Estimation of Potential Output in India

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Potential output refers to the highest level of output that can be sustained over the long term. It is assumed that the existence of a limit of output is due to natural and institutional constraints. If actual GDP rises and stays above potential output, then (in the absence of wage and price controls) inflation tends to increase as demand exceeds supply. Likewise, if output is below potential level, inflation will decelerate as suppliers lower prices to fill their excess production capacity. The issue of estimating potential output is, therefore, critically important in understanding the overall inflationary dynamics of the economy. Against this background, this paper presents empirical estimates of potential output in India using several advanced econometric methods based on both monthly and quarterly data. Selection of an appropriate method is validated against its out-of-sample forecasts as well as from the spectral density properties. For monthly data, the estimate of the potential growth rate for the Indian economy is found to converge within the range 9.4 percent to 9.7 percent for most of the methods. For quarterly data, these methods consistently produce potential output near to 9.0 percent. The diagnostics of the empirical methodologies suggest that unobserved component models are most efficient methods for estimation of quarterly potential output.

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Introduction

The overall stance of monetary and credit policy in India is to provide adequate liquidity to meet genuine credit requirements and support investment demand in the economy while keeping the price level within limit. One of the major issues in the formulation of the monetary policy is to determine whether the economy is operating above or below its maximum sustainable level. The path of the maximum sustainable level, commonly known as the potential output, indicates that level of output that is consistent with stable price level. In other words, potential output is the maximum output an economy could

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produce without putting pressure on price level. It is that level of output at which the aggregate demand and supply in the economy are balanced, so that, inflation tends to its long-run expected value, if other factors remain constant. Once potential (capacity) output is estimated, the capacity utilization rate can be constructed as a ratio of the actual level of output to the potential output. The capacity utilization generally conforms to that of a full input point on a production function with the qualification that capacity represents a realistically sustainable maximum level of output for a given industry, rather than some higher unsustainable short term maximum.

Output gap, which is the discrepancy between the actual output and the potential output, indicates the presence of disequilibrium in the economy. When the actual output exceed the potential output, i.e. the output gap becomes positive, the rising demand leads to an increase in the price level, if temporary supply factors are held constant. Such instances are seen as a source for inflationary pressures and as a signal for the central bank to tighten monetary policy. In case of a negative output gap, inflation tends to fall. The idea of potential output is, therefore, essential to capture the process of inflation dynamics in the economy. However, potential output cannot be observed directly and needs to be estimated.

The objective of this study is to estimate the potential output for the Indian economy using various univariate and multivariate techniques. Both annual and quarterly data of output [Gross Domestic Product (GDP)] are used to estimate the potential output, both at the aggregate and at the three prime sector level, viz., agriculture and allied, industry and services sectors. Selection of the method to estimate potential output is done through the application of spectral analysis as well through regression analysis. The method that explains the larger proportion of spectral mass in the range of business cycle frequencies (i.e. from 5 quarters to 32 quarters or 15 months to 96 months) is selected for estimation of the potential output. Alternatively, the estimate of output gap, which explains maximum inflation or is having minimum root mean square error (RMSE) is selected to estimate the potential output.

The rest of the paper is organized as follows: a priori the debate on the use of potential output as a variable for demand pressure is presented in Section I. Methodological developments, with special emphasis to recent literature, over a historical perspective are provided in Section II. Section III reviews a few recent empirical literatures at the national as well as international level. Empirical estimates of potential output in India under various methods are presented in Section IV. Finally, Section V concludes the paper with a few policy implications.

Section I
Potential Output and Inflation: Alternative Views

If the real output grows rapidly in the future, the competition for scarce productive resources could put upward pressure on wages and other production costs and ultimately inflation could be raised. Most economic forecasters believe inflationary pressures build after potential output rises above a certain level. Some analysts, however, claimed that the historical relationship is no longer valid because the present economies are more open today and hence allowing imported goods to relieve any shortage of domestic capacity. Inflationary pressures typically emerge when the overall demand for goods and services grows faster than the supply, causing a decrease in the amount of unused productive resources, or economic slack mostly captured through unemployment rate, which measures unused resources in the labour market. Inflationary pressures can be judged by comparing the current capacity utilization rate with an estimated stable inflation rate. When capacity utilization is at the stable inflation rate, inflation tends neither to increase nor to decrease. The concept is similar to the natural rate of unemployment, the unemployment rate for which inflation neither increases nor decreases, but uses capacity utilization rather than unemployment as the measure of economic slack.

Some analysts contend that potential output has become a less dependable indicator of inflationary pressures. Critics of it believe that potential output as an inflation indicator tend to over simplify the

description of both monetary policy formulation and the inflationary process. For example in an article appeared in the Wall Street Journal on February 14, 1995, it is indicated that monetary policy should not be guided by using capacity utilization as an indicator of inflation. It is argued that, in practice, a simple relationship between capacity utilization and the overall inflation rate may not exist. Influences on inflation other than resource utilization routinely appear in economic models. Economic developments abroad and foreign exchange rate swings can effect domestic inflation directly through changes in prices of imports and indirectly through competing goods effects on domestic strategic price setting behavior. Therefore, use of potential output as a variable indicating demand pressures has its own limitations.

Section II
A Review of Methodology and Literature

At the outset it may be stated that, though the concept is theoretically appealing, empirical estimation of potential output is not straight forward. It has a long history and still remains a topic of intense debate. Accordingly, the methodology presented here provides a broad literature review over the developments of nearly five decades. In particular, we present a synoptic view of various techniques those are developed since 1960, excluding typical survey-based measures of capacity variables.

II.1 Early Developments

In an early attempt, Klein (1960) and Klein and Summers (1967), while working at the Wharton School of Finance and Commerce at Pennsylvania University, evolved a methodology (which was subsequently called as "Wharton School Technique") to estimate the potential output and capacity utilization rates relating to the US economy. They defined the capacity of an industry as the maximum sustainable level of output the industry can attain within a very short time if the demand for its product were not a constraining factor, when

the industry is operating its existing stock of capital at its customary level of intensity. Subsequently, many other organizations in US, viz., the US Department of Commerce, the Bureau of Census, etc., also started computing potential output series based on the similar methodology. This method uses time series data only on output and involves marking of peak levels of output and fitting piece-wise linear function by joining successive peaks with straight line to estimate the trend in potential output. For the points before the first peak and after the last peak, capacity output are estimated by extrapolation of the fitted curve. The method is also known as trend-through-peaks method. Despite the simplicity and easiness in implementation, a major drawback of the method is that it does not establish any links between output and other economic variables, like actual supplies of inputs, technological progress, etc., which might have impact on capacity output. Besides, this approach relies on the existence of recent peaks in output in order to provide up-to-date/updated estimates of capacity output. The method, therefore, seems incapable of accounting for situations arising out of prolonged recession or stagnation.

Interest in measuring the capacity output for the Indian economy goes back to 1970s (Divatia and Varma, 1970). They concentrated on the manufacturing industries in India and their estimate of the capacity variables covering the period 1960-68 was published in the RBI Bulletin, April, 1970. The methodology suggested by them is actually a modified version of Wharton School Index in which monthly data (without seasonal adjustment) instead of quarterly indices (quarterly average of monthly seasonally adjusted series) was used. Moreover, in this approach, peak monthly production indices in a year are taken as potential production for all the months of the year. Thus the estimated potential production function shows several discrete jumps at the time points corresponding to changes in the level of potential production. Though, their method provides a useful alternative measure of potential utilization, it was severely criticized mainly on sustainability ground. Moreover, when several firms are aggregated at the industry level, discrete jump is an unrealistic

assumption - a smooth curve as suggested by Wharton School method may be a more faithful description of the reality in this case. Apart from these drawbacks, the method also fails to establish any macro-economic linkage among various production-related variables.

