Output gap measurement and the New Keynesian Phillips curve for China☆

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ABSTRACT

The New Keynesian Phillips curve implies that the output gap, the deviation of the actual output from its natural level due to nominal rigidities, drives the dynamics of inflation relative to expected inflation and lagged inflation. This paper exploits the empirical success of the New Keynesian Phillips curve in explaining China’s inflation dynamics with a new measure of the output gap. We estimate the output gap using the Bayesian multivariate Beveridge–Nelson decomposition method, based on a multivariate dynamic model featuring distinct interactions among inflation, money, and real output in China. The empirical results using quarterly data spanning 1979–2010 show that the new measure of the output gap outperforms the traditional measures in fitting the New Keynesian Phillips curve. This result provides useful insights for inflation dynamics and monetary policy analysis in China.

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1. Introduction

In recent years, the empirical validity of the microeconomic foundations of the New Keynesian Phillips curve (NKPC) with rational expectations has attracted considerable attention from both policymakers and academic researchers. The NKPC model has been extended from the pure forward-looking versions with solely rational expectations as in Roberts (1995), to the recently developed hybrid versions with both expected and lagged inflation in the model as in Gali and Gertler (1999), Gali et al. (2005), Sbordone (2005), Rudd and Whelan (2006) and Zhang et al. (2008; 2009). The continuously growing literature concerning the NKPC modeling reflects how the understanding of inflation dynamics has progressed over time. It also indicates that the baseline tradeoff depicted by the NKPC remains a useful component in monetary policy analysis after decades of investigation.

Nevertheless, the empirical validity of the NKPC has been mixed when the model is confronted with realized data. In particular, Gali and Gertler (1999) argue that the empirical success of the NKPC is contingent on the labor income share, rather than the more common output gap, being utilized in the regression. Despite similar arguments in Gali et al. (2005), output gap measures remain prevalent in both theoretical and empirical monetary policy analysis frameworks.1

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, e.g., the filter of Hodrick and Prescott (1997) (hereafter HP), 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

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1 See, for example, Fuhrer and Moore (1995), Judd and Rudebusch (1998), Clarida et al. (1999), Rudebusch (2002), Estrella and Fuhrer (2003), Ireland (2004), to name a few.
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 either the trend or the cycle of the underlying variable (e.g. the HP 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 and Nelson (1981) (hereafter BN) decomposition method). For example, Apel and Jansson (1999), King and Morley (2007), and Basistha and Startz (2008) estimate the natural rates of output and unemployment jointly. Laubach and Williams (2003) and Garnier and Wilhelmsen (2009) estimate the natural rates of output and interest jointly, while Berger (2011) estimate 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 BN 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 inflation, money, and real output. Based on this multivariate model, we estimate the gaps of output, money, and inflation jointly with reliable error bands. Most previous works estimate a particular natural rate, e.g., potential output, core inflation, or the NAIRU (i.e. non-accelerating inflation rate of unemployment), although they may use information in other variables. Second, we apply the multivariate BN decomposition based on a vector autoregression (VAR) model, instead of assuming an unobserved components (UC) model and estimating the components by the Kalman filter. Because prices and quantities adjust eventually, the BN decomposition produces the statistical counterparts of the natural rate and the gap with less restriction than the Kalman filter.

Based on the preceding setup, we obtain the multivariate model-based output gap and estimate the NKPC with the new output gap measure for China with quarterly data spanning 1979Q1–2010Q3. In common with the recent developments in the NKPC literature (e.g. Zhang et al., 2008), and also based on the persuasive arguments of Rudd and Whelan (2007), we extend the hybrid NKPC model by adding richer inflation dynamics than the stylized model proposed by Gali and Gertler (1999).

The paper is structured as follows. Section 2 describes the data used in the empirical analysis. Section 3 discusses the specification of the multivariate model and estimation method, with the NKPC model using the new output gap measure explored in Section 4. Section 5 concludes the paper.

2. The data

The raw data involved in our baseline empirical work spans the first quarter of 1979 to the third quarter of 2010 (i.e. 1979Q1–2010Q3), which corresponds to the post-reform era of the Chinese economy. Because the gap measures for the NKPC modeling are estimated in a multivariate dynamic model, which features the basic interactions among the real economy, inflation, and monetary policy in China, the empirical estimations involve series for inflation, real GDP, and monetary aggregate (M2).

