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Estimating output gaps in Asia: A cross-country study ☆

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We estimate output gaps for Hong Kong, Indonesia, Japan, Korea, Malaysia, the Philippines, Singapore, and Taiwan, using the Hodrick–Prescott (HP) filter, a band-pass (BP) filter, the Beveridge–Nelson (BN) filter and unobservable-components (UC) techniques. Three conclusions are notable. First, the gaps resulting from the BN filter, which is "one-sided," differ from the other filters that are "two-sided." Second, the UC approach has the advantage that it allows confidence bands for the gap to be constructed and that it yields estimates of the growth rate of potential. Third, the HP, UC, and BP gaps are similar. *J. Japanese Int. Economies* **18** (1) (2004) 115–136. Hong Kong Monetary Authority, Hong Kong Institute for Monetary Research, Citibank Tower, 3 Garden Road, Central, Hong Kong, China; University of Basel, Basel, Switzerland; CEPR, London, UK.

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1. Introduction

Monetary policy in Asian economies has historically been conducted using the exchange rate as an intermediate objective. In recent years, however, a growing number of central banks have started to gear policy directly to the ultimate target of low and stable inflation. Korea and Thailand have adopted formal inflation-targeting frameworks, and Indonesia and the Philippines are moving in the same direction. While Japan and Singapore do not employ explicit inflation targeting, the monetary authorities in these economies have maintained low inflation since the mid-1980s and are plainly gearing policy to price stability, in the case of Singapore by actively managing the exchange rate.[1] By contrast, Hong Kong and Malaysia have maintained fixed exchange rate regimes.

The increased emphasis on inflation in the formulation of policy has direct implications for the central bank's choice of indicators. In particular, the output gap—the difference between actual and potential output—has become a more important policy indicator. This reflects the large body of evidence from a range of economies indicating that inflationary pressures tend to increase as output rises, and decline when output falls, relative to potential.[2] The importance of the output gap for the setting of monetary policy is also apparent from the fact that it is typically highly significant in estimated reaction functions for central banks operating under floating exchange rates.[3]

Unfortunately, the output gap is an unobserved variable. To study its role in the inflation process and to use it as an indicator in the setting of monetary policy one must therefore estimate it. As noted by Coe and McDermott (1997), little empirical research has been devoted to the study of output gaps in Asia. Since Asian economies have experienced rapid growth and have been exposed to large disturbances, in particular to a sharp contraction in economic activity during the Asian crisis in the late 1990s, the time series behaviour of real output in the region may differ from that in other advanced economies. In turn, this raises the issue whether the same techniques that have been used to compute output gaps in other economies are appropriate also in the Asian context. For instance, it is an empirical issue how well the behaviour of the output gap during the regional financial crisis in 1997–1998 is captured by filters that do not explicitly assume that there is a discrete structural break in the time series for output.

Before proceeding, it should be recognised that there is a large body of work on ways in which measures of potential output and the output gap can be constructed. Several different research strategies have been applied in the literature. These may be usefully thought of as either following an atheoretical approach, a structural approach or a mixed approach.

[1] In many ways, the monetary policy regimes of Japan and Singapore may be thought of as implicit inflation targeting.

[2] See for instance the October 1999 special issue of the *Journal of Monetary Economics*, entitled "The return of the Phillips curve." BIS (1997, 2001a, 2001b) contains a number of references to central bank research on the inflation process, including the role of the output gap.

[3] Taylor (1993) and the subsequent literature on the "Taylor rule" (e.g., Clarida et al., 1998) indicate that central banks in advanced economies appear to set interest rates in response to movements in the output gap. Corbo (2002) demonstrates that the same is the case for a number of economies in Latin America. Apparently no similar study has been conducted on data from Asian economies.