The National Conference Board (NCB) of the US adopted a technique for estimating capacity output on the basis of capital-output ratios. The basic assumption made in this approach is that the lowest capital output ratio corresponds to the capacity output. The estimates of capacity output are then obtained from capital stock divided by minimum capital output-ratio. This approach show significant improvements over Wharton School technique, in a sense that they make use of at least one important input, capital stock, to estimate capacity output. However, the reliability of these measures depends heavily on the accuracy of the measurement of capital, which in practice is really formidable. Secondly, it ignores various other important factors, viz., the impact of technological innovations on output, the impact of labour productivity and labour availability constraint on output, etc.

Subsequently, Klein and Preston (1967) proposed a sector-oriented production function approach (also known as growth accounting approach) for estimation of potential output. As per this approach, the potential output is defined as a full output which could be produced during any given time if all inputs are fully utilized. Accordingly, for each sector of the economy, actual output is expressed as a function of man-hours employed, real utilized capital and a proxy for technical change. Capacity output is then calculated by using (i) available man-hours (including fractional unemployment) in place of man-hours employed and (ii) fully utilized capital (i.e. available capital) in place of utilized capital in these estimated production functions (without re-estimating the parameters). Conceptually, this technique is very sound and is improvement over the methods stated above in the sense that it correlates output with related economic variables. However, it has the limitations involved in estimating the production function. In addition, it is difficult to

determine real capital utilized and available man-hours at different sector/industry level. Moreover, this technique ignores the impact of total factor productivity on output.

The Organization for Economic Co-operation and Development (OECD), France, adopted a technique which is considered as improvement over the production function approach suggested by Klein and Preston (1967). In first step, the OECD uses actual capital (instead of using utilized capital as done by Klein and Preston) along with labour to explain output in the production function. In the second step, the capacity output are estimated by replacing the employed labour with the labour force (or potential employment) in the estimated production function giving due importance to the total factor productivity (in contrast Klein and Preston ignored the use of total factor productivity).

II.2 Recent Developments

Since early 1980s, two basic methodologies viz., statistical de-trending and estimation of structural relationships are extensively used for estimating potential output. In addition, recent years have witnessed applications of dynamic stochastic general equilibrium (DSGE) models for estimation. The statistical de-trending method attempt to separate a time series into permanent (trend) and cyclical components, whereas, the structural relationships method (basically a variant of production function approach) attempt to isolate the effects of structural and cyclical influences on output, using economic theory.

In practice, both univariate and multivariate approaches are applied. The univariate approach includes the Beveridge and Nelson, decomposition (1981), Univariate Unobserved Components (UUC) model (Watson, 1986; Clark, 1987), Band-Pass (BP) filter (Baxter and King, 1995) and Hodrick-Prescott (HP) filter (Hodrick and Prescott, 1997). The multivariate approach includes the Production Function, Structural Vector Auto-regression (SVAR) and Multivariate Unobserved Components (MUC) model. These methods are discussed below:

II.2.1. The Hodrick-Prescott (HP) filter

The Hodrick-Prescott (HP) filter is a simple statistical smoothing procedure and has become popular because of its flexibility in extracting a trend from macro economic data. HP filter fits a trend line through all the observations of the given series, regardless of any structural breaks that might have occurred, by making the regression coefficients themselves vary over time. This is done by finding a trend output that minimizes a combination of the gap between actual output and the trend output at any time and the rate of change in trend output at the last point of time (T).

More precisely for a given actual output Y(t), the trend output Y*(t) is estimated by minimizing

$$\sum_{t=1}^{T}\left(Y(t)-Y^{*}(t)\right)^{2} + \lambda\sum_{t=2}^{T-1}\left[\left(Y^{*}(t+1)-Y^{*}(t)\right)-\left(Y^{*}(t)-Y^{*}(t-1)\right)\right]^{2}$$

Where λ is a weighting factor that determines the degree of smoothness of the trend. A low value of λ will produce a trend output that follows actual output more closely, whereas a high value of λ reduces sensitivity of the trend output to short term fluctuations in actual output and in the limit the trend tends to the mean growth rate for the whole estimation period. Though a lot of subjectivity is involved in determining the appropriate value of λ depending upon the nature of the series, it is set to 14400 for monthly data, 1600 for quarterly data and 100 for annual data. The properties and shortcomings of the HP filter have been well documented (Harvey and Jaeger, 1993). The advantage of the HP filter is that stationary is retained for the output gap over a wide range of smoothing values and it allows the trend to change over time. HP filter has several drawbacks, including the arbitrary choices of the smoothing parameter λ and having high end sample biases.

II.2.2. Beveridge-Nelson (BN) Decomposition

Trend cycle decomposition is motivated by the idea that the log of aggregate output is usefully thought of as the sum of components

that accounts for long term growth and a stationary, transitory deviation from trend[1]. Beveridge-Nelson (BN) decomposition is a detrending method using unobserved components. Output is assumed to contain unobserved permanent component consisting of a random walk with drift and temporary component consisting of a stationary autoregressive process. BN decomposition implies that much of the variation in output is variation in trend, while the cycle component is small and noisy. BN decomposition assumes a perfect negative correlation between trend and cycle innovations that is a property of the estimated trend and cycle, not the unobserved components.

Consider an ARMA(p,q) model for the changes in output:

$$\phi(L)\Delta y_t = c + \theta(L)\varepsilon_t, \ \ \varepsilon_t \sim \text{iid N}(0,\sigma^2),$$

where $\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \ldots - \phi_p L^p$
$\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \ldots + \theta_q L^q$

and where $|\phi| < 1$ and $|\theta| < 1$.

Note that the BN trend for the ARMA model may be derived from its moving average representation (Wold form) as:

$$\Delta y_t = \mu + \psi(L)\varepsilon_t \text{ where } \psi(L) = \phi(L)^{-1}\theta(L) = \sum_{j=0}^{\infty}\psi_j L^j.$$

This ARMA form fully describes the joint distribution of the $\{y_t\}$ and therefore the conditional distribution of future observations given the past are unique. The BN decomposition is given by:

$$y_t = y_0 + \delta\ t + \psi(1)\sum_{j=1}^{t}\varepsilon_j + \widetilde{\varepsilon}_t$$

where $\widetilde{\varepsilon}_t = \psi(L)\varepsilon_t, \psi(L) = \sum_{k=0}^{\infty}\psi_k L^k, \psi_k = -\sum_{j=k+1}^{\infty}\psi_j,$

$TD_t = y_0 + \delta\ t =$ deterministic trend,

$TS_t = \sum_{j=1}^{t}\varepsilon_j =$ stochastic trend,

and $C_t = \widetilde{\varepsilon} =$ temporary or cyclical component.

To proceed with the decomposition, an ARMA(p,q) is estimated on the changes in output. Various ARMA models are estimated and the Schwarz criterion is used to select the best model. Then the series is decomposed into stationary and trend components using the BN decomposition technique described above.

II.2.3. Unobserved Components (UC) Model

The Unobserved Components (UC) approach introduced by Harvey (1985) and Clark (1987), implies a very smooth trend and a cycle that is large in amplitude and highly persistent. The UC model decomposes the output y_t into two independent components[2]: a stochastic trend component, τ_t and a cyclical component, c_t.

$$y_t = \tau_t + c_t$$

The stochastic trend $\{\tau_t\}$ assumed to be a random walk with mean growth rate μ.

$$\tau_t = \mu + \tau_{t-1} + \eta_t, \quad \eta_t \sim \text{i.i.d.N}(0, \sigma_\eta^2)$$

In some implementations the rate of drift μ is also allowed to evolve as a random walk and sometimes an irregular term is added, although these changes have little influence on the estimated cycle component for output.

The cyclical component $\{c_t\}$ assumed to be a stationary and invertible ARMA(p,q) process with innovations that may be contemporaneously cross correlated with trend innovations.

$$\phi_p(L)c_t = \theta_q(L)\varepsilon_t, \; \varepsilon_t \sim \text{i.i.d.N}(0, \sigma_\varepsilon^2),$$

$$Cov(\eta_t, \varepsilon_{t\pm k}) = \begin{cases} \sigma_{\eta\varepsilon} \; for \; k = 0 \\ 0 \; otherwise \end{cases}$$

Harvey *op. cit.*, Clark *op. cit.* and Harvey and Jaeger (1993) suggest specifying p=2 and q=0, which allows the cycle process to be periodic in the sense of having a peak in its spectral density function.