To facilitate comparisons with the literature, we measure inflation by using the year-on-year CPI growth rate. The data are obtained from China Monthly Economic Index (CMEI) of National Bureau of Statistics (NBS), with the last month observation of each quarter used as the corresponding quarterly observation. Quarterly data for M2 over the underlying sample is obtained from International Financial Statistics (IFS). 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 of 1992–2010 (with 1997 as the base year). The real GDP data of quarterly frequency prior to 1992 are not available and they are obtained by using the method of Abeyesinghe and Rajaguru (2004).

Note that Abeyesinghe 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 annual-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.

Among the three variables, inflation is our primary interest. Fig. 1 plots the CPI inflation series in the period 1979Q1–2010Q3. 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 another three 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 1979, as documented in Zhang (2011), but also indicate dynamic interactions among the 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 the “adjustment, reform, revitalization, and improvement” of 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 the prices that had previously been set by government agencies. The purchasing prices of major agricultural products increased first, followed by the prices of industrial producers. These adjustments drove the overall CPI inflation to jump from 1.9% in 1979 to 7.5% in 1980.

In conjunction with this growing inflation, the growth rate of real output in the early 1980s was also accelerating. Fig. 2 shows that the year-on-year growth rate of real GDP in China reached 7.7% in 1979 and grew further to 7.8% in 1980, which was accompanied by an astonishing rate of growth in monetary supply. The central government responded to these high rates of growth in prices and real economy by suppressing the drastic growth in investments (especially infrastructural investment) via credit controls, which dampened both inflation and real economic growth by early 1981.

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 accommodative levels of 40% in 1985 and nearly 50% in 1986. As a result, there was evidence of overheating, with inflation peaking in 1985 and 1986. The tightening of credit controls 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% in 1988. In response to such extraordinary inflation rates, the central government tightened money and credit supply and substantively reduced fixed investment. The tighter monetary policy conditions towards 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 constritive. Because of this 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 liquidity scarcity among enterprises in China. As a result, both economic growth and inflation declined to a relatively low level (below 5%) in 1991.

In the early 1990s, however, agricultural prices were adjusted upwards 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 control, with money supply growing at over 50%. This proactive policy led inflation to increase in 1992 and peak in 1994 (as attested to in Fig. 1). Following a number of tightening policy measures in 1994, inflation started to decelerate in 1995 and continued to decline until the late 1990s.

Since the end of the 1990s, China experienced mild deflation in 1998–2000, with relatively low and stable inflation for the rest of the time. It is worth noting, however, that the Chinese CPI 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) and accommodative monetary policies (e.g. the 4-trillion Yuan stimulus package in 2008–2009).

3. The multivariate dynamic model and the output gap estimates

3.1. The multivariate dynamic model

The construction of the multivariate dynamic model was based on distinctive features of interactions among real GDP, inflation, and M2 in China. It should be noted that although the People’s Bank of China (PBOC) has recently promoted the development of market-based interest rates as policy instruments (e.g. the Shanghai interbank offered rate was launched by the PBOC in January 2007), quantity-based monetary instruments remain the main instruments of the PBOC, as explicitly stated in its quarterly Monetary Policy Report.\(^2\)

To facilitate notation, we use \(y_t\) to denote an \(N\)-variate I(1) sequence such that for all \(t\), \(E(Δy_t) = μ\) where in our case \(N = 3\) and \(y_t\) is the vector of real GDP, inflation, and M2 (in natural logarithm, expect for inflation). The gap measures for the underlying three 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 \(y_{t}^p\) and a transitory component \(c_t\) (i.e. gaps), where

\[
y_t^p = \lim_{T \to \infty} E_t(y_{t+1-\mu})
\]

\[
y_t^p = \lim_{T \to \infty} E_t \left( y_t \right) = \sum_{s=1}^{T} (Δy_{t+s} - μ)\]

and

\[
c_t = -\sum_{s=1}^{T} E_t(Δy_{t+s} - μ).
\]