The first strategy sees the problem as a statistical exercise in which actual data on output are used to construct an estimate of potential output. The simplest example of this approach is to regress the logarithm of actual output on a time trend and, perhaps, a squared time trend, and use the residuals as a measure of the output gap. Other approaches are to employ the popular Hodrick–Prescott (HP) filter (1997), the band-pass (BP) filter proposed by Baxter and King (1999), the (BN) filter proposed Beveridge and Nelson (1981) or the unobservable-components (UC) time-series approach proposed by Watson (1986) and Clark (1989).

Structural approaches exploit economic theory to estimate potential output. Typically, data on employment and estimates of the capital stock are used to fit a production function. Given assumptions about "normal" levels of employment, productivity and the utilisation of the capital stock, measures of potential output can then be constructed. While the guidance of theory is attractive, the data requirements are quite demanding, particularly for emerging market or newly industrialised economies for which information, or long time series, on key variables in many cases are missing. Moreover, the use of structural information is a potential source of specification error. For instance, output gap estimates may be poor if the production function is misspecified.

A third strategy, the mixed approach, is to combine a time series model with structural economic information. Kuttner (1994) uses a UC model and data on actual output and inflation to estimate the output gap in the USA.[4] While this approach is attractive, a critical assumption is that the relationship between the output gap and inflation is stable during the sample period. This assumption may be particularly debatable in economies that have experienced large structural changes.

This paper provides a comparative study of the estimation of output gaps in Asia. Since the results may vary between economies depending on the time series behaviour of output, we use data from eight economies: Hong Kong, Indonesia, Japan, Korea, Malaysia, the Philippines, Singapore, and Taiwan.[5] The data set is quarterly and starts, depending on the economy, between the early 1970s and the early 1980s. Moreover, the fact that there are several ways in which to compute output gaps raises the issue whether different methods give rise to conflicting estimates and whether a method that works well in one economy may not perform well in another. To explore these concerns, we use four methods: the HP, BN, and BP filters, and the UC model. The reason we focus on atheoretical, as opposed to structural and mixed, approaches is that the latter require economic relationships to have remained stable during the sample period. While this assumption may be reasonable for more advanced economies, the emerging market economies we are studying here have undergone a deep and far-reaching economic transformation in the data period. We are therefore hesitant to assume that the relationship between inflation and the output gap is stable in the sample. Moreover, the lack of data makes it difficult to estimate output gaps using a production function approach.

[4] Gerlach and Smets (1997, 1999) use this strategy to estimate output gaps in the G-7 countries and in the euro-zone.

[5] We used data from all Asian economies for which we could find quarterly GDP data going back at least to the early 1980s.

The rest of the paper is organised as follows. In Section 2 we review the approaches used to compute the output gap. Since the UC model of the output gap may be less well known we discuss its specification and estimation in some detail. In Section 3 we turn to the empirical work. We distinguish between methods on the basis of the data they use to estimate the current output gap. *Two-sided* methods make use of the full sample to compute the output gap. By contrast, *one-sided* methods compute the output gap using only current and past data. In Section 4 we report our main conclusions. We find that the different methods appear to work well in the Asian context. The UC model has the two advantages that it allows confidence bands for the output gap to be estimated and that it yields plausible estimates of the growth rate of potential. Furthermore, the two-sided methods give rise to better historical estimates of the output gap than the one-sided methods. Finally, the output gaps estimated using the HP, BP, and UC approaches appear quite similar. It therefore seems likely that the dominance of the HP filter in applied work is likely to continue.

2. Methodology

As noted in the introduction, we assess the output gap in four different ways. The first method is the UC model proposed by Watson (1986) and extended by Clark (1989). This model has two important features. First, the filter used to estimate the output gap stems from a time series model and is thus model and data dependent. This suggests that this filter may perform well in a range of economies with potentially sharply different time-series behaviour of output. Second, the filter provides a confidence band for the estimate of the output gap. Since it is important from a policy perspective to know the degree of uncertainty about the state of the economy, this is a desirable characteristic.