This set up implies that trend and cycle innovations are uncorrelated. Thus the model is augmented to include the condition $\sigma_{\eta\varepsilon} = 0$. Therefore,

$$c_t = \phi_1 c_{t-1} + \phi_2 c_{t-2} + \varepsilon_t; \ \varepsilon_t \sim \text{i.i.d.N}(0, \sigma_\varepsilon^2),$$

$E(\eta_t, \varepsilon_s) = 0 \ \text{for all } t \text{ and } s$

where the roots of $\left(1 - \phi_1 L - \phi_2 L^2\right) = 0$ lie outside the unit circle. Taking both τ_t and c_t as unobserved state variables, this model could be written in the state space form as follows:

$$y_t = \begin{bmatrix} 1 & 1 & 0 \end{bmatrix} \begin{bmatrix} \tau_t \\ c_t \\ c_{t-1} \end{bmatrix}$$

$$\begin{bmatrix} \tau_t \\ c_t \\ c_{t-1} \end{bmatrix} = \begin{bmatrix} \mu \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & \phi_1 & \phi_2 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \tau_{t-1} \\ c_{t-1} \\ c_{t-2} \end{bmatrix} + \begin{bmatrix} \eta_t \\ \varepsilon_t \\ 0 \end{bmatrix}$$

The parameters are estimated from data $(y_1, y_2, \ldots, y_n)$ by the maximum likelihood method of Harvey (1981) based on the prediction error decomposition. Given estimated parameters, the Kalman filter generates the expectation of the trend (and cycle) conditional on data through time t:

$$\hat{\tau}_{t/t} = E\left[\tau_t / \Omega_t\right] \text{ and } \hat{c}_{t/t} = E\left[c_t / \Omega_t\right], \text{ where } \Omega_t = (y_1, y_2, \ldots, y_t).$$

II.2.3.1 Formulation of the problem under Multivariate Unobserved Components (MUC) setup

In general, estimation of potential output using multivariate unobserved components model is explored through the Monetary Condition Index[3] (MCI). The MCI captures the general orientation of the monetary policy affecting the aggregate demand with the objective to control the inflation rate. Considering the MCI index as an

exogenous variable, the aggregate demand equation has been assumed to be a function of MCI. The observed output, y_t, has been decomposed into two parts: μ_t^y, the permanent trend (potential output) and z_t, the temporary trend reverting component (output gap).

$$\log(y_t) = \mu_t^y + z_t + e_{1t}, \quad E(e_{1t}) = 0, \quad Var(e_{1t}) = \sigma_{e1}^2 \tag{1}$$

The potential output is modeled as local linear trend.

$$\mu_t^y = \mu_{t-1}^y + \beta_{t-1}^y + \eta_{1t}, \; E(\eta_{1t}) = 0, \qquad Var(\eta_{1t}) = \sigma_{\eta1}^2 \tag{2}$$

$$\beta_t^y = \beta_{t-1}^y + \varsigma_{1t}, \qquad\qquad E(\varsigma_{1t}) = 0, \qquad Var(\varsigma_{1t}) = \sigma_{\varsigma1}^2 \tag{3}$$

The Wholesale price index (WPI) has been decomposed into two parts: the forecastable core part and the stochastic non-core part.

$$\log(WPI_t) = \mu_t^{core} + e_{2t}, \quad E(e_{2t}) = 0, \quad Var(e_{2t}) = \sigma_{e2}^2 \tag{4}$$

The output gap dynamics have been assumed to be influenced by the MCI and price level core part dynamics have been influenced by the output gap as well as the cost of industrial production and crude oil prices,

$$z_t = \phi_1 z_{t-1} + \phi_2 MCI_t + \varepsilon_t, \; E(\varepsilon_t) = 0, \qquad Var(\varepsilon_t) = \sigma_\varepsilon^2 \tag{5}$$

$$\mu_t^{core} = \mu_{t-1}^{core} + \delta_1 z_{t-1} + \delta_2 \log(INDRM_{t-1}) + \delta_3 \log(Indian\_Oil_{t-2}),$$
$$E(e_{2t}) = 0, \quad Var(e_{2t}) = \sigma_{e2}^2 \tag{6}$$

The model, consisting of the equations from (1) to (6), can be re-written in its state-space realization and can be estimated by using the Kalman filter and maximum likelihood.

II.2.4. The Band-Pass (BP) Filter

An ideal low-pass filter removes high-frequency cycles from the data, whereas an ideal high-pass filter removes low frequencies from the data and an ideal band-pass filter removes both low and high frequencies. The Baxter and King (1995) filter is a band-pass filter of finite order K which is optimal in the sense that it is an approximate band-pass filter with trend reducing properties and symmetric weights.

The BP filter is designed to pass through components of time series with fluctuations between 6 and 32 quarters while removing higher and lower frequencies.

It is a finite approximation of an infinite moving average filter:

$$\widetilde{y}_t = \sum_{h=-K}^{K} a_h L^h y_t$$

where $\widetilde{y}_t$ is the filtered time series from the original time series y_t and a_h are the weights.

The weights a_h can be derived from the inverse Fourier transform of the frequency response function. Baxter and King adjust the band-pass filter with a constraint that the gain is zero at zero frequency. This constraint implies that the sum of the moving average coefficients must be zero. Thus, the weights a_h are obtained by solving the minimization problem:

$$\underset{a_h}{Min} \ \ Q = \int_{-\pi}^{\pi} |\ \beta(\omega) - \alpha(\omega)\ |^2 \ d\omega, \text{ such that } \alpha(0) = 0.$$

Where $\beta(\omega)$ is the Fourier transform of an 'ideal' filter with cut off frequencies ω_1 & ω_2 and $\alpha(\omega)$ is the Fourier transform of the approximate filter.

Solving the minimization problem leads to:

$$a_h = b_h + \theta; h = 0, \ \pm 1, \ \pm 2, \ \dots, \ \pm K$$

Where b_h are the weights of the ideal low-pass filter and θ is a constant that depends on the maximum lag length, K and are given by:

$$b_0 = \frac{\omega_2 - \omega_1}{\pi} \ \ and \ \ b_h = \frac{1}{h\pi}(\sin \ \omega_2 h - \sin \ \omega_1 h) \ \ for \ h = \pm 1, \ \pm 2, \ \dots$$

$$\theta = \frac{-\sum\limits_{h=-K}^{K} b_h}{2K + 1}$$

Baxter and King propose setting K=12, $\omega_1 = 2\pi \dfrac{1}{32}$ and $\omega_2 = 2\pi \dfrac{1}{6}$ or $2\pi \dfrac{1}{2}$ for quarterly data and K=3, $\omega_1 = 2\pi \dfrac{1}{8}$ and $\omega_2 = \pi$ for annual data. The filtered series is the cyclical component and the trend component is just the difference between the actual series and the cycle.

II.2.5. The Production Function Approach

In the view of macro economic analysis, the most important limitation of all the above methods is that they are largely mechanistic and bring to bear no information about the structural constraints and limitations on production through the availability of production factors or other endogenous influences. Thus, the above methods may be inconsistent with what is known or being assumed about the growth in capital, labour supply or factor productivity or may be unsustainable because of inflationary pressures. The production function approach attempts to overcome these shortcomings while adjusting also for the limiting influence of demand pressure on employment and inflation.

In its simplest form, this approach postulates a two factor Cobb-Douglass production function for the business sector with proxy for technical change:

$$\log(Y) = \log(C) + \delta\, t + \alpha \log(L) + (1 - \alpha) \log(K) + \log(E)$$

i.e., $y = c + \delta\, t + \alpha\, l + (1 - \alpha)\, k + e$

where Y, L and K are the value added, labour input and capital stock of the business sector respectively, E is the total factor productivity, C, δ are constants and α is average labour share parameter. Lower case letters indicate natural logarithms.