Note that the permanent component \(y_{t}^p\) represents a slowly evolving mean growth rate and the transitory component \(c_t\) is a stationary cyclical element embedded in the underlying vector \(y_t\). As will be evident in the following section, our main objective of using the main equations in this subsection is to obtain the stationary cyclical element embedded in the underlying vector \(y_t\) and the output gap measures. To estimate \(c_t\) in Eq. (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 model. To be more specific, we first specify a VAR model for \(Δy_t\) as

\[
φ(L)(Δy_t - μ) = w_t
\]

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

Next, let for all \(t\),

\[
s_t = \begin{bmatrix}
Δy_{t} - μ \\
Δy_{t-p} - μ
\end{bmatrix}
\]

and then we have a standard linear state-space model for \(Δy_t\) such that for all \(t\),

\[
\begin{cases}
s_t = As_{t-1} + Bz_t \\
Δy_t = μ + Cs_t
\end{cases}
\]

where \(z_t \sim \text{IN}(0, I_t)\). Comparing Eqs. (3) and (5), we derive the coefficient matrices of \(A, B,\) and \(C\) as follows:

\[
A = \begin{bmatrix}
φ_1 & \ldots & φ_p \\
I_{(p-1)N} & \ldots & I_{(p-1)N}
\end{bmatrix} \Sigma_{1/2}^{-1} \begin{bmatrix}
O_{(p-1)N \times N} \\
I_N
\end{bmatrix}
\]

\[
B = O_{(p-1)N \times N}
\]

\[
C = I_{N \times (p-1)N}
\]
We assume that the eigenvalues of $A$ are all less than 1. Then for all $t$,

$$c_t = -C(I_n + A)^{-1} A S_t$$

$$= W_1 (\Delta Y_t - \mu) + 1 + W_p (\Delta Y_{t-p} + 1 - \mu)$$

(7)

where $[W_1 \ldots W_p] = -C(I_n - A)^{-1} A$.

Note that for Eq. (7), the eigenvalues of $A$ are less than 1 if $\{S_t\}$ is 1 (0). This guarantees that $\sum T^A$ converges and equals $(I_n - A)^{-1} A$. By definition (as in Eq. (4)), $\{S_t\}$ is the first difference of $I(1)$ series, so that $\{S_t\}$ is indeed I(0).

3.2. The estimation method and the results

Now we consider the estimation of the model parameters by using the Bayesian 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 Bayesian 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. demean the data) and rewrite Eq. (3) as $\phi(L) \Delta Y_t = \nu_t$. Let $II = [\phi_1, \ldots, \phi_p]$. Then for $t = p + 1, \ldots, T$, $\Delta Y_t = I \Delta Y_{t-1} + \nu_t$. Also let

$$Y = \begin{bmatrix} \Delta y_{p+1} \\ \vdots \\ \Delta y_t \\ \vdots \end{bmatrix}, \quad X = \begin{bmatrix} s_{p} \\ \vdots \\ s_{t-1} \\ \vdots \end{bmatrix}, \quad U = \begin{bmatrix} W_{p+1} \\ \vdots \\ W_t \end{bmatrix}$$

and let $y = vec(Y), \pi = vec(IX'), u = vec(U)$ (vec denotes vector operator). Then we have

$$y = (I_p \otimes \Sigma) \pi + u, \quad u = N(0, \Sigma \otimes I_p).$$

(9)

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

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

and assume a normal-Wishart prior such that $\pi | \Sigma \sim N(\pi_0, \Sigma_0)$, and $\Sigma | \pi \sim W_{\Sigma_0}(-n_0, S_0)$. Then we have

$$p(\pi | \Sigma, y, X) \propto \left\{ \left\{ \Sigma \otimes (X' X)^{-1} \right\}^{-1} + V_0^{-1} \right\}^{-1}$$

$$\Sigma^{-1} | \pi \sim \Sigma_{\pi} \sim W_{\Sigma_0}(T - p + n_0, \left[ (Y' - \Pi X')(\Pi' - \Pi X')^{-1} + S_0^{-1} \right]^{-1})$$

(10)

where $\pi_0 = \left\{ \left\{ \Sigma \otimes (X' X)^{-1} \right\}^{-1} + V_0^{-1} \right\}^{-1} \left\{ \left\{ \Sigma \otimes (X' X)^{-1} \right\}^{-1} \right\}^{-1} + V_0^{-1}$, and $\Pi$ is the ordinary least squares (OLS) estimator of $\pi$.

