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The Frontiers in Economic and Management Research attempts to provide a platform for the Chinese scholars in Mainland China to communicate with their peers overseas in economic and management research. The journal aims to publish articles that have conducted quality as well as innovative research, and that investigate major issues in economic and management research, and that address major economic and management issues in the Chinese market. The journal encourages cross-fertilization of ideas among the fields of thinking and application of advanced analytical techniques in the research. It is also the journal's intention to suggest directions for future research, through the articles, to the Chinese scholars and to provide insights and readings for classroom use. The journal will make efforts to contribute to the development of economic and management research in Mainland China.

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Remarks from the Editor-in-Chief

The Frontiers in Economic and Management Research is published by the Business School of Jilin University in association with the Research Center for Quantitative Economics, Jilin University. The journal attempts to provide a platform for the Chinese scholars in Mainland China to communicate with their peers overseas in economic and management research. Quantitative analysis and methods are given priority by the editors. Independent and innovative thinking is highly encouraged. The journal will make efforts to contribute to the development of economic and management research in China.

The journal aims to publish articles that have conducted quality as well as innovative research, and that investigate major issues in economic and management research, and that address major economic and management issues in the Chinese market. The journal encourages cross-fertilization of ideas among the fields of thinking and application of advanced analytical techniques in the research. It is also the journal's intention to suggest directions for future research, through the articles, to the Chinese scholars and to provide insights and readings for class room use. The journal will ensure that the articles published here meet the international professional standards for quality of content and exposition.

Authors from home and abroad are all welcome to submit your manuscripts to the journal.

Prof. Jinquan LIU
Editor-in-Chief

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Estimating Potential Output for Mainland China

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Abstract: Measuring the Mainland output gap appropriately is essential to determine whether the economy has entered an overheating phase. However, the Mainland GDP is characterized by a sequence of structural changes and tends to fluctuate due to external or domestic shocks. Thus, the volatility and uncertainty of Mainland China's potential output are higher than in developed economies. To allow for this parameter estimation uncertainty, this paper aims at estimating Mainland potential output and the output gap based on state space models from a Bayesian perspective. Empirical analysis shows that Mainland China has experienced three expansionary periods, interrupted by several sharp but short periods of slowdown. The gradual easing of the output gap fluctuation during post-reform period demonstrates that Mainland China has successfully achieved the soft landing without causing big swings in the overall economic growth. Compared to the two severe recessions occurred to the Taiwan economy during the 2000s, Mainland China appeared to enter a period of economic upswing after year 2002. Moreover, the financial crisis of 2008 has minor impact on the Mainland economy. The Mainland output gap rebounded with a short lag behind the financial crisis and returned to levels that prevailed before 2008 while Taiwan's potential output is still at a lower level than in the 1990s.

Key Words: Potential Output; Output Gap; Kalman Filter; Bayesian Approach; Seasonal Unit Root.

1 Introduction

Potential output and the output gap are measured with large degree of uncertainty.① This has recently become a major concern in the investigation of the Mainland output gap. Since the late 1970s, the Mainland government has implemented a series of macroeconomic and structural reform policies and induced a sequence of structural changes in the behavior of real and potential GDP (see e.g., Gerlach and Peng, 2006). As a transition economy, Mainland GDP tends to fluctuate due to external

① See e.g. Cross et al. (1997), Staiger et al. (1997), Orphanides and Van Norden (2002), Ehrmann and Smets (2003).

or domestic shocks, and the volatility and the uncertainty of Mainland potential output are higher than in developed economies. Motivated by a desire to allow for this parameter estimation uncertainty, this paper aims at estimating Mainland potential output and the output gap based on state space models from a Bayesian perspective.

Very few empirical studies have been done to estimate Mainland potential output, with the exceptions of Scheibe (2003), Gerlach and Peng (2006) and Zheng et al., (2009). The frequently used tools are the HP filter and the production function approach. However, previous literature documents that the production function approach relies on an overly simplistic representation of the production technology (Cerra and Saxena, 2000) and it is inappropriate to apply the production function approach to countries with scarcity of data (see e. g., Gerlach and Peng, 2006, Maliszewski, 2010). As for the HP filter, it may suffer from its high end-sample bias and the lack of fundamental economic justification (Scheibe, 2003; Fuentes et al., 2007; Maliszewski, 2010; Proietti and Musso, 2007). Moreover, none of these papers utilize Bayesian approach to estimate potential output and the output gap.