The above production function is estimated at different sub sector level, for given sample average labour shares. The estimated residuals from these equations are then smoothed to give measures

of trend total factor productivity, e*. The trend total factor productivity series, e*, is substituted back into the production function along with actual capital stock, k, and estimates of potential employment, l*, as:

$$y^* = c + \alpha \, l^* + (1 - \alpha) \, k + e^*$$

II.2.6. Structural Vector Autoregression (SVAR) system

The SVAR method uses information from a number of variables that may be considered to have a high degree of relationship, such as GDP, capacity utilisation and domestic inflation, to estimate the potential GDP and output gap. The SVAR methodology utilizes the relationship between inflation and growth to distinguish between permanent and transitory movement in output – faster growth with lower inflation indicates that the economy at that time is operating below potential, while the emergence of inflation in the face of growth suggest that output is above potential.

In the present study, the estimate of SVAR is done following the methodology of Blanchard and Quah (1989), with the exception that inflation is used in place of the unemployment rate. By imposing identifying restrictions on the relationship between output and inflation, the regression residuals are divided into the effects of supply and demand shocks in each period on output and inflation. The output gap is then defined as the component of the forecast error of output attributed to the demand shock – the shortfall or surplus of output above or below potential due solely to demand side factors.

The SVAR identifies restriction on the long-run effects of shocks on output and inflation, while the effects of both shocks are left unconstrained in the short-run[4]. The restrictions imposed are that demand shocks affect the long-run price level but not the long-run output level, while supply shocks can have permanent effects on both output and price level. Thus a positive supply shock leads to a permanent increase in the GDP level, while a positive demand shock

leads to higher output in the short-run.

As the impact of output growth on inflation can be observed with a time lag, the variables used in SVAR are the contemporaneous growth rate of output and two quarters ahead change in price level. Let z be a vector of two stationary variables $z_t = \{\Delta y_t, \Delta p_t\}$, where y_t is GDP and p_t is the domestic price level. Then the variables can be written as a function of the underlying structural shocks,

$$z_t = B_0 \varepsilon_t + B_1 \varepsilon_{t-1} + B_2 \varepsilon_{t-2} + - - - = \sum_{j=0}^{\infty} B_j \varepsilon_{t-j}$$

where B is a (2x2) matrix of coefficients and ε_t is white noise residuals that capture demand and supply shocks. The model identifies two structural shocks: one demand shock and the other supply shock. It is assumed that the demand shock does not have a long-term effect on output, but that they allow for a more persistent effect on GDP. The supply shock is assumed to have a long-term effect on GDP.

By arranging the two uncorrelated structural shocks as

$$\varepsilon_t = \{\varepsilon_t^S, \varepsilon_t^D\}$$

where ε_t^S is an aggregate supply shock and ε_t^D is an aggregate demand shock, the change in GDP can be written as,

$$\Delta y_t = \sum_{j=0}^{\infty} \beta_{1j} \varepsilon_{t-j}^S + \sum_{j=0}^{\infty} \beta_{2j} \varepsilon_{t-j}^D$$

The restriction that aggregate demand shocks cannot have a long-term effect on GDP, is implemented by imposing $\sum_{j=0}^{\infty} \beta_{2j} = 0$.

In a SVAR model, potential GDP (the long-term trend) is represented by the term $\sum_{j=0}^{\infty} \beta_{1j} \varepsilon_{t-j}^S$, which is accumulated supply shocks, while the output gap is the share of GDP that is explained by the demand shock.

II.2.7. Dynamic Stochastic General Equilibrium (DSGE) Approach

Dynamic Stochastic General Equilibrium (DSGE) models contain many features of the real business cycle literature and allow for rigidities and imperfections in markets (these are often referred to as New Keynesian models). These provide more-realistic, yet still theoretically elegant, representations of the economy, and their development has been an exciting area of research in macroeconomics in recent years. Under this approach, potential output is defined as the level of output that an economy could attain if the inefficiencies resulting from nominal wage and price rigidities were removed. That is, if wages and prices were fully flexible. The definition of potential output as a flexible price equilibrium has much in common with the more conventional definition. The DSGE definition accords with the idea that potential output is the level of output at which inflation tends neither to rise nor to fall. However, the DSGE view of potential output also has important differences with the earlier approaches to estimating potential output. For example, in many DSGE models, potential output can undergo swings over the business cycle, a result that should not be surprising considering that the early real business cycle models viewed the business cycle as being primarily an efficient response to shocks to the economy. In addition, fiscal policy shocks, changes in households' preferences with regard to saving and consumption, changes in preferences about leisure that affect labour supply, and terms-of-trade shocks can all cause potential output to fluctuate. In contrast, production function (growth-accounting) approaches to estimating potential output generally assume that such shocks have no important effects on potential output at business-cycle frequencies (Mishkin, 2007). As a consequence, their estimates typically have smaller fluctuations than measures of potential output derived from DSGE models, and thus the output gaps in the current generation of DSGE models tend to be less variable than conventional measures and can be quite different for particular periods (Neiss and Nelson, 2005; Edge, Kiley and Laforte, 2007).

Section III
Recent Empirical Literature

Empirical literature on estimation of potential output is large and growing rapidly. Most central banks, especially in developed nations, critically monitor the trends in potential output. Instead of using a single approach, several approaches are used on a regular basis. Gerlach and Smets (1999) explored an Multivariate Unobserved Components (MUC) model to estimate the output gap for the European Monetary Unit area and found that an increase in the output gap by one percentage point raises the inflation by 0.2 percent in the next quarter and an one percentage point increase in the real interest rate reduces next quarter output gap by approximately 0.1 per cent. The output gap was postulated as a function of its own lags and to a lagged real interest rate.

Clauss (2000) estimated potential output for the New Zealand economy through the Structural Vector Autoregression (SVAR) methodology, under the assumption of that demand-side disturbance have no long-run effect on output, while the productivity shocks are assumed to have a permanent effect on output and accordingly potential output is associated with the productivity shocks. Apart from the aggregate output, the rate of employment and capacity utilization were used to estimate the potential output under the SVAR framework.

Cerra and Saxena (2000) applied both UUC and MUC models to estimate the output gap for Sweden. In the multivariate case, inflation and unemployment both were applied separately to estimate the output gap. Scott (2000) estimated the output gap for the New Zealand economy using MUC model, by assuming a common output gap for Gross Domestic Product (GDP), unemployment rate and capacity utilization.

For Norway, Bjoruland *et al.* (2005) compared different univariate and multivariate methods to estimate the output gap. The models under the multivariate framework were found to have been superior to the univariate counterparts in estimating the output gap. The univariate methods include the HP filter; the BP filter and UUC

model, while the multivariate methods include the MUC model and SVAR. Under the multivariate framework, unemployment rate and/or inflation were incorporated as the other economic variables.

Llosa and Miller (2005) estimated the output gap for Peru based on the MUC model through a system of structural equations consisting of four variables, viz., an index of real monetary conditions, domestic inflation, imported inflation and inflation expectation. Sarikaya et al. (2005) estimated the potential output and output gap for the Turkish economy using MUC approach, through a semi structural model. The model consists of five equations, consisting of observable variables: inflation rate, real GDP, real effective exchange rate, real interest rate based on 3-month Treasury auction and a demand index, constructed from the Business Tendency Survey.

In the context of India, generally, the HP-filter is being widely applied to estimate the output gap for the industrial sector [Collen and Chang (1999), Ray and Chatterjee (2001)]. Donde and Saggar (1999) applied both HP- filter and UUC model to estimate the potential output for the industrial sector in India. They further applied the HP- filter to estimate the potential output for the Indian economy based on annual observation during 1950-51 to 2000-01.

Section IV
Empirical Estimation of Potential Output in India

Empirical estimates of potential output in India are worked out based on various approaches as indicated above. However, due to data limitations, particularly on employment, production function approach is not attempted. In addition, due to lack of conceptual clarity, estimates based on DSGE models are not worked out. Empirical estimates are presented separately using both monthly and quarterly data.

