Output Gap Estimation and Monetary Policy in China
Chengsi Zhang, Butan Zhang, Zhe Lu, and Yasutomo Murasawa

ABSTRACT: Using the Bayesian multivariate Beveridge–Nelson decomposition method, this paper estimates China’s output gap based on a multivariate dynamic model featuring distinct interactions among real output, inflation, money, and the exchange rate in China during the period 1980–2010. The authors compare the statistical nature and potential forecasting effects of the resulting multivariate gap measure on monetary policy with those of the output gap measures based on univariate models. The empirical results show that only the measure based on the multivariate system significantly predicts monetary policy, which indicates that the output gap estimated by the multivariate system contains more information than the traditional measures for macroeconomic policy adjustments do.

KEY WORDS: Bayesian estimator, monetary policy, output gap.

The output gap, that is, the difference between actual and potential (or natural) output, plays a vital role in the monetary transmission mechanism (Gerlach and Smets 1999). Although recent developments in the new Keynesian theory of business cycles have provided a precise definition of the output gap as the deviation of output from its equilibrium level, or the natural rate, in the absence of nominal rigidities, there remains considerable debate over the estimation of the natural rate and hence the output gap. In the new neoclassical synthesis literature, the natural rate is the equilibrium rate under flexible prices, and the gap is the difference between the actual and natural rates caused by price (wage) rigidity. Alternatively, one may define the natural rate as the time-varying steady-state equilibrium rate. Then the natural rate is the permanent (trend) component, and the gap is the transitory (cycle) component. Simple detrending methods used in empirical macroeconomics, for example the filter of Hodrick and Prescott (1997) (hereafter “the Hodrick–Prescott filter”), approximate one of these decompositions.

Measuring deviation cycles requires estimations of the natural rate and the gap, on which a sizeable amount of literature exists. The history of the literature may be traced back to Mitchell (1927) and Burns and Mitchell (1946), who focused on the deviations from a full-employment level of output. Basistha and Nelson (2007) categorize the ensuing literature into two groups, statistical and economic. The statistical approach either imposes smoothness on one of two components, the trend or the cycle of the underlying variable (e.g., the Hodrick–Prescott filter), or does not directly impose prior smoothness on either component but “lets the data speak for itself” through a time series model (e.g., the Beveridge–Nelson decomposition method; hereafter the Beveridge–Nelson decomposition method).
method”). For example, Apel and Jansson (1999), Basistha and Startz (2008), and King and Morley (2007) estimate the natural rates of output and unemployment jointly. Garnier and Wilhelmsen (2009) and Laubach and Williams (2003) estimate the natural rates of output and interest jointly, while Berger (2011) estimates the natural rates of output, inflation, and unemployment jointly.

This paper focuses on China’s data and has two notable features compared to the previous works in the output gap measurement literature. First, we note that the variables jointly studied in the existing research of the Beveridge–Nelson method cannot sufficiently capture the typical nature of Chinese macroeconomic dynamics, as we will discuss in the following section. Therefore, we construct a multivariate dynamic model featuring distinct interactions among real output, inflation, money, and effective exchange rate. Using this multivariate model, we estimate the gap of output for China (with reliable error bands). Most previous works estimate a particular natural rate, for example potential output, core inflation, or the nonaccelerating inflation rate of unemployment (NAIRU), although they may use information provided by other variables. Second, we apply the multivariate Beveridge–Nelson decomposition method using a vector autoregression (VAR) model, instead of assuming an unobserved components (UC) model and estimating the components using the Kalman filter. The procedure of using the VAR to obtain the long-run forecast used in Beveridge–Nelson decomposition is proposed in Stock and Watson (1988) and elaborated in Morley (2002). Because prices and quantities adjust eventually, the Beveridge–Nelson decomposition produces the statistical counterparts of the natural rate and the gap with fewer restrictions than the Kalman filter.1

In this study, we obtained the multivariate model-based output gap and compared its information content’s ability to predict monetary policy movements with traditional output gap measures for China, using quarterly data spanning the years 1980–2010. The comparisons of alternative output gap measures’ power to predict monetary policy were accomplished by performing standard Granger causality tests based on a stationary VAR model, which is consistent with the multivariate model in our output gap estimations.