In practice, the posterior inference relies on 10,000 Gibbs draws, discarding the first 1000 draws. For each draw of $\pi$, we construct $W$ and thereby $c_t$ according to Eq. (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.

Note that we also consider the real output gaps derived from the HP filter, a fitted linear and quadratic function of time in the empirical estimation of the NKPC for China. As an illustration, Fig. 3 plots the alternative output gaps, with BNGAP, HPGAP, LDGAP, and QDGAP denoting the output gap measures based on the multivariate BN approach, the HP filter, and the linear and the quadratic detrending methods respectively. The point estimates of all the output gaps are mostly around $\pm 5\%$ which seems reasonable compared with various estimates in the standard literature. Although the general pattern of the alternative output gaps is 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 Fig. 3 also reveals that the timing of local peaks and troughs of the different output gaps have considerable differences. Whether these differences, perceptible in the graphical representation, can produce significantly different results in the NKPC estimation is not obvious. It turns out in the following study that only the multivariate model-based output gap is a statistically significant driving force for inflation in the NKPC framework.

4. The New Keynesian Phillips curve for China

4.1. The NKPC model

Recent studies, including Gali and Gertler (1999) and Gali et al. (2001), Woodford (2002), Sbordone (2002), Linde (2005), Rudd and Whelan (2005), and Zhang et al. (2008), have provoked a fierce debate as to the empirical success of the NKPC in relation to its theoretical underpinnings. The focus of the debate centers on whether the output gap is a valid driving force in the NKPC. Gali and Gertler (1999) argue that the labor income share, rather than the output gap, is the appropriate measure of marginal cost in the NKPC model. Further, their results suggest that forward-looking behavior is far more important than the backward-looking element. Nevertheless, their findings have been challenged by the ensuing studies from different perspectives. For instance, Rudd and Whelan (2005) estimate a reduced form VAR model incorporating the NKPC and find that the labor share is not a valid inflation driving force. Using an output gap measure constructed in line with general equilibrium models, Neiss and Nelson (2005) also suggest that the output gap-based NKPC explains inflation dynamics better than the one advocated by Gali and Gertler (1999). Zhang et al. (2008) show that traditional output gap measures, rather than the labor income share, are valid inflation pressure in the NKPC once the serial correlation problem is properly addressed.

To date, there is little consensus on whether the output gap plays a significant role in the NKPC. To investigate the empirical validity of the NKPC with different output gap measures for China, we note that the stylized specification of the NKPC in Gali and Gertler (1999) is insufficient to capture inflation dynamics of quarterly frequency. Therefore, extending the lagged inflation structure in the NKPC could
be a rewarding innovation. As we show below, this extension can be derived from the micro economic foundations of inflation similar to that used in the standard literature.

To be specific, we assume an economic environment similar to Calvo’s (1983) model, in which firms are able to revise their prices in any given period with a fixed probability \( (1 - \theta) \). We assume both “forward-” and “backward-looking” firms co-exist in the economy with a proportion of \( \omega \) and \( (1 - \omega) \) respectively. Further, we extend the rule of the recent pricing behavior of the backward-looking firms to incorporate a weighted process of past inflation, instead of a stylized one lag of inflation inertia.

Based on the regular assumptions in Calvo’s model and log-linear approximations, it is possible to obtain the (log) aggregate price level as

\[
p_t = \theta p_{t-1} + (1 - \theta)p_t^*\tag{12}
\]

where \( p_t^* \) is the new price set in period \( t \). Let \( p_t^f \) be the price set by forward-looking firms and \( p_t^b \) be the price set by backward-looking firms at time \( t \). Then the new price (relative to the aggregate price) can be expressed as a convex combination of \( p_t^f \) and \( p_t^b \), viz.

\[
p_t^b - p_t = \omega \left( p_{t-1}^b - p_t + (1 - \omega) \left( p_t^b - p_t \right) \right).\tag{13}
\]