IV.1. Estimates of Potential Output for monthly IIP series

Estimates of potential output for the monthly series are obtained by using seven alternative methods, consisting of four univariate and

three multivariate methods. The univariate methods consist of HP filter, BP filter, BN-decomposition and UUC methods, while the multivariate methods includes the MUC (based on MCI) and two SVAR estimates – based on WPI and MCI, respectively. The sample covers the period from April 1994 to December 2007. For HP-filter, the parameter used to smooth the data has been set at 14400, while for the BP-filter the estimates are obtained within the specified range between 15 to 60 months.

The estimates of potential growth rate, based on the alternative methodologies, are presented in Table 1. As can be observed from the table, the estimate of the potential growth rate for the Indian economy has been found to have varied in the range from 8.2 percent to 10.2 percent. However, the estimate of 8.2 percent, derived based on the MUC methodology, seems to be on the lower side compared to the alternative methodologies. The estimates of the potential growth rates, based on the HP-filter, BP-filter, UUC and the two SVAR methodologies are found to have converged, within the range 9.4 percent to 9.7 percent.
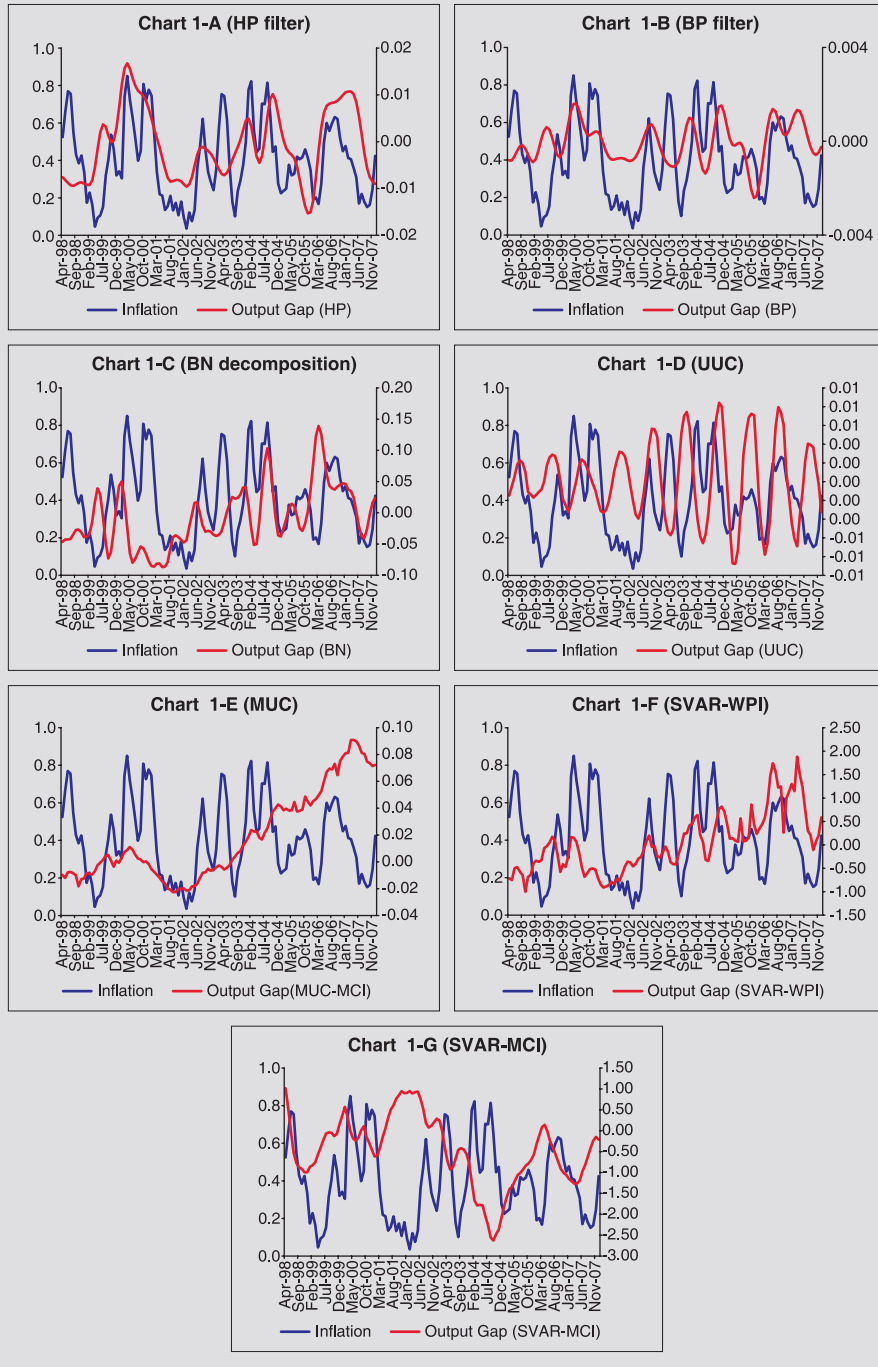
Table 1: Estimate of Potential Growth Rates based on monthly data

Methods	Potential Growth Rate
HP	9.5
BP	9.4
BN	10.2
UUC	9.7
MUC	8.2
SVAR - WPI	9.4
SVAR - MCI	9.5

IV.2. Estimates of Potential Output for quarterly GDP series

Estimates of potential output for the quarterly series are obtained by using eight alternative methods, consisting of four univariate and four multivariate methods. Apart from using the same set of univariate and multivariate methods, used to estimate the potential output for the monthly data, one alternative method of MUC has been used. The

Chart-1: Plot of Inflation Rate (month-over-month) and estimates of Output Gap

Chart 1-A (HP filter)

Chart 1-B (BP filter)

Chart 1-C (BN decomposition)

Chart 1-D (UUC)

Chart 1-E (MUC)

Chart 1-F (SVAR-WPI)

Chart 1-G (SVAR-MCI)

two alternative methods of MUC are based on MCI and Capacity Utilization (CU), where the estimate of CU is based on the survey conducted by the National Council of Applied Economic Research (NCAER), New Delhi. The sample covers the period from the first quarter (April- June) of the financial year 1996-97 to third quarter (October – December) of the financial year 2007-08. For HP-filter, the parameter used to smooth the data has been set at 1600, while for the BP-filter the estimates are obtained within the specified range between 5 to 24 quarters.