Data and Stylized Facts

The raw data involved in our baseline empirical work spans the first quarter of 1980 to the third quarter of 2010 (i.e., 1980Q1–2010Q3), which corresponds to the postreform era of the Chinese economy. Because the gap measures are estimated in a multivariate dynamic model, which features the basic interactions among the real economy, inflation, monetary policy, and exchange rate policy in China, the empirical estimations involve series for real gross domestic product (GDP), inflation, monetary aggregate (M2), and the nominal effective exchange rate (NEER) of the renminbi (RMB).

To facilitate comparisons with the literature, we measure inflation by using the year-on-year growth rate of the consumer price index (CPI). The data are obtained from the China Monthly Economic Index of the National Bureau of Statistics (NBS), with the last month’s observation of each quarter used as the corresponding quarterly observation. Quarterly data for M2 and the nominal effective exchange rate over the underlying sample is obtained from International Financial Statistics. In addition, quarterly data for real GDP are calculated by using the level of nominal GDP and the growth rate of real GDP published by China’s NBS for the period 1992–2010 (with 1997 as the base year). The real GDP data of quarterly frequency prior to 1992 are not available but are obtained by using the method of Abeysinghe and Rajaguru (2004).
Note that Abeysinghe and Rajaguru’s (2004) methodology is effectively the Chow–Lin estimation method in the spirit of Chow and Lin (1971). The basic idea is to find the GDP-related quarterly series and derive a forecasting equation by running a regression of annual GDP on year-related series. Quarterly figures of the related series are used to forecast the quarterly GDP series, which are then adjusted to match the annual aggregates. The estimated quarterly real GDP series based on this method seem to match the officially published annual data quite convincingly.

To provide further illustration, Figure 1 plots year-on-year growth rates (i.e., $100 \times [\ln(X_t) - \ln(X_{t-1})]$) of the CPI, real GDP, M2, and NEER in the period 1980Q1–2010Q3. This figure shows that inflation in China was relatively low in the early 1980s, but trended upward in the late 1980s and mid-1990s, before dropping sharply by the late 1990s and remaining relatively low and stable ever since (with three other notable peaks around 2005, 2008, and 2010). The profound variations in the inflation process not only reflect the evolution of price adjustment and liberalization in China since the early 1980s, as documented in Zhang (2011), but also indicate dynamic interactions among real output, inflation, and macroeconomic policy.

For example, the early stage of price adjustment in China commenced in 1979 and was spurred by the government policy of adjusting, reforming, revitalizing, and improving the national economy. Through this policy guideline, the central government of China intended to promote real economic development, particularly the development of the agricultural and industrial sectors. To achieve this goal, the central government decided to liberalize prices, which had previously been set by government agencies. The purchase price of major agricultural products increased first, followed by the prices of industrial products. These adjustments drove overall inflation, as measured by the CPI, to jump from 1.9 percent in 1979 to 7.5 percent in 1980.

In conjunction with this growing inflation, the growth rate of real output in the early 1980s was also accelerating. Figure 1 shows that the year-on-year growth rate of real GDP in China reached 7.5 percent in 1980, grew to over 8.0 percent in late 1980, and was accompanied by an astonishing rate of growth in monetary supply. The central government responded to these high rates of growth in prices and the real economy by using credit controls to suppress the drastic growth in investments (especially infrastructure investment). This dampened both inflation and real economic growth by early 1981.

![Figure 1. China’s CPI inflation and growth rates of real GDP, M2, and exchange rate: 1980Q1–2010Q3](image-url)
Countercyclical macro policies, however, were not implemented in a timely and effective manner. Despite a transitory drop in 1982, growth rates of both M2 and domestic credit in China exhibited an upward trend in late 1982, with unprecedented levels of the growth rates reaching 40 percent in 1985 and nearly 50 percent in 1986. As a result, there was evidence of overheating, with inflation peaking in 1985 and 1986. The tightening of money and credit in 1986 dampened inflation, but it was effective for only a very short period of time. Because of further liberalization and the deregulation of prices in 1987, inflation rebounded to a high of 25 percent in 1988. In response to such extraordinary inflation rates, the central government tightened money and the credit supply and substantially reduced fixed investments. The tighter monetary policy conditions toward the end of the 1980s successfully curbed inflation.