Next, following Woodford (2003), the pricing behavior of the forward-looking firms can be written as

\[
p_t^f - p_t = \theta \sum_{j=0}^{\infty} \left( \theta \beta \right)^j E_t p_{t+j+1} + \left( 1 - \theta \beta \right) \sum_{j=0}^{\infty} \left( \theta \beta \right)^j E_t \pi_{t+j+1} + \left( 1 - \theta \beta \right) \sum_{j=0}^{\infty} \left( \theta \beta \right)^j E_t \pi_{t+j+1} + \theta \beta \left( p_t^f - p_t + 1 \right) \tag{14}
\]

where \( \beta \) denotes a subjective discount factor, \( \varsigma \) is introduced by the procedure of log-linearization, and \( \gamma \) denotes the real marginal cost or real output gap. Iterating Eq. (14) gives

\[
p_t^b - p_t = \theta \gamma \left( p_{t-1}^b - p_t + \gamma \right) + \left( 1 - \theta \beta \right) \sum_{j=0}^{\infty} \left( \theta \beta \right)^j E_t \pi_{t+j+1} + \theta \beta \left( p_t^f - p_t + 1 \right) \tag{15}
\]

In terms of the backward-looking firms, the standard literature (e.g. Gali and Gertler, 1999) often assumes a rule of thumb of backward-looking behavior in the following formulation, viz.

\[
p_t^b - p_t = p_t^b - p_t + \pi_{t-1}. \tag{16}
\]

However, inflation inertia in Eq. (16) is confined to a single lag, which may neglect the importance of other historical inflation in predicting current inflation. In particular, if we interpret one period as being short, the backward-looking agents are likely to take more than one period to respond fully to changes in actual inflation. Therefore, it would appear reasonable to replace \( \pi_{t-1} \) in Eq. (16) with a weighted average of inflation over several periods in the past. As such, we extend Eq. (16) in the following way:

\[
p_t^b - p_t = \left( p_t^b - p_t + \pi_{t-1} \right) + \rho^*(L) \Delta \pi_{t-1} \tag{17}
\]

where \( \rho^*(L) = \rho_t^1 + \rho_t^2 L + \rho_t^3 L^2 + \ldots + \rho_t^k L^k \) is a polynomial lag operator. In practice, the optimal lag order can be chosen following some empirical rule established over time.

Combining Eqs. (12)–(17), we can obtain the extended specification of the New Keynesian Phillips curve in the form

\[
\pi_t = \alpha_0 E_{t} \pi_{t+1} + \alpha_0 \pi_{t-1} + \alpha_0 \pi_{t-1} + \alpha_0 \gamma_{t+1} + \gamma_{t+1} \tag{18}
\]

where the coefficients in Eq. (18) are functions of deep parameters in the preceding equations. Note that the specification of Eq. (18) is effectively a reparametrization of the standard NKPC and has two distinct advantages. First, the backward-looking coefficient, \( \alpha_0 \), can be estimated with sufficient precision even if the individual coefficients on lagged inflation are imprecisely estimated due to possible multi-collinearity between the lagged values. Another advantage of the reparameterization is that the convex restriction of \( \alpha_0 + \alpha_f = 1 \) can be easily imposed, which alleviate potential nonstationarity in the empirical regressions.

4.2. The empirical results of the NKPC

To estimate the extended model, we use GMM estimation to account for endogeneity in the NKPC model. We employ as instrumental variables (IV) two lags of each of the output gap and M2 gap, in conjunction with the predetermined lagged dependent variable (i.e. lagged inflation) in the baseline model, which appears to be reasonably conservative and sufficient in explaining the dynamics of the extended NKPC model.

To investigate the role of the multivariate model-based output gap as well as the traditional output gap measures in the NKPC, we compare the estimates of the NKPC pertaining to the BNGAP, HPGAP, LDGAP, and QDGAP which are derived in Section 3. The data used in our empirical studies span 1979Q1–2010Q3 prior to lag adjustment. The optimal lag order of the NKPC model is chosen by IV serial correlation test in Godfrey’s (1994) to ensure that the model is free of serial correlation (with maximum 8 lags). Inflation expectations are measured by rational expectations (i.e. realized future inflation are used as expected inflation).

Based on the above construction, we summarize in Table 1 the key coefficient estimates of the NKPC model in conjunction with the statistics of our interest over the sample. In addition to the coefficient estimates, we also report p-values of the joint significance test on the extra lagged inflation from order two onwards \( \alpha_f(L) \) to check whether the augmentation of the lag structure in the NKPC is warranted. As diagnostic tests in the GMM estimation, the p-values of Godfrey’s (1994) IV serial correlation test (denoted p-auto) and Stock and Yogo’s (2004) weak IV test statistics (denoted Weak-IV) are reported in the last two columns of Table 1.