Table 2: Estimate of Potential Growth Rates based on quarterly data
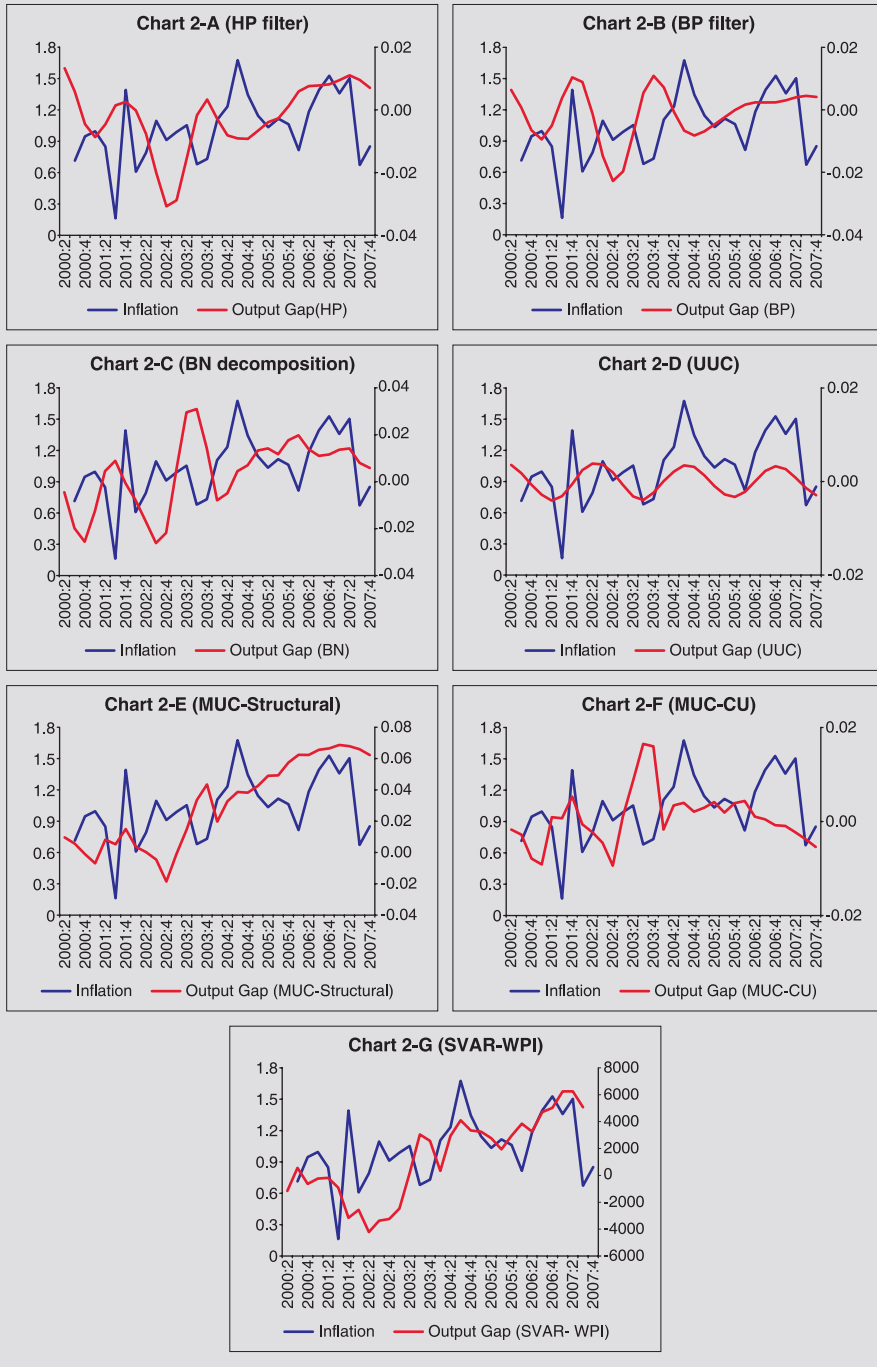
Methods	Potential Growth Rate
HP	8.5
BP	8.9
BN	9.0
UUC	9.2
MUC - Structural	8.1
MUC - CU	9.5
SVAR - WPI	9.0
SVAR - MCI	9.2

The estimates of potential growth rate, based on the eight alternative methodologies, are presented in Table 2. As can be observed from the table, the estimate of the potential growth rate for the Indian economy, based on the GDP, has been found to have varied in the range from 8.1 percent to 9.5 percent. The estimates of the potential growth rates, based on the BP-filter, BN decomposition, UUC and the two SVAR methodologies are found to have concentrated near 9.0 percent.

IV.3. Selection of the method of estimation of output gap

As mentioned earlier, selection of the method to estimate output gap can be done by either spectral analysis or regression analysis. In the regression analysis, one can fit a regression equation and assess the out-of-sample forecasting performance of the equation based on certain statistical criteria, like Mean Square Error (MSE), Root Mean

Chart-2: Plot of Inflation Rate (quarter-over-quarter) and estimates of Output Gap

Chart 2-A (HP filter)

Inflation — Output Gap(HP)

Chart 2-B (BP filter)

Inflation — Output Gap (BP)

Chart 2-C (BN decomposition)

Inflation — Output Gap (BN)

Chart 2-D (UUC)

Inflation — Output Gap (UUC)

Chart 2-E (MUC-Structural)

Inflation — Output Gap (MUC-Structural)

Chart 2-F (MUC-CU)

Inflation — Output Gap (MUC-CU)

Chart 2-G (SVAR-WPI)

Inflation — Output Gap (SVAR- WPI)

Square Error (RMSE), $\bar{R}^2$ etc. The equation, corresponding to the estimate of output gap, having minimum MSE or RMSE or maximum $\bar{R}^2$ may be selected to estimate the potential output. In the spectral analysis, the method that explains the larger proportion of spectral mass in the range of business cycle frequencies (i.e. from 5-quarters to 32-quarters or 15-months to 96-months) may be selected for estimation of the potential output.

IV.3.1. Selection of the estimate of output gap by regression analysis

To assess the ability and significance of the relationship between inflation and the estimated output gap, the following equation has been estimated, as proposed by Coe and McDermott (1997). Inflation, used in the equation, is measured by the changes in the price level over the previous period as compared to the same period last year. This measure of inflation helps in assessing the impact of the demand conditions, reflected through the output gap, on inflation. For the monthly series, WPI is used to measure the inflation, while GDP deflator is used to measure the quarterly inflation. Before empirical analysis, both the WPI and GDP are seasonally adjusted using the X-12-ARIMA technique.

$$inflation_t = c + \sum_{i=0}^{m} \beta_i \Delta z_{t-i} + \sum_{i=0}^{n} \gamma_i \, inflation_{t-i} + \varepsilon_{1t} \qquad (7)$$

where *inflation* denotes the inflation rate estimated based on the monthly WPI or quarterly GDP series. The constant term 'c' included in the equation, indicates the contribution of the non-inflationary level of the output gap. The lag length 'm' is determined by the Akaike's Information Criterion (AIC).

IV.3.2. Selection of the method for estimation of monthly output gap

For selection of the method to estimate output gap by regression analysis, we divide the full sample period into two sub-samples. The first sample, known as the in-sample, covering the period from April 1994 to June 2006, is used to estimate the parameters of the equation,

while the second-sample, known as the out-of-sample, covering the period from July 2006 to December 2007, is used to assess the forecasting ability of the output gap estimates through RMSE and $\bar{R}^2$.

Table 3 presents the out-of-sample RMSE of the alternative equations based on the estimates of output gap by different methodologies. From the table, it can be observed that, based on the HP-filter estimate of output gap, the RMSE is found to be least at 0.542, while $\bar{R}$ is found to be maximum at 0.89. Thus regression analysis prefers the application of HP-filter to estimate the potential output in the monthly IIP series.

Table 3: Estimate of the equation based on monthly data

Methods	$\bar{R}^2$	RMSE
HP	0.89	0.542
BP	0.88	0.565
BN	0.88	0.569
UUC	0.86	0.611
MUC	0.88	0.561
SVAR - WPI	0.88	0.578
SVAR - MCI	0.86	0.609

Table 4 presents the percentages of the spectral mass lying within the defined range of business cycle of the alternative methods. Data covers the period from April 1994 to December 2007. As can be observed from the table, the UUC method, which explains 98.1 per cent within the business cycle frequency, is the most proficient at isolating output gap in the monthly industrial production at the

Table 4: Percentage of Spectral mass within the business cycle frequency

Methods	Percentage
HP	91.7
BP	95.3
BN	69.3
UUC	98.1
MUC	66.9
SVAR - WPI	49.0
SVAR - MCI	46.9

medium term. The BP filter is also relatively proficient, which explains 95.3 per cent of the total variation. This suggests the selection of UUC method to estimate the potential output in the monthly IIP series.

IV.3.3. Selection of the method for estimation of quarterly output gap

For selection of the method to estimate quarterly output gap by regression analysis, we divide the full sample period into in-sample and out-of-sample, as defined above. The in-sample covers the period from 1996-97:Q1 to 2004-05:Q4, while the out-of-sample covers the period from 2005-06:Q1 to 2007-08:Q3. The forecasting ability of the output gap estimates are assessed through out-of-sample RMSE and $\bar{R}^2$.

Table 5 presents the out-of-sample RMSE of the alternative equations based on the estimates of output gap by different methodologies. From the table it can be observed that, the RMSE is found to be least in case of UUC, while $\bar{R}^2$ is found to be marginally higher in HP compared to UUC. Thus the UUC method can be used to estimate the potential output in the quarterly GDP series. As the RMSE of HP is found to be the second least and thus one can apply HP-filter also to estimate the quarterly potential output.