Applying Bayesian inference to Mainland data has some advantages as compared to the classical framework, like HP filter and the production function approach. First, classical frameworks consider the unknown parameters as fixed coefficients, while Bayesian inference treats them as random variables. The posterior distribution can provide a better estimate of the parameters that are constantly subject to shocks. The second motivation is due to the results of Maliszewski (2010) and Harjes and Ricci's (2008) that a Bayesian approach provides more robust estimates for transition economies undertaking large structural changes or with possible large data measurement error. Salas (2010) also indicates that some classical methods are inappropriate when dealing with short time series. Finally, the confidence bounds associated with the estimated state variables can be obtained while these confidence bonds are very difficult if not impossible to be calculated in the production function approach.

Our data consists of Mainland GDP at yearly and quarterly frequency. Since the quarterly data is seasonally unadjusted, a seasonal unit root rather than a regular unit root is embedded in Watson's decomposition methods. Our findings can be summarized as follows. First, Mainland China has experienced three expansionary periods, interrupted by several sharp but short periods of slowdown. These dramatic turning points are linked to a stop-and-go pattern of economic liberalization and macroeconomic policies. Second, the gradual easing of the output gap fluctuation during the post-reform period demonstrates that Mainland China has successfully achieved the soft landing without causing big swings in the overall economic growth. Finally, irrespective of the data frequency, all output gaps show that China is entering a period of economic upswing after year 2002. However, the growth path is much slower than in the pre-reform period.

Since there exist strong economic and financial linkages between Mainland China and Taiwan, a comparison with Taiwan's output gap is also provided in this paper. Two interesting differences arise when the output gaps of these two economies after year 2000 are compared. First, Taiwan suffered from an abrupt decrease in investment and consumption that resulted in a negative GDP growth rate in 2001. By contrast, Mainland China appeared to enter a period of economic upswing after year 2002. Second, we find that the financial crisis of 2008 has minor impact on the Mainland economy. The Mainland output gap rebounded with a short lag after the financial crisis and returned to levels that prevailed before 2008 while Taiwan's potential output is still at a lower level than in the 1990s.

The plan of this paper is as follows. We briefly review the state space model, Watson decomposition method and the corresponding sampling algorithm in Section 2. Empirical results with Mainland China's yearly and quarterly data are reported in Section 3, while Section 4 contains conclusions.

2 Econometric Models

In this section, we provide summary of State Space models and Kalman Filters, Watson's decomposition, and the sampling algorithm of Watson's model.

2.1 A Summary of State Space Models and Kalman Filter

State space models (SSM) can be formulated in a variety of ways. One important class of SSM is given by Gaussian linear state-space models, also called dynamic linear models (DLM). The general DLM can be written as:

$$\begin{aligned} Y_t &= F_t\theta_t + v_t, v_t \sim \mathrm{NID}(0, V_t) \\ \theta_t &= G_t\theta_{t-1} + \omega_t, \omega_t \sim \mathrm{NID}(0, W_t) \end{aligned} \tag{1}$$

where $\theta_t, Y_t, v_t, \omega_t$ are the state variables, observed variables, measurement error terms, and disturbance terms, respectively. F_t and G_t are known matrices and could be time-varying or time-invariant. The state variables θ_t is assumed to follow Gaussian distribution and θ_0 has initial prior

$$\theta_0 \mid D_0 \sim N(m_0, C_0) \tag{2}$$

Let D_{t-1} denotes the information provided by past observations $Y_1, \dots, Y_{t-1}$ and $e_t = Y_t - F_t a_t$ is the forecast error where a_t is the conditional expectation of θ_t as defined below. For estimating the state variables we need to compute the conditional densities $p(\theta_s \mid D_t)$. When $s = t$, the Kalman Filter recursion is applied to compute the conditional densities, $p(\theta_t \mid D_t)$. If

$$\theta_{t-1} \mid D_{t-1} \sim N(m_{t-1}, C_{t-1}) \tag{3}$$

then the Kalman Filter for model (1) is

$$\begin{aligned}
a_t &= E(\theta_t \mid D_{t-1}) = G_t m_{t-1} \\
R_t &= \mathrm{Var}(\theta_t \mid D_{t-1}) = G_t C_{t-1} G'_t + W_t \\
f_t &= E(Y_t \mid D_{t-1}) = F_t a_t \\
Q_t &= \mathrm{Var}(Y_t \mid D_{t-1}) = F_t R_t F'_t + V_t \\
m_t &= E(\theta_t \mid D_t) = a_t + R_t F'_t Q_t^{-1} e_t \\
C_t &= \mathrm{Var}(\theta_t \mid D_t) = R_t - R_t F'_t Q_t^{-1} F_t R_t
\end{aligned} \tag{4}$$