Although the tightening of macro policy in the late 1980s had the effect of cooling down inflation (and economic growth), it proved to be too constricting. Because of the strict credit control in 1988 and 1989, the industrial sector witnessed a substantial reduction in its output in the ensuing three years, which consequently caused a serious problem of scarce liquidity among enterprises in China. As a result, both economic growth and inflation declined to a relatively low level (below 5 percent) in 1991.

In the early 1990s, however, agricultural prices were adjusted upward to market levels and price controls were eliminated in the industrial and retail sectors. In the meantime, the central government encouraged investment by aggressively loosening credit controls, causing the supply to grow at over 50 percent. This proactive policy led inflation to increase in 1992 and peak in 1994 (as attested to in Figure 1). Following the implementation of a number of tightening measures in 1994, inflation started to decelerate in 1995 and continued to decline until the late 1990s.

China experienced mild deflation in 1998–2000, and has had relatively low and stable inflation since then. The exchange rate and the growth rate of real GDP manifest a similar pattern, with far less variation over the past decade. It is worth noting, however, that as measured by the CPI, Chinese inflation in mid-2004, late 2008, and late 2010 reached local peaks because of investment booms (in particular, the boom in the real estate market), RMB appreciations, and accommodative monetary policies (e.g., the RMB4 trillion stimulus package in 2008–9). These interactions among the real economy, inflation, monetary policy, and exchange rate policy feature multivariate dynamic links among the underlying variables and motivate us to estimate output gap by constructing a multivariate model that captures these links.²

The Multivariate Dynamic Model and the Output Gap Estimates

The Multivariate Dynamic Model

The construction of the multivariate dynamic model was based on the traditional new Keynesian policy analysis framework, which highlights an IS (investment and saving) equation, a Phillips curve equation, and a policy reaction function, as in the papers by Clarida et al. (1999), Stock and Watson (2002), and Woodford (2003), among many other important studies. Although this policy analysis framework is general and appears to work well in the United States (and many other developed countries), there is a notable distinction between the United States and China in terms of monetary policy tools. In China, monetary aggregates, rather than interest rates, have been used as a monetary policy tool since the early 1980s. Although the People’s Bank of China (PBOC) has recently
promoted the development of market-based interest rates (e.g., the Shanghai interbank offered rate launched by the PBOC in January 2007) as policy instruments, quantity-based monetary instruments remain the main instruments of the PBOC, as explicitly stated in its quarterly Monetary Policy Report (The People’s Bank of China 2012). Therefore, our model reflects the distinctive features of interactions among China’s real GDP, inflation, money (M2), and exchange rate.

The use of monetary growth as China’s monetary policy tool also mimics the underlying theory of a monetary policy reaction function (e.g., the Taylor rule), which posits that monetary policy tools react to changes in real economic activity (e.g., real GDP gap) and the inflation rate. Indeed, the important feature of the PBOC’s monetary policy reaction function is that the PBOC looks at real economic performance (instead of interest rates) to adjust its broad money supply mechanism, in accordance with the Law of the People’s Republic of China on the People’s Bank of China enacted in 1995.

To facilitate notation, we use $y_t$ to denote an $N$-variate I(1) sequence such that for all $t$, $E(Dyt) = \mu$. In our case $N = 4$ and $y_t$ is the vector of real GDP, inflation, M2, and the nominal effective exchange rate of RMB (all variables are in natural logarithm, except for inflation). The gap measures for the underlying four variables are obtained by applying Beveridge and Nelson’s (1981) decomposition method to the multivariate model. By construction, the vector $y_t$ (with sample size $T$) can be decomposed into a permanent component $y_t^*$ and a transitory component $c_t$ (i.e., gaps), where

$$y_t^* = \lim_{T \to \infty} E_t (y_{t+T} - T\mu) = \lim_{T \to \infty} E_t \left( y_t + \sum_{s=1}^{T} (\Delta y_{t+s} - \mu) \right) = y_t + \sum_{s=1}^{\infty} E_t (\Delta y_{t+s} - \mu)$$

(1) and

$$c_t = -\sum_{s=1}^{\infty} E_t (\Delta y_{t+s} - \mu).$$

(2)

Note that the permanent component $y_t^*$ represents a slowly evolving mean growth rate and the transitory component $c_t$ is a stationary cyclical element embedded in the underlying vector $y_t$.