Table 5: Estimate of the equation based on quarterly data

Methods	$\bar{R}^2$	RMSE
HP	0.31	1.083
BP	0.13	1.202
BN	0.18	1.151
UUC	0.30	1.067
MUC - Structural	0.22	1.113
MUC - CU	0.15	1.178
SVAR - WPI	0.05	1.225
SVAR - MCI	0.06	1.218

Table 6 presents the percentages of the spectral mass lying within the business cycle frequency range of the alternative methods. The sample covers the period from 1996-97:Q1 to 2007-08:Q3. It can be observed from the table that both UUC and MUC- Structural methods,

Table 6: Percentage of Spectral mass within the business cycle frequency

Methods	Percentage
HP	98.7
BP	99.6
BN	94.6
UUC	99.7
MUC - Structural	99.7
MUC - CU	84.0
SVAR - WPI	97.3
SVAR - MCI	32.7

which explains 99.7 per cent within the business cycle frequency, are the most proficient methods to estimate the output gap in the quarterly GDP. The BP filter is also relatively proficient explaining 99.6 per cent of the total variation. This criterion of selection of the method to estimate output gap suggests UUC or MUC- Structural method as the most proficient methods for estimation of potential output in the quarterly GDP.

Section V
Conclusion

As an economic concept, the definition of potential output is not unambiguous. The idea of potential output is essential not to capture the output, but the process of inflation dynamics in the economy. No statistical measure, however sophisticated, is available which could reasonably capture the overall demand of the economy, except potential output. The crux of modern monetary policy making lies with the understanding of demand process and thus the concept of potential output is critically important. The path of the maximum sustainable level indicates that level of output that is consistent with stable price level. In other words, potential output is the maximum output an economy could produce without putting pressure on price level. That is potential output is that level of output at which the aggregate demand and supply in the economy are balanced, so that, inflation tends to its long-run expected value, if other factors remains

constant. Output gap, which is the discrepancy between the actual output and the potential output, indicates the presence of disequilibrium in the economy. When the actual output exceeds the potential output, i.e. the output gap becomes positive, the rising demand leads to an increase in the price level, if temporary supply factors are held constant. In case of a negative output gap, inflation tends to fall.

In this paper, empirical estimates of potential output in India are presented using several advanced econometric methods. The selection of an appropriate method to estimate output gap is done by either spectral analysis or regression analysis. While in the regression analysis, the out-of-sample forecasting performance of the regression equation of potential output explaining inflation is used, in the spectral analysis, the method that explains the larger proportion of spectral mass in the range of business cycle frequencies (i.e. from 5-quarters to 32-quarters or 15-months to 96-months) is used.

For monthly data, the estimate of the potential growth rate for the Indian economy is found to vary in the range from 8.2 percent to 10.2 percent. The estimates of the potential growth rates, based on the HP-filter, BP-filter, UUC model and the two SVAR methodologies converge within the range from 9.4 percent to 9.7 percent. For quarterly data, the estimates of the potential growth rate for the Indian economy vary in the range from 8.1 percent to 9.5 percent and methods like BP-filter, BN decomposition, UUC model and the two SVAR methodologies produce potential output consistently near 9.0 percent. The diagnostics of the empirical methodologies suggest that UUC or MUC- structural method are most efficient methods for estimation of quarterly potential output.

Notes

[1] We follow custom in referring stationary, transitory deviation from trend as the 'cycle' even if it is not periodic.

[2] Beveridge-Nelson decomposition assumes a perfect negative correlation between shocks to the trend and cycle, whereas Unobserved Components model assumes the shocks to trend and cycle are uncorrelated.

[3] See Annexure-I for description of MCI and construction of MCI in India.

[4] This is against the unrestricted VAR methodology, where the effects of shocks on all variables are left unconstrained at all horizons.

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Annexure-I

Monetary Condition Index

Monetary Condition Index (MCI) is weighted average of changes in an interest rate and exchange rate relative to their values in a base period. The weights on the interest rate and exchange rate measure the relative effects of these variables on the target variables like aggregate demand or inflation over some period. The extent of monetary tightening or loosening compared to a previous period may be judged by observing at the two principal channels of transmission process – the interest rates and the exchange rates. MCI are computed to infer the extent of internal and external influences on the overall monetary conditions of a country. Algebraically, an MCI is written as,

$$MCI_t = \theta_r(r_t - r_0) + \theta_e(e_t - e_0)$$

where r and e represents the interest rates and exchange rates, and θ_e and θ_r are the corresponding weights, respectively. An increase in the MCI, which may occur due to an increase in the interest rates or exchange rates, leads to fall in the aggregate demand or inflation. Thus an increase in MCI, lowers both aggregate demand and price level and it reflects monetary tightening.

Estimation of MCI weights:

Generally, the weights used to compile MCI are derived based on four alternative methodologies and are described as follows:

(a) Single Equation based:

The relative weights that measure the relative impact of interest and exchange rates on aggregate demand can be derived directly by estimating an aggregate demand equation. The Deutsche Bank derives the weights from an aggregate demand equation.

(b) Model based:

Weights may also be estimated based on prior estimates of aggregate demand equations of existing models. The OECD bases the weights on the MCI from its Interlink Model.

(c) Trade share based:

Weights may also be derived based on the exchange rate variable as a function of the long-run export to GDP ratio. The interest rate weight is then calculated as one minus the exchange rate weight. The weights are interpreted as a crude relative measure of the effect of the exchange rate on GDP *vis-à-vis* the interest rate effect on GDP. J.P. Morgan constructs a real MCI for the UK based on this methodology.

(d) Multiple equation based:

The weights for the MCI may also be derived based on unrestricted vector autoregression methodology. MCI weights are obtained based on the impulse response function of aggregate output to a shock to each of the interest rate and exchange rate. Generally, weights are based on the cumulative average responsiveness to the shocks till the responses die out. If the variables are found to possess long-run equilibrium relationship, the weights can be derived based on the impulse response function under the cointegration framework (Batini and Turnbull, 2002).

Construction of MCI for India

For the Indian economy, not much work has been done to construct MCI. Kannan *et al* (2006) constructed two MCI for the Indian economy. The first MCI, defined as *narrow MCI*, was constructed based on interest rate and exchange rate, while the second MCI, defined as *broad MCI,* was constructed by incorporating credit growth along with the two rates. The weights were derived based on the single equation estimates of the coefficients of the variables on

the overall gross domestic product (GDP) excluding the agriculture
& allied activities and the community, personal and social services.

For our empirical analysis, the MCI is constructed based on the
broad definition as defined in Kannan *op cit.* The form of the MCI is
as follows,

$$MCI_t = \theta_r(r_t - r_0) + \theta_e(e_t - e_0) + \theta_c(c_t - c_0)$$

As the multiplication of MCI by a constant does not make any
difference in the index, the MCI can be expressed in terms of the ratios,

$$MCI_t = (r_t - r_0) + (\theta_e / \theta_r)(e_t - e_0) + (\theta_c / \theta_r)(c_t - c_0)$$

The ratios θ_e / θ_r and θ_c / θ_r are critical in computing MCI, while the
first ratio indicates the relative importance of exchange rate vis-à-vis
the interest rate, the second ratio indicates the relative importance of
credit growth vis-à-vis the interest rate.

The weights in the MCI are derived based on the multiple
equation methodology. The interest rate is represented by the average
of the weighted call money rate (CMR), while exchange rate is
represented by the 36-country trade based effective exchange rate of
the Indian Rupee (either nominal (NEER36) or real (REER36)) and
non-food credit (NFC) growth. Both the NEER36 and REER36 are
adjusted by deviation from it base value of 100.

(a) Monthly MCI

For deriving the weights of the monthly MCI, initially, the
variables were tested for order of integration. The widely applied
Augmented Dickey-Fuller (ADF) test was applied to determine the
order of integration. Due to lack of monthly GDP, the Index of Industrial
Production (IIP) is used to represent the output. Empirical results
related to the ADF test are presented in Table A1. From the table, it can
be observed that the annual point-to-point growth in IIP, CMR and
NEER36 are I(0), while, annual point-to-point growth in NFC is I(1).
The sample covers the period from April 1994 to December 2007.