The Godfrey IV serial correlation test is implemented by adding appropriate lagged residuals from the initial estimation to the regressors from the initial model and checking their joint significance by the Lagrange Multiplier (LM) principle. This test is used to check the possibility of disturbance serial correlation in the IV estimations with null hypothesis of no serial correlation. Therefore, a large p-value indicates no significant serial correlation in the regression and vice versa. The Stock–Yogo weak instrument test provides diagnostic information on to what extent the underlying instruments are weak in the estimation. The statistics reported in Table 1 are the Cragg–Donald statistics, with larger values indicating stronger IV sets. It should be noted, however, that the Cragg–Donald statistics is only valid for two stage least squares estimator and other K-class estimators. We report here for the NKPC model estimated by GMM with continuously updating algorithm for comparative purposes.

Several interesting findings emerge from Table 1. First, the coefficient estimates of \( \alpha_0 \) show that the multivariate model-based output gap (i.e. BNGAP) obtains intuitive (positive) sign and is statistically significant at 5% level. The magnitude of the estimate on the BNGAP is 0.18, indicating that a 1% increase in the output gap will lead to 0.18% rise in inflation, ceteris paribus. This is well in accord with the established economic theory as indicated, for example, in Roberts (1995). However, coefficient estimates on the traditional output gap measures appear quite different from that on the BNGAP. Table 1 shows that the estimates on the traditional output gap measures are insignificant in all cases, which suggest that these output gap measures are not a significant driving force for inflation in the NKPC.

Second, serial correlation is generally absent in the extended NKPC model. The absence of serial correlation indicates that the extended NKPC model (18) is more plausible than the stylized specification in
the literature (e.g., Gali and Gertler, 1999) in explaining China’s inflation dynamics. In addition, the p-values of the joint significance tests on the extra lagged inflation (from order two onwards) are smaller than 1% in the regressions for BNGAP (insignificant for LDGAP and QDGAP in regressions without the convex restriction), indicating the statistically significant role of the extra lagged inflation in the NKPC model.

Another important finding in Table 1 is that the forward-looking component is in general predominant while the backward-looking element appears quantitatively less important (0.698 vs. 0.370 in the regression for BNGAP). This finding seems to be consistent with Gali and Gertler (1999) who claim that inflation expectations play a predominant role while lagged inflation is negligible in the NKPC. We note, however, that the backward-looking component in our model is indispensable because the lagged inflation is statistically significant and the relative importance of the forward- and backward-looking components can vary over time (Zhang et al., 2008). Although not the principal focus of the present study, it is also notable that the role (coefficients) of the forward- and backward-looking elements in the NKPC seems to change over time.

To assess the robustness of the baseline findings, the lower panel of Table 1 also reports GMM estimation results for the NKPC model with convex restriction of $\alpha_x = 1$. By construction, imposing such a convex restriction can mitigate nonstationarity concern in inflation series. The corresponding results in Table 1 show that the baseline finding has no substantial change when the convex restriction is imposed. In practice we also examined the robustness of our finding by using the BNGAP estimated by an augmented multivariate model with exchange rates. The corresponding results also provide clear support for the extension of the lagged inflation dynamics in the stylized NKPC.

5. Conclusions

This paper empirically investigates the New Keynesian Phillips curve model using a new measure of the output gap, the multivariate model-based output gap, and in this context, establishes that the new output gap measure is a valid driving force for inflation in the NKPC model. Our baseline model for inflation dynamics is an extension of the standard NKPC. The extended model can be easily rationalized in terms of sticky price setting of backward-looking firms without altering the standard assumption of rational expectations in the New Keynesian theory.

The empirical results in the present study also find that the traditional output gap measures are not significant driving forces for inflation in the NKPC model for China. Although the studies of Roberts (1998), Adam and Padula (2003), and Zhang et al. (2009) provide supporting evidence on the empirical validity of the traditional output gap measures in the NKPC, they either consider the possible non-rationality of inflation forecasts or use observed inflation forecasts (surveys) in the NKPC context. Departures from rational expectations should, however, be adopted with caution in that rational expectations have been one of the milestone assumptions of macroeconomics for decades (Roberts, 1998) and the NKPC has been developed from microeconomic foundations under rational expectations.

