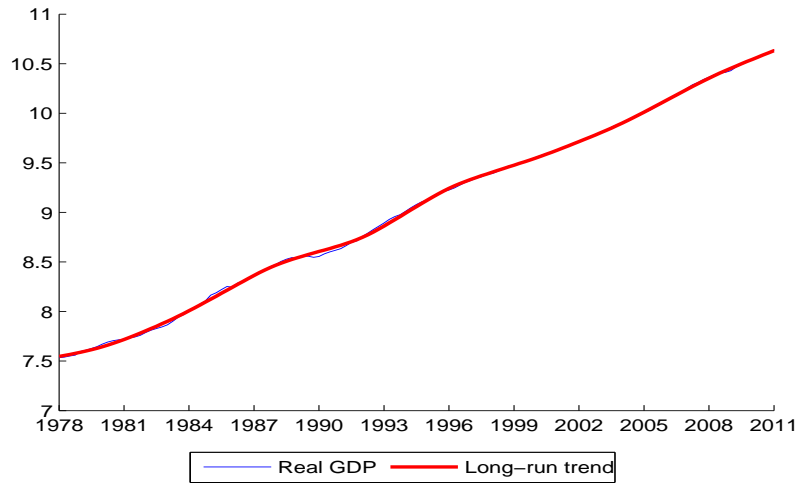


Figure 8: Log real GDP and long-run trend.

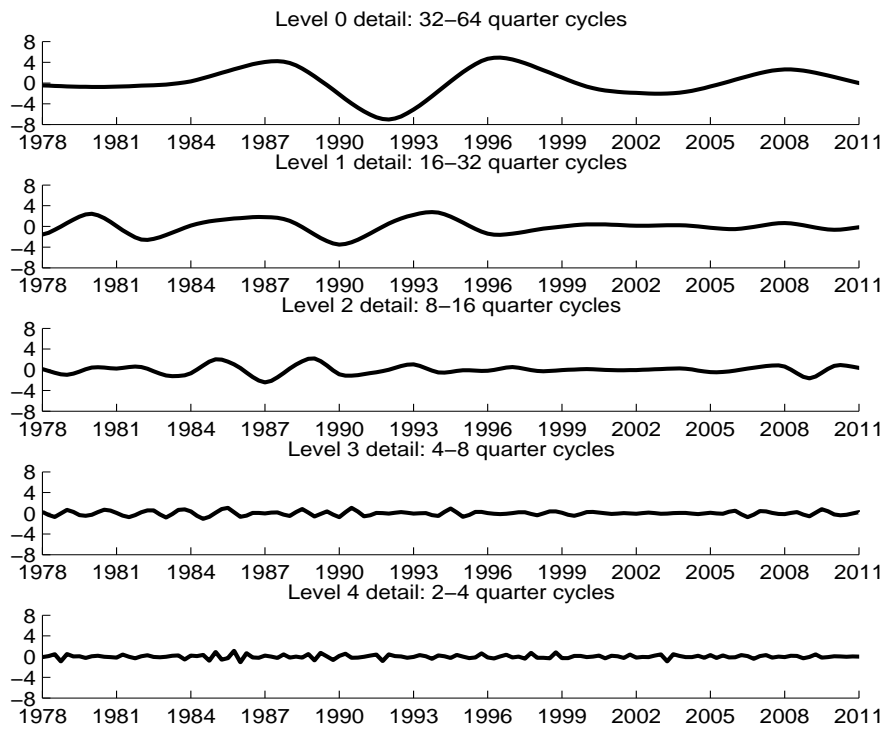


Figure 9: Cycle components of log real GDP, measured as percent deviation from the long-run trend.

The wavelet-filtered series reveals interesting changes in the volatility of the business-cycle component at various scales. Most of the volatility in the period from 1978 to mid-1980s was due to cycles of 16-32 quarters. Most of the volatility in the late 1980s was due to lower frequency cycles of 8-16 quarters. The volatility from early to mid 1990s was almost due to cycles of 16-32 and 32-64 quarters.

At the scale corresponding to 32-64 quarter cycle, the largest fluctuations occurred from the late of 1980s to the mid-1990s, with nearly 8% deviations from the long-run trend. In this period, China not only experienced some important political events such as the Tiananmen Square incident and Deng Xiaoping's "Southern Tour", but also started a series of market-oriented economic reforms in financial market, foreign exchange system, fiscal decentralization, SOEs and so on. That is to say, China was in a period of dramatic institutional change which established the fundamental conditions for the stability of macroeconomy in the following years. This is consistent with the good institution hypothesis proposed in this paper.

At the scale corresponding to business cycles (4-32 quarters), the fluctuations seem relatively large in the whole period before mid-1990 and became more benign and stable in the second half of the reform period. Natural interpretation of the changes in the business cycle frequencies is the good policy hypothesis. According to this view, lower output volatility is a result of central bankers' great emphasis on, and success at, controlling inflation. The idea holds that monetary policy may have been important in reducing output volatility to the extent that policy changes have resulted in lower and more stable inflation¹⁰). Accordingly, the level and volatility of China's inflation increase substantially till the mid-1990s, and drop and remain stable after the 1990s. This evolution of inflation suggests that the better implementation of monetary policies can have a positive effect on the moderation.

At the scale corresponding to cycle with less than 4 quarters, there is no significant change in the volatility, which is inconsistent with good practice hypothesis. While at the lower frequencies (periodicity of 4-8 quarters), we can find weak evidence for the reduction of volatility.

Taken together, the above wavelet-filtered results show that the decline in output volatility appears to be evenly distributed across frequencies, rather than concentrated at particular frequencies. This is consistent with the good luck hypothesis, which implies that the fall in volatility can be accounted for by a decline in the variance of structural disturbances hitting the economy.

These results have two important implications. Firstly, since the mid-1990s, the volatility has been relatively small at all frequencies, which is consistent with the evidence of the conditional Markov chain model. Secondly, the results do not definitely rule out any one of the four potential explanations.

4. Conclusions

In this paper, we use the conditional Markov chain model to identify the timing of China's Great Moderation and document some stylized facts about China's business cycles. First, according to the structure changes in variance, with the break date at 1995Q1, China's business cycle has change from the "Boom-bust Cycle" to the "Great Moderation". Next, according to the regime switches in the mean of growth rate, we can identify 5 recessions during 1978Q2-2011Q2, which are consistent with the process of China's economy. Focused on the recent business cycle, we also find that while Great Moderation was interrupted in 2006-2007 due to the economic overheating, it came back soon during the Global Financial Crisis. Furthermore, in the post-2009 period, China's economy appears neither overheating nor 'double dip'.

We have extended the basic ideas of Ahmed et al. (2004) to investigate the sources of China's Great Moderation. Specially, we account for the transitional features of China and propose a new hypothesis - good institutions, which is related to the supply side and plausibly generate cycles in output and productivity growth that display high persistence. The wavelet-filtered series reveal that a decline in output volatility appears to be evenly distributed across frequencies. These results lend considerable support to the potential explanations of good luck, good policy and good institution, with weaker though nontrivial evidence for the good practice hypothesis.

¹⁰) Summers (2005) summarizes several ways the low and stable inflation could contribute to more stable output growth.

However, it should be noted that, this is only a tentative exploration of the sources of the Great Moderation. The issues such as the dominant explanation and the corresponding dynamic theoretical mechanism still require more work (Huang et al., 2014, 2016; Liu et al., 2014). We leave this for a future research.

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