Table A1: Augmented Dickey-Fuller Unit Root Test

	At level			At first difference			Remark
	Test Statistic	Critical Value	Form of the ADF regression	Test Statistic	Critical Value	Form of the ADF regression	
IIP_g	-3.095 (0.029)	-2.881	Constant	---	---	---	I(0)
CMR	-7.739 (0.000)	-3.437	Constant, Linear Trend	---	---	---	I(0)
NEER36	-3.832 (0.003)	-3.437	Constant	---	---	---	I(0)
NFC_g	-0.616 (0.449)	-1.943	None	-13.940 (0.000)	-1.943	None	I(1)

Note: Figures in the parentheses indicate the p-values corresponding to the null hypothesis of existence of unit roots.

To derive the weights for the MCI, we applied the method of unrestricted vector autoregression using the variables IIP_g, CMR, NEER36 and the first difference of NFC_g. The impulse responses of IIP_g to shock of each of the other variables are found to have died after a period of 30-months. The following graphs present the impulse response function of IIP_g to the other variables.
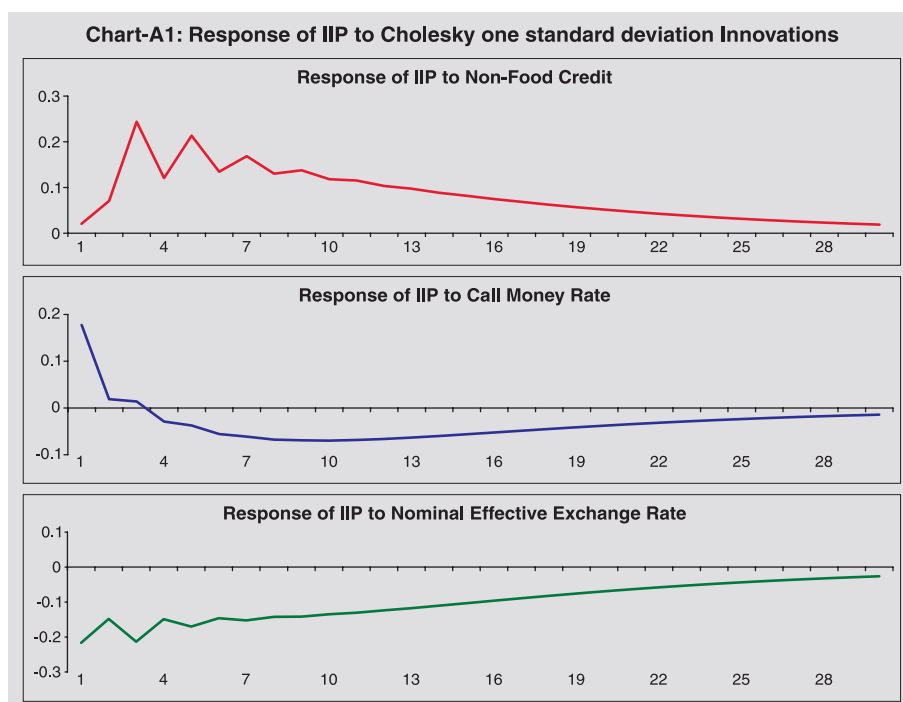
Chart-A1: Response of IIP to Cholesky one standard deviation Innovations

The weights for the MCI are derived as the cumulative average responsiveness to the shocks till 30-months.

Based on the above analysis, the MCI can be represented as,

$$MCI_t = (r_t - r_0) + 3.198(e_t - e_0) - 2.597(c_t - c_0)$$
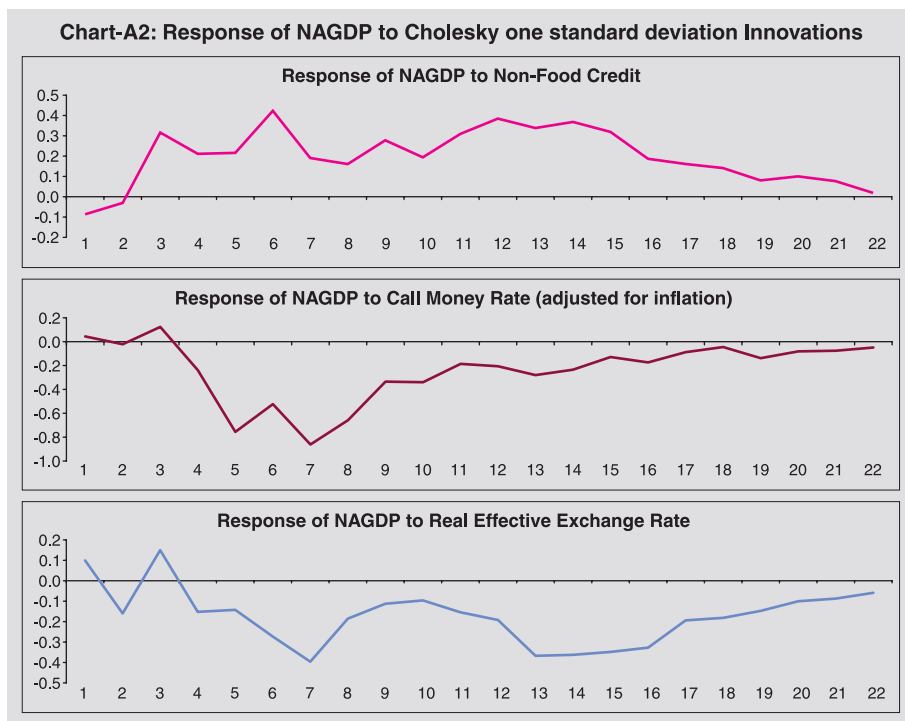
(b) Quarterly MCI

For deriving the weights of the quarterly MCI, initially, the variables were tested for order of integration using ADF. The quarterly non-agricultural GDP (NAGDP) is used to represent the output. Empirical results related to the ADF test are presented in Table A-2. From Table A2, it can be observed that the annual point-to-point growth in NAGDP and NFC, CMR (adjusted for inflation) and REER36 are I(0), while, NEER36 is I(1). The sample covers the period from 1993-94:Q1 to 2007-08:Q3.

To derive the weights for the MCI, we applied the method of unrestricted vector autoregression using the variables NAGDP_g, CMR, NFC_g, REER36 and the first difference of NEER36. The impulse responses of NAGDP_g to shock of each of the other variables, *viz.* CMR, NFC_g and REER36 are found to have died

Table A2: Augmented Dickey-Fuller Unit Root Test

	At level			At first difference			Remark
	Test Statistic	Critical Value	Form of the ADF regression	Test Statistic	Critical Value	Form of the ADF regression	
NAGDP_g	-3.152 (0.028)	-2.913	Constant	---	---	---	I(0)
CMR	-3.237 (0.002)	-1.946	None	---	---	---	I(0)
NEER36	-2.358 (0.158)	-2.913	Constant	-7.521 (0.000)	-1.947	None	I(1)
REER36	-2.322 (0.021)	-1.946	None	---	---	---	I(0)
NFC_g	-4.656 (0.002)	-3.488	Constant, Linear Trend	---	---	---	I(0)

Note: Figures in the parentheses indicate the p-values corresponding to the null hypothesis of existence of unit roots.

Chart-A2: Response of NAGDP to Cholesky one standard deviation Innovations

Response of NAGDP to Non-Food Credit

Response of NAGDP to Call Money Rate (adjusted for inflation)

Response of NAGDP to Real Effective Exchange Rate

after a period of 22-quarters. The following graphs present the impulse response function of NAGDP_g to the other variables.

The weights for the MCI are derived as the cumulative average responsiveness to the shocks till 22-quarters.

Based on the above analysis, the MCI can be represented as,

$$MCI_t = (r_t - r_0) + 0.721(e_t - e_0) - 0.830(c_t - c_0)$$