When $s < t$, the concept of smoothing is applied. If

$$\theta_t \mid D_T \sim N(m_T, C_T) \tag{5}$$

then the smoothing recursion for model (1) is

$$\begin{aligned}
h_t &= E(\theta_t \mid \theta_{t+1} D_t) = m_t + C_t G'_{t+1} R_{t+1}^{-1} (\theta_{t+1} - a_{t+1}) \\
H_t &= \mathrm{Var}(\theta_t \mid \theta_{t+1}, D_t) = C_t - C_t G'_{t+1} R_{t+1}^{-1} G_{t+1} C_t, \quad t = T-1, \ldots, 0
\end{aligned} \tag{6}$$

Excellent exposition of DLM can be found in West and Harrison (1997), Koopman and Ooms (2006) and Petris, Petrone and Campagnoli (2009).

2.2 Watson's Decomposition

Watson (1986) decomposed observed GDP as the sum of potential GDP and output gap and the model is listed below.

$$y_t = y_t^p + z_t \tag{7}$$

$$y_t^p = y_{t-1}^p + \mu_y + e_{yt}, e_{yt} \sim \mathrm{NID}(0, \sigma_y^2) \tag{8}$$

$$z_t = \phi_1 z_{t-1} + \phi_2 z_{t-2} + e_{zt}, e_{zt} \sim \mathrm{NID}(0, \sigma_z^2) \tag{9}$$

where y_t is observed output, and y_t^p denotes potential GDP.

It is worth noting that different dynamic behavior plays the central role for the decomposition. Potential GDP follows a random walk with drift which governs the long term behavior of y_t whereas output gap determines the short-run behavior. In order for the model to be identifiable, y_t^p cannot have short run dynamics. For seasonally adjusted data or yearly data, y_t has a unit root and so does y_t^p .

However, we frequently observe seasonal unit root rather than regular unit root for seasonally unadjusted series. Since the Mainland GDP available at quarterly frequency is seasonally unadjusted, the potential GDP should be respecified accordingly. According to Lin and Chen (2013), we adapt Eq. (8) by switching from regular unit root to seasonal unit root. This means that Eq. (8) is replaced by:

$$y_t^p = \alpha + y_{t-4}^p + e_{yt}, e_{yt} \sim \mathrm{NID}(0, \sigma_y^2) \tag{10}$$

The corresponding SSM are

$$y_t = [1\quad 0\quad 0\quad 0\quad 1\quad 0\quad 0]\begin{bmatrix} y_t^p \\ y_{t-1}^p \\ y_{t-2}^p \\ y_{t-3}^p \\ z_t \\ z_{t-1} \\ \alpha_t \end{bmatrix} \tag{11}$$

$$\begin{bmatrix} y_t^p \\ y_{t-1}^p \\ y_{t-2}^p \\ y_{t-3}^p \\ z_t \\ z_{t-1} \\ \alpha_t \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \phi_1 & \phi_2 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} y_{t-1}^p \\ y_{t-2}^p \\ y_{t-3}^p \\ y_{t-4}^p \\ z_{t-1} \\ z_{t-2} \\ \alpha_{t-1} \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} e_{pt} \\ e_{zt} \end{bmatrix} \tag{12}$$

and the resulting DLM are

$$G = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \phi_1 & \phi_2 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}, W = \begin{bmatrix} \sigma_p^2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_z^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$F = [1\quad 0\quad 0\quad 0\quad 1\quad 0\quad 0], V = [0]$$