To estimate $c_t$, in Equation (2), we need to rewrite the right-hand side of the equation in an estimatable form by employing an unrestricted vector autoregression (VAR) model and a state-space form. That is, we first specify a VAR model for $\Delta y_t$ as

$$\Phi(L)(\Delta y_t - \mu) = w_t,$$

(3)

where $\Phi(L)$ denotes a vector lag polynomial, and the disturbance $w_t$ is Gaussian white noise (i.e., $w_t \sim \text{IN}(0, \Sigma)$).

Next, for all $t$, let

$$s_t = \begin{bmatrix} \Delta y_t - \mu \\ \vdots \\ \Delta y_{t-p+1} - \mu \end{bmatrix},$$

(4)

We then have a standard linear state-space model for $\Delta y_t$ such that for all $t$,

$$\begin{cases} s_t = As_{t-1} + Bz_t \\ \Delta y_t = \mu + Cs_t, \end{cases}$$

(5)
where $z_t \sim IN(0, I_n)$. Comparing Equations (3) and (5), we derive the coefficient matrices of $A$, $B$, and $C$ as follows:

$$A = \begin{bmatrix} \Phi_1 & \Phi_p \\ I_{(p-1)N} & O_{(p-1)N \times N} \end{bmatrix}$$

$$B = \begin{bmatrix} \Sigma^{1/2} \\ O_{(p-1)N \times N} \end{bmatrix}$$

$$C = \begin{bmatrix} I_N & O_{(p-1)N \times N} \end{bmatrix}.$$  \hspace{1cm} (6)

We assume that the eigenvalues of $A$ are all less than 1. Then for all $t$,

$$c_t = -C(I_{pN} - A)^{-1} A \Delta y_{t-1} + W_p (\Delta y_{t-p+1} - \mu),$$  \hspace{1cm} (7)

where $[W_1, ..., W_p] = -C(I_{pN} - A)^{-1} A$.

Note that for Equation (7), the eigenvalues of $A$ are less than 1 if $\{s_t\}$ is I(0). This guarantees that $\Sigma^t A^t$ converges and equals $(I_{pN} - A)^{-1} A$. By definition (as in Equation (4)), $\{s_t\}$ is the first difference of the I(1) series, so that $\{s_t\}$ is indeed I(0).4

**The Estimation Method and the Results**

Now we consider the estimation of the model parameters by using the Gibbs sampling method. The Gibbs sampling approach is essentially an algorithm to generate a sequence of samples from the joint probability distribution of the underlying random variables. The algorithm generates an instance from the distribution of each variable in turn, conditional on the current values of the other variables. The sequence of samples constitutes a Markov chain and thereby the Gibbs sampling method is also an example of a Markov chain Monte Carlo algorithm.

Prior to the application of the Gibbs sampling method, we need to rewrite the VAR Model (3) into a normal linear form. For simplicity we can assume that $\mu = 0$ (e.g., by demeaning the data) and rewrite Equation (3) as $\Phi(L) \Delta y_t = w_t$. Let $\Pi = [\Phi_1, ..., \Phi_p]$. Then for $t = p + 1, ..., T$, $\Delta y_t = \Pi s_{t-1} + w_t$. Also let

$$Y = \begin{bmatrix} \Delta y'_{p+1} \\ \Delta y'_{T} \end{bmatrix}, \quad X = \begin{bmatrix} s'_{p} \\ \Pi s'_{T-1} \end{bmatrix}, \quad U = \begin{bmatrix} w'_{p+1} \\ w'_{T} \end{bmatrix},$$  \hspace{1cm} (8)

and let $y = \text{vec}(Y)$, $\pi = \text{vec}(\Pi)$, $u = \text{vec}(U)$ ($\text{vec}$ denotes vector operator). Then we have

$$y = (I_N \otimes X) \pi + u, \quad u \sim N(0, \Sigma \otimes I_T).$$  \hspace{1cm} (9)