Although our findings as to the relatively small role played by backward-looking behavior in the NKPC is broadly in agreement with Gali and Gertler (1999), their results imply an unintuitive sign on the coefficient of the output gap. The current paper, however, demonstrates that the NKPC is empirically coherent when the multivariate model-based output gap measure is used. This result implies that monetary policy models should not derive current inflation from expected inflation alone. In particular, since it is well established that monetary policy responds to the output gap, our empirical evidence that the output gap plays a significant role in the NKPC provides an important mechanism through which monetary policy drives inflation.

As a final comment, we note that the new output-gap measure proposed in the present paper is likely to be superior in general in the NKPC framework since our method has both economic and statistical foundations. Output gap measures based on ad hoc detrending methods have no such foundation. The HP filter, for example, has a statistical foundation, but it assumes an extremely simple univariate model 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 in the NKPC modeling. Future work of using the multivariate model-based output gap to investigate the empirical performance of the NKPC for other countries is clearly warranted.

Table 1

<table>
<thead>
<tr>
<th></th>
<th>$\alpha_x$</th>
<th>$\alpha_y$</th>
<th>$\alpha_e$</th>
<th>$\alpha_e/\lambda$</th>
<th>p-auto</th>
<th>Weak IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>BNGAP</td>
<td>0.698***</td>
<td>0.370***</td>
<td>0.183**</td>
<td>0.001***</td>
<td>0.548</td>
<td>6.55</td>
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<tr>
<td>(0.105)</td>
<td>(0.087)</td>
<td>(0.081)</td>
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<tr>
<td>HPGAP</td>
<td>0.511***</td>
<td>0.528***</td>
<td>0.021</td>
<td>0.000***</td>
<td>0.513</td>
<td>9.76</td>
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<td>(0.064)</td>
<td>(0.058)</td>
<td>(0.047)</td>
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</tr>
<tr>
<td>LDGAP</td>
<td>1.111***</td>
<td>−0.105</td>
<td>−0.048</td>
<td>0.085*</td>
<td>0.532</td>
<td>8.97</td>
</tr>
<tr>
<td>(0.268)</td>
<td>(0.245)</td>
<td>(0.076)</td>
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<tr>
<td>QDGAP</td>
<td>1.196***</td>
<td>−0.215</td>
<td>0.073</td>
<td>0.419</td>
<td>0.523</td>
<td>8.98</td>
</tr>
<tr>
<td>(0.267)</td>
<td>(0.256)</td>
<td>(0.081)</td>
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<tr>
<td>Convex restriction BNGAP</td>
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<td>0.302***</td>
<td>0.183**</td>
<td>0.000***</td>
<td>0.548</td>
<td>6.55</td>
</tr>
<tr>
<td>(0.105)</td>
<td>(0.105)</td>
<td>(0.084)</td>
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<tr>
<td>HPGAP</td>
<td>0.511***</td>
<td>0.489***</td>
<td>0.022</td>
<td>0.000***</td>
<td>0.513</td>
<td>9.76</td>
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<td>(0.064)</td>
<td>(0.064)</td>
<td>(0.068)</td>
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<tr>
<td>LDGAP</td>
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<tr>
<td>QDGAP</td>
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<td>(0.267)</td>
<td>(0.076)</td>
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</table>

Notes: Sample spans 1979–2010 prior to lag adjustments. The estimation results are based on continuously updating GMM with Marquardt optimization algorithm. IV set includes two lags of each of the output gap and M2 gap, plus lagged inflation in the regression model. Inflation expectations are measured by rational expectations. White heteroskedasticity-robust standard errors are reported in parentheses. The statistics reported under $\alpha_x$ refer to p-values of joint significance test on lagged inflation above order 1 (lag order is specified by IV auto-correlation test); ***, **, and *** denote statistical significance at the 10%, 5%, and 1% levels respectively. BNGAP, HPGAP, and QDGAP denote output gap measures based on HP filter, linear detrending method, and quadratic detrending method respectively; p-auto denotes p-value of IV auto-correlation test (up to lag 4) of Godfrey (1994), under the null hypothesis of no serial correlation; Weak-IV denotes Cragg–Donald F-statistic of Stock and Yogo (2004).