2.3 Sampling Algorithms for Watson's Models

In Watson's model, we can partition unknown parameters ψ as follows: $\psi = (\psi_1, \psi_2)$, where $\psi_1 = (\phi_1, \phi_2)$, and $\psi_2 = ((\sigma_y^2)^{-1})$, $((\sigma_z^2)^{-1})$. Applying the ideas of conjugate prior, we assume the hyperparameters for the precisions are gamma priors with mean a and variance b. Since the output gap in Watson's mode is an AR(2) process, ϕ_1 and ϕ_2 must lie in the stationarity constraint defined by

$$\phi_1 + \phi_2 < 1, \phi_1 + \phi_2 > -1, |\phi_2| < 1. \tag{13}$$

In this way, the posterior $p(\phi_1, \phi_2 \mid \sigma_y^2, \sigma_z^2, y_{0:T})$ is not a standard distribution but we can apply adaptive rejection Metropolis sampling (ARMS) to draw from their joint full conditional distribution. The detailed algorithms are summarized in Algorithm1.

Algorithm 1 Algorithm for Watson's model (for quarterly data)

1: Set up the **DLM** model by Eq. (11) and (12).

2: Initialize: set unknown parameters $\psi_2 = (\sigma_y^{2(0)}, \sigma_z^{2(0)})$.

3: **for** $i = 1 : N$ **do**

4: Draw $\phi_1^{(i)}, \phi_2^{(i)}$ simultaneously from $p(\phi_1, \phi_2 \mid y_{0:T}, \psi_2 = \psi_2^{(i-1)})$ by the Metropolis Hastings algorithm.

5: Draw $\theta_{0:T}^{(i)}$ from $p(\theta_{0:T} \mid y_{1:T}, \psi_1 = \psi_1^{(i)}, \psi_2 = \psi_2^{(i-1)})$ using Forward Filtering Backward Sampling Algorithm (**FFBS**).

6: Draw $(\sigma_y^2)^{-1}$ and $(\sigma_z^2)^{-1}$ from the following posterior densities

$$(\sigma_y^2)^{-1} \mid \cdots \sim G\left(\frac{T}{2} + \frac{a_y^2}{b_y}, \frac{a_y}{b_y} + \frac{1}{2}\sum_{t=1}^{T}(\theta_{t,1} - (G_t\theta_{t-1})_1)^2\right)$$

and

$$(\sigma_z^2)^{-1} \mid \cdots \sim G\left(\frac{T}{2} + \frac{a_z^2}{b_z}, \frac{a_z}{b_z} + \frac{1}{2}\sum_{t=1}^{T}(\theta_{t,5} - (G_t\theta_{t-1})_5)^2\right)$$

respectively.

7: **end for**

8: After M times "burning-in" iterations, compute the ergodic average of states and parameters.

For more details, see Chen and Lin (2012) or Chen (2011).

3 Empirical Results

All data are mainly taken from AREMOS database and the Taiwan Economic Journal (TEJ). The Mainland GDP on a yearly basis is ranging between 1978 to 2009. The Mainland GDP on a quarterly basis is seasonally unadjusted and available since 1991:04. Thus, the quarterly Mainland GDP is spanning from 1992:1 to 2010:2, while the data set for the Taiwan economy is quarterly ranging between 1982:1 to 2010:2 (Table 1).

Table 1 Empirical Results of Watson's Model

Parameter	Mainland China		Taiwan
	Yearly Data 1978-2009	Quarterly Data 1992Q1-2009Q2	Quarterly Data 1982Q1-2009Q2
α	0.1024	0.1062	0.0561
	(0.0022)	(0.0045)	(0.0006)
ϕ_1	0.5330	0.2574	0.5143
	(0.0139)	(0.0200)	(0.0089)