Based on the setup of Equation (9), the Gibbs sampling simulates $p(\pi, \Sigma | y, X)$ by drawing from $p(\pi | \Sigma, y, X)$ and $p(\Sigma | \pi, y, X)$ sequentially. By Bayes’s theorem,

$$p(\pi | \Sigma, y, X) \propto p(y, X | \pi, \Sigma) p(\pi | \Sigma)$$

$$p(\Sigma | \pi, y, X) \propto p(y, X | \pi, \Sigma) p(\Sigma | \pi).$$  \hspace{1cm} (10)
Assume a normal-Wishart prior such that \( \pi | \Sigma \sim N(\pi_0, V_0) \), and \( \Sigma^{-1} | \pi \sim W_N(n_0, S_0) \). Then we have

\[
\begin{align*}
\pi, \Sigma, y, X & \sim N\left( \pi_*, \left[ \Sigma \otimes (X'X)^{-1} \right]^{-1} + V_0^{-1} \right) \\
\Sigma^{-1}, \pi, y, X & \sim W_N \left( T - p + n_0, \left[ (Y' - \Pi X')(Y' - \Pi X')' + S_0^{-1} \right]^{-1} \right),
\end{align*}
\]

(11)

where \( \pi_* = \left\{ \left[ \Sigma \otimes (X'X)^{-1} \right]^{-1} + V_0^{-1} \right\}^{-1} \left\{ \left[ \Sigma \otimes (X'X)^{-1} \right]^{-1} \hat{\pi} + V_0^{-1} \pi_0 \right\} \), and \( \hat{\pi} \) is the ordinary least squares estimator of \( \pi \). In practice, the posterior inference relies on 10,000 Gibbs draws, discarding the first 1,000 draws. For each draw of \( \pi \), we construct \( W \) and thereby \( c_t \) according to Equation (7). Since the posterior distribution of \( W \) might not have a finite mean, we use the sample median of \( c_t \) for each \( t \) as a point estimate of the gap.

It should be noted that we also consider the real output gaps derived from the Hodrick–Prescott filter, a fitted linear and quadratic function of time, and a band-pass filter (i.e., the Christiano and Fitzgerald 2003 fixed-length symmetric filter) for comparison purposes. As an illustration, Figure 2 plots the multivariate model-based output gap and the alternative output gaps, with BNGAP, HPGAP, LDGAP, QDGAP, and CFGAP denoting the output gap measures based on the multivariate Beveridge–Nelson approach, the Hodrick–Prescott filter, the linear and the quadratic detrending methods, and the band-pass filter, respectively. The point estimates of all the output gaps are predominantly around ±6 percent, which seems reasonable when compared with various estimates in the standard literature.

Although the general patterns of the alternative output gaps are all similar, the different individual series do not behave exactly the same across time. For instance, the LDGAP and QDGAP are more volatile than the other output gaps. Further inspection of Figure 2 also reveals that the timing of local peaks and troughs in the different output gaps show considerable differences. In addition, there is a lead–lag relation between the multivariate model-based output gap and the other gap measures, and they have no contemporary correlation. These differences reflect the differences of the information sets embedded in the different methods.

Whether these differences, perceptible in the graphical representation, can produce significantly different results in the Granger causality tests between output gap and monetary policy (in a VAR model) is not obvious. As discussed in the following section, only the multivariate model-based output gap is a statistically significant driving force for monetary policy adjustment in China.

Comparisons

Based on the estimation results in the preceding section, we compare the statistical nature of the multivariate model-based output gap and traditional output gap measures. Table 1 summarizes the descriptive statistics of the alternative output gap measures over the period 1980–2010. It shows that different output gap measures manifest rather different magnitudes in the sample mean, median, maximum, minimum, and volatility (standard deviation). In addition, the statistics for skewness, kurtosis, and the Jarque–Bera test for normality suggest that the underlying output measures have marked differences in their marginal distributions. For example, the \( p \)-values of the Jarque–Bera test for BNGAP,
QDGAP, and CFGAP are 0.04, 0.07, and 0.00, respectively, which indicates that the normality hypothesis for these three measures is rejected at the 5, 10, and 1 percent levels, respectively. In contrast, the normality hypothesis pertaining to HPGAP and LDGAP cannot be rejected at conventional levels of significance.