Continued

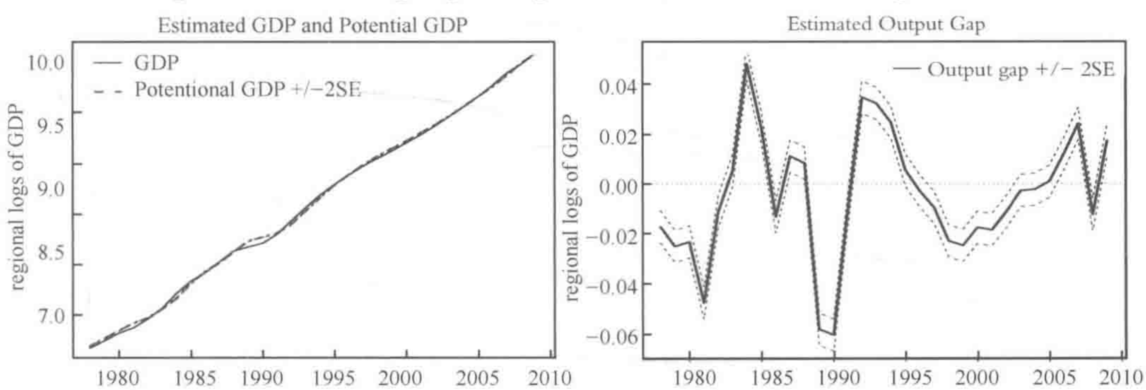
Parameter	Mainland China		Taiwan
	Yearly Data 1978-2009	Quarterly Data 1992Q1-2009Q2	Quarterly Data 1982Q1-2009Q2
ϕ_2	−0.0958 (0.0055)	0.3939 (0.0200)	0.4744 (0.0088)
σ_y	0.0020 (0.0004)	0.0797 (0.0075)	0.0063 (0.0015)
σ_z	0.0328 (0.0027)	0.0729 (0.0062)	0.1360 (0.0080)

Note: The number in each cell reports, in parentheses, the standard errors of parameter estimates

3.1 Output Gap Estimated at a Yearly Frequency

We first investigate the output gap derived from yearly data. Table 1 summarizes parameter posterior means for Watson's model and Figure 1 displays the evolution of the estimated potential output and output gap (posterior mean).[①] Considering the parameter uncertainty, we calculate 95% confidence bounds around the potential output and the output gap.

Figure 1 shows that Mainland China has experienced three expansionary periods, interrupted by several sharp but short-lived periods of slowdown. The dramatic turning points of business cycles are related to the structural changes of market liberalization and macroeconomic policies. The stop-and-go pattern has become a characteristic of the Mainland China's post-1978 economy. What is remarkable in the post-reform period is the gradual easing of the cyclical fluctuation. During 1994 to 1996, the Mainland government implemented a series of measure to cool down the overheated economy. The evolution of the output gap demonstrates that Mainland China has successfully achieved the soft landing without causing big swings in the overall economic growth.



(a) Yearly GDP and Potential GDP (b) Output GDP

① To conserve space we do not report the diagnostic plots in this section, but they are available from the authors upon request.

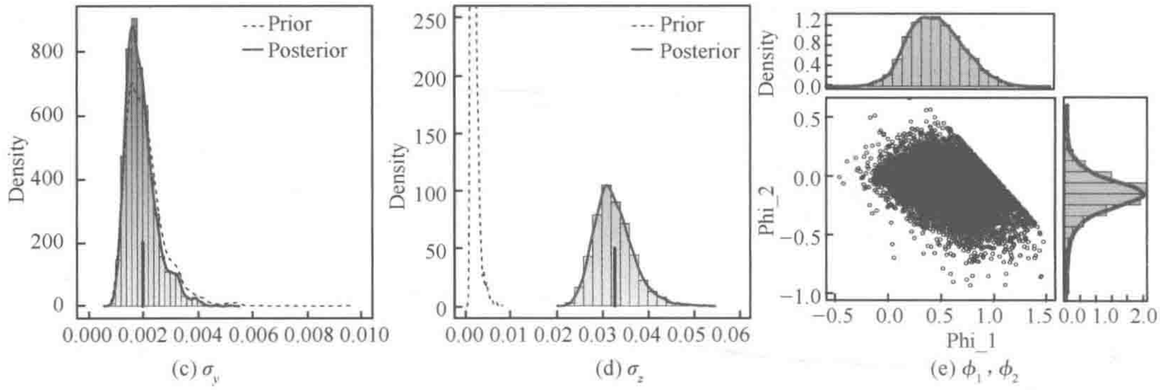


Figure 1 Estimating Results of Watson's Model with Yearly Data

Panels (c) and (d) of Figure 1 help show that the posterior distribution is a compromise between the initial prior belief and the information in the data. The actual number of posterior mean is shown by a vertical line. The dashed and solid lines show respectively the prior and posterior distribution, which are substantially different in location. These summaries demonstrate that the initial prior brief has only a modest effect on the posterior shrinkage. In other words, our sampling algorithms appear to be robust to the change in prior specification. Moreover, the bivariate scatterplots of ϕ_1 and ϕ_2, together with their corresponding marginal histograms are put in Panels (e). Panels (e) shows that there is a dependence between ϕ_1 and ϕ_2. This confirms that drawing these pairs of parameters simultaneously is essential in improving the mixing of the chain.

3.2 Output Gap Estimated at a Quarterly Frequency

We then proceed with investigating the estimated output gap at a quarterly frequency. From Table 1 and Panel A of Figure 2, we make the following observations. First, when seasonal unit root is explicitly considered, the estimates of the quarterly output gap exhibit no seasonal fluctuation and the evolution of the output gap are generally in accordance with the yearly output gap.① Thus, one can estimate Mainland output gap directly with seasonally unadjusted data without employing any traditional seasonal adjustment methods. Second, the quarterly output gap presents more variability than yearly data. For example, the posterior mean of quarterly σ_2 is doubled compared with the σ_2 derived from yearly data. Finally, no matter the data frequency, all output gaps show that Mainland China is entering a period of economic upswing after

① Unreported results show that the unit root specification transfers the strong seasonality from observed data to output gap and cannot yield sensible estimates. These results confirm the basic findings of Lin and Chen (2013). We do not report these to conserve space.

year 2002. However, the growth path is much slower than in the pre-reform period.

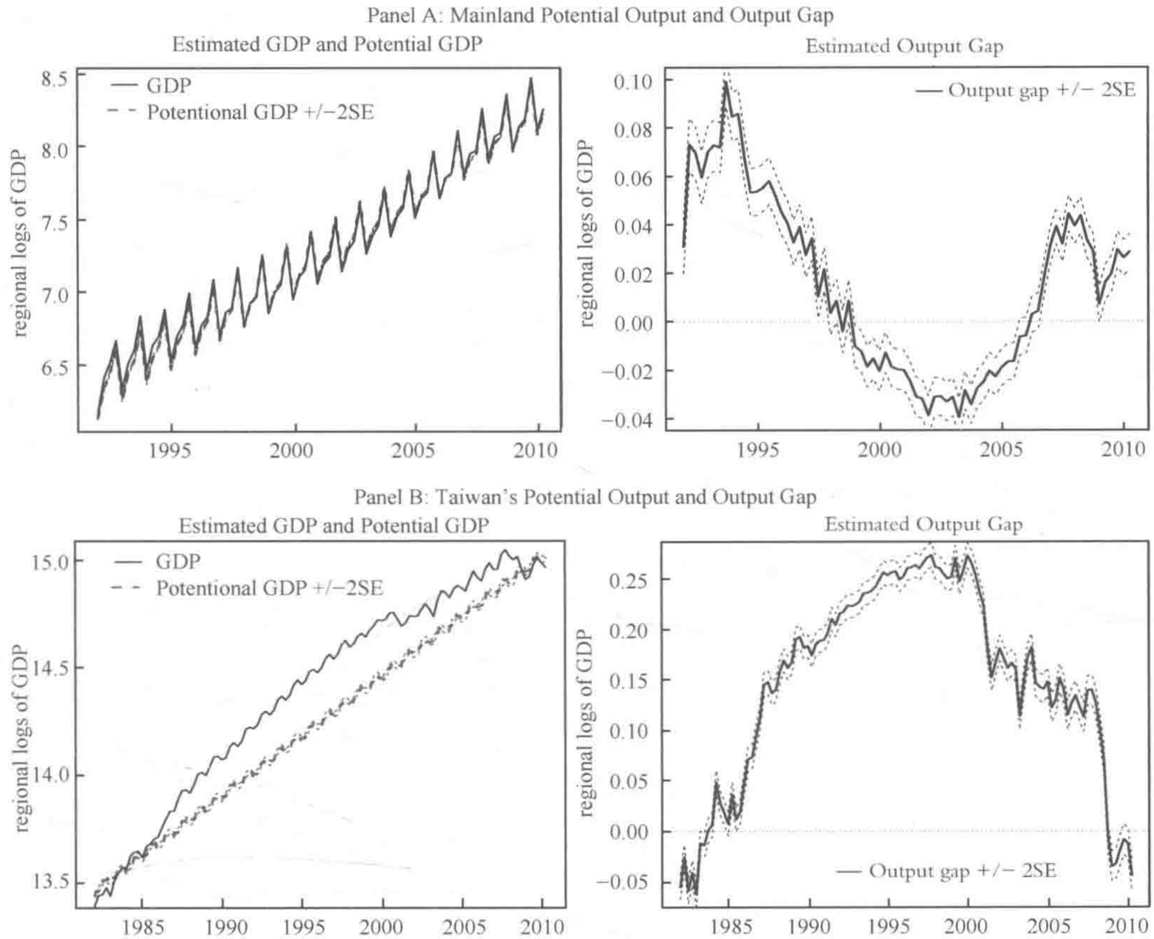


Figure 2 Watson's Model with Quarterly Data

We believe, however, caution should be taken when explaining the negative output gap of Mainland China. In Watson's decomposition method, the potential output is defined as the trend component of GDP. Deviations of actual output from potential output lead to output gaps. As a rapidly developing economy, Mainland China's annual growth rate of real GDP is 10% on average but is not expected to maintain such high real growth rate forever. Also, the government may take strong measures to cool down the overheated economy at some stages. The negative output gap since the early 2000s, for example, is resulted from the lower growth rate of GDP compared to the boom years in the late 1990s. Thus, a negative output gap should not be explained as a recession.

3.3 A Comparison with the Taiwan's Output Gap

Since there exist strong economic and financial linkages between Mainland China and Taiwan, a comparison with the Taiwan's output gap is provided in this section. The estimation results of Taiwan data are added in the last column of Table 1 and Panel B of Figure 2. Figure 2 shows that Taiwan and Mainland China have experienced a progressive strengthening of economic growth and sustained a growth rate in GDP above 7 percent in the early 1990s. However, the evolution of Both Sides output gaps are quite different in the period after year 2000.