In addition, to show that individual measures of the output gap convey different information, we also report correlation coefficients between the underlying measures. The results in Table 2 suggest that the correlations between the different output gap measures vary strikingly. In particular, the correlations between the BNGAP and other output gap measures are generally very small (except for the correlation between BNGAP and CFGAP), while the correlations between the other measures are relatively large, which indicates that the information embedded in the BNGAP is different from that in other output gap measures.

The different statistical natures of the alternative output gap measures are also evident in their probability densities. Figure 3 plots the empirical probability density distributions of the four output gap measures (estimated using the Epanechnikov kernel method). As Figure 3 shows, the probability density distributions for the underlying output gap measures are strikingly different. Whether these differences are also reflected in monetary policy analysis that involves the output gap is an empirical issue and we examined this by constructing a standard stationary VAR model and conducting Granger causality tests for the relevant variables.
To be consistent with the multivariate dynamic model used in estimating the BNGAP, we employed a stationary VAR model containing the BNGAP and the growth rates of CPI, M2, and NEER. All variables used in this VAR model are stationary (confirmed by standard unit root tests). As discussed above, the dynamic interactions among these four variables can mimic the dynamic evolution of macroeconomic performance in China since the 1980s, and we used the VAR model to capture their interactions and focus on the predictive power of the output gap with respect to money policy (monetary growth).

Table 3 reports the results ($p$-values) of Granger causality tests of the alternative output gaps' ability to predict monetary growth in China over the period 1980–2010. By definition, the Granger causality test effectively tests for whether the output gap contains predictive power in relation to monetary growth and a small $p$-value (e.g., smaller than 10 percent) indicates that the null hypothesis of no causality (i.e., the output gap does not predict monetary growth) can be rejected and vice versa. The results in Table 3 show that the $p$-value of the Granger causality test for BNGAP is 0.05 while the $p$-values for most other output gap measures are greater than 10 percent (except for the CFGAP). These results indicate that only the multivariate model-based output gap (i.e., BNGAP) contains significant predictive information on monetary growth, while the traditional univariate model-based output gap measures have little forecasting power in relation to monetary growth in China (except for the CFGAP, which is also significant).

It may be noted that we gauge the success of the output gap measures by their ability to predict monetary policy measured by monetary growth. Another tool may be the success of the output gap measures in capturing commonly known recessions, which is beyond the scope of the current paper but deserves further investigation in future research. Also note that monetary growth is used as a monetary policy indicator for China in our analysis because although interest rate is a well-known monetary policy instrument in the developed...
countries, it is not a prevailing policy tool used in China. While the PBOC has recently promoted the development of market-based interest rates as policy instruments, available observations for these market-based interest rates are rather limited given the recentness of this development. More importantly, China’s benchmark interest rates, which are adjusted by the PBOC, change very infrequently and hence provide very limited information about monetary policy adjustment over time in China (see Figure 4). Therefore, M2 (instead of an interest rate) is used as the baseline monetary policy indicator for China in this paper, although it may be valuable for future research to use interest rates or a combination of both M2 and interest rates to measure monetary policy in China.

Another issue worthy of attention is our VARs’ possible contamination with endogeneity resulting from measurement errors. According to Morley (2011), under the Beveridge–Nelson-as-estimate interpretation, the estimated components of the Beveridge–Nelson decomposition will contain a large degree of measurement error, which may plague inferences about the coefficients and subsequently about the Granger causality tests in the VAR analysis. Alternatively, however, the Beveridge–Nelson trend and the implied transitory component can, under the Beveridge–Nelson-as-definition interpretation, be treated as regular data in any regression analysis (assuming a reasonable model of the autocovariance structure and precise parameter estimates). To what extent the underlying

Table 3. Granger causality tests of output gaps on monetary growth

<table>
<thead>
<tr>
<th>Null hypothesis: output gap does not Granger cause M2 growth</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>BNGAP</td>
<td>0.052*</td>
</tr>
<tr>
<td>HPGAP</td>
<td>0.189</td>
</tr>
<tr>
<td>LDGAP</td>
<td>0.499</td>
</tr>
<tr>
<td>QDGAP</td>
<td>0.458</td>
</tr>
<tr>
<td>CFGAP</td>
<td>0.015**</td>
</tr>
</tbody>
</table>

Notes: The p-values associated with the Wald statistics in Granger causality tests are reported. The sample spans 1980Q1–2010Q3 prior to lag adjustment. The optimal lag length is specified by Schwarz information criterion (with maximum eight lags). * Statistical significance at the 10 percent level; ** statistical significance at the 5 percent level.