Two interesting differences arise when we compare the output gaps of these two economies after year 2000. First, Taiwan was characterized by two sharp decreases in GDP during 2000s and encountered her first negative GDP growth rate in 2001. The recession in Taiwan was associated with relatively low growth rate in private consumption and gross investment. Especially for gross investment, its yearly growth rate is −26.83% and it slows down for subsequent years. By contrast, Mainland China's yearly growth rate in consumption and investment are on average 11.72% and 18.72% respectively during 2000s. Meanwhile, a remarkable increases in the scale of foreign investment from Taiwan occurred in 2002, The actual utilized foreign capital by Taiwan grew 400% higher than in the previous year. Moreover, this rapid growth of foreign investment from Taiwan sustained a strong momentum in subsequent years.

Second, we find that the financial crisis of 2008 has minor impact on the Mainland economy. Although Mainland China accounts for a large proportion of the entire world's exports, the contribution of exports to GDP is merely 3%. Thus, the export slump will not doom Mainland China's economy. Panel A of Figure 2 demonstrates that the output gap rebounded with a short lag behind the financial crisis and returned to levels that prevailed before 2008. On the contrary, Taiwan's exports contribute more than domestic demand to it's economic growth. The contribution of exports to real GDP is over 10%. Since Taiwan is a leading exporter of high-technology and electronic components, the financial crisis resulted in a more severe recession. Although Taiwan's GDP has gradually recovered in the late 2009, the potential output is still at a lower level than in the 1990s without taking advantage of a domestic driver.

4 Conclusions

This paper aims at estimating Mainland potential output and the output gap based on state space models from a Bayesian perspective. Our data consists of Mainland GDP at yearly and quarterly frequency. Since the quarterly data is seasonally unadjusted, a seasonal unit root rather than a regular unit root is embedded in Watson's decomposition methods. Empirical results show that Mainland China has experienced three expansionary periods, interrupted by several sharp but short periods of slowdown. The gradual easing of the output gap fluctuation during post-reform period demonstrates that Mainland China has successfully achieved the soft landing without causing big swings in the overall economic growth.

Since there exist strong economic and financial linkages between Mainland China and Taiwan, a comparison with the Taiwan's output gap is also provided in this paper. Two interesting differences arise when compares the Mainland output gap with the Taiwanis output gap after year 2000. Mainland China appeared to enter a period of economic upswing after year 2002 while Taiwan sill suffered from a prolonged decrease in investment and consumption. We also find that the financial crisis of 2008 has minor impact on the Mainland Economy. The Mainland output gap rebounded with a short lag behind the financial crisis and returned to levels that prevailed before 2008 while Taiwan's potential output is still at a lower level than in the 1990s.

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