Figure 4. China’s benchmark interest rates for three-month deposits and six-month loans

Source: People’s Bank of China (www.pbc.gov.cn).
VARs’ analysis is affected by the potential measurement error problem remains unclear. Future research may be warranted to examine this relevant issue.

Overall, our finding reflects the fact that the output gap based on the multivariate dynamic model contains richer information than the univariate models. This result reinforces the baseline argument that univariate models are likely to omit useful information embedded in endogenously interacted variables and that consequently, the gap estimates based on univariate models do not provide useful information in terms of predicting monetary growth in China. The finding also indicates that it may be preferable for researchers and policy makers to consider the multivariate model-based output gap measure in monetary policy analysis. This conclusion applies, at the very least, to monetary policy analysis for China.

Conclusions

This paper proposes a new multivariate dynamic model-based output gap estimation method for the Chinese economy. Our multivariate model for the output gap estimation is a modification of the standard new Keynesian monetary policy analysis framework (e.g., Smets and Wouters 2002). The modified model can reasonably be rationalized in terms of the actual features of the Chinese macroeconomy without altering the standard assumption in new Keynesian theory of sticky prices.

The paper then empirically investigates the different statistical natures of the multivariate model-based output gap and the traditional output gap measures, and establishes that the new output gap measure contains significant predictive power in relation to monetary growth in China. The empirical results in the present study also find that most traditional output gap measures are not significant driving forces of monetary growth in the monetary policy analysis framework for China.

As a final comment, we note that the new output-gap measure proposed in the present paper is likely to be a superior tool of monetary policy analysis in general since our method has both economic and statistical foundations. Output gap measures based on ad hoc detrending methods have no such foundation. The Hodrick–Prescott filter, for example, has a statistical foundation, but it assumes a univariate model that is extremely simple compared to ours. Effectively, our multivariate model-based output gap contains richer information than the traditional measures and hence better mimics the real economic slump, thus highlighting the interactions between real economic activity and monetary policy. Future work using the multivariate model-based output gap to investigate the empirical performance of alternative monetary policy frameworks for other countries is clearly warranted.

Notes

1. One important distinction between the Beveridge–Nelson decomposition and UC models is that while UC models restrict the correlation between the trend and cycle shocks to zero, Beveridge–Nelson decomposition does not assume this in the most general case. This is important for the U.S. economy because the estimated correlation is high (see Morley et al., 2003), but the importance is not clear for the Chinese economy. We conjecture, however, that the (multivariate) UC decomposition is as good as the multivariate Beveridge–Nelson decomposition if the correlation between the trend and cycle components are nonzero.

2. Although the different reactions of monetary policy to the output gap at different times are not the focus of the present paper, we acknowledge that the preferences of the central bank of China may have differed significantly over the period 1980–2010, when the preference of monetary
policy for price stability and output stability may not have stayed constant. In a period when price stability is the overriding goal of monetary policy, a negative supply shock may lead the central bank to tighten monetary policy more than in a period when the central bank also cares about output stability and follows an accommodative policy. Thus, output gap changes do not lead to taking the same monetary policy actions throughout such a long time period. We thank the referee for pointing out this issue for us.

3. See also Burdekin and Siklos (2008) for a recent empirical investigation and Geiger (2008) for a more comprehensive survey. To be consistent with the literature and make our analysis operational, we incorporate M2 (instead of an interest rate) as the baseline monetary policy indicator.

4. Because the multivariate Beveridge–Nelson decomposition method also underlies the assumption that the variables in the system are not cointegrated, in practice, we also performed the Johansen cointegration test (allowing for linear deterministic trend) for the underlying variables and the results indicate no significant cointegrating relationships among the variables at conventional levels of significance.

References