We also compute output gaps using the HP filter that is commonly used to compute measures of the gap and the BP filter proposed by Baxter–King (1999). The HP and BP filters share the feature that they do not entail any estimation. To apply the HP filter, the analyst sets the smoothing parameter, λ. While deciding upon an appropriate value for it is not a simple exercise, in practise researchers typically set it equal to 1600 for quarterly data. To apply the BP filter, a frequency band must be determined. In business cycle studies this is typically set equal to between 6 and 32 quarters. Finally, we consider the BN filter proposed by Beveridge and Nelson (1981). This filter is one-sided in that it uses only data from $0, \ldots, t-1, t$ to construct the output gap at time t. By contrast, the HP and BP filters are typically used to estimate the output gap at t using the full data set, $0, \ldots, t-1, t, t+1, \ldots, T$.[6] Another important difference is that the BN filter depends on the data in that the estimates of the output gap are obtained by first fitting an ARMA model to the quarterly growth rate of real GDP.

The empirical work is divided into two parts. In the first part we investigate two-sided estimates, and in the second part one-sided estimates, of the output gap. Before turning to

[6] Baxter and King (1999) recommend dropping the first and last 12 observations in quarterly data sets. Moreover, they note that the performance of the HP filter deteriorates sharply towards the beginning and end of the sample.

the empirical work, however, we review the UC model, which is less well known than the other models considered.

The specification for output follows Watson (1986). Let y_t, y_t^{p}, and z_t denote the logarithms of actual and potential output and the output gap. Of course, we only have data on actual output and the purpose of the exercise is to estimate the latter two variables. To do so, we start from the identity

$$y_t \equiv y_t^{\mathrm{p}} + z_t, \tag{1}$$

that is, actual output is defined as the sum of potential output and the output gap. Next we assume that potential output follows a random walk with drift,

$$y_t^{\mathrm{p}} = \mu_{t-1} + y_{t-1}^{\mathrm{p}} + \varepsilon_t^y, \tag{2}$$

where μ_t captures the rate of growth of potential output and where $\varepsilon_t^y \sim N(0, \sigma_y^2)$. We allow μ_t to vary over the sample period as suggested by Clark (1989). Formally we let the drift parameter follow a random walk:

$$\mu_t = \mu_{t-1} + \varepsilon_t^{\mu}, \tag{3}$$

where $\varepsilon_t^{\mu} \sim N(0, \sigma_{\mu}^2)$. Note that if $\sigma_{\mu}^2 = 0$, the rate of growth is constant over the sample. This is the assumption made by Watson (1986). While it seems to fit the US data quite well, the results in Gerlach and Smets (1997) indicate that this assumption is restrictive for many other economies. We therefore let the rate of growth vary over time.

Finally, we assume a time series process for the output gap, z_t. The UC model assumes that the gap evolves over time according to a second-order auto-regressive process

$$z_t = \phi_1 z_{t-1} + \phi_2 z_{t-2} + \varepsilon_t^z, \tag{4}$$

where $\varepsilon_t^z \sim N(0, \sigma_z^2)$.[7] One implication of the choice of an AR(2) process is that, depending on the estimates of the AR-parameters, z_t may have complex roots and, if so, obey a cyclical process.[8]

Before proceeding, it is worth noting that King and Rebelo (1993) demonstrate that the HP filter can be thought of as imposing (untested) restrictions on the more general UC model.[9] If these restrictions are accepted by the data, the HP filter will generate estimates

[7] As noted by an anonymous referee, one could allow for a more complicated AR-structure for the gap. Empirically, however, higher order terms are typically insignificant. Since it is difficult to estimate models using maximum likelihood in the presence of superfluous parameters (since the likelihood function is flat), we proceed under the assumption that the AR(2) specification is correct.

[8] Yin-Wong Cheung has pointed out that the growth rate of real output is non-stationary since Eqs. (1) and (2) imply that it depends on the growth rate of potential, μ, which by Eq. (3) is non-stationary. However, this hypothesis is easily rejected by the data. This seems due to the fact that the variance of the shocks to potential output is much smaller than the variance of the shocks to the output gap so that the time series behaviour of Δy is dominated by Δz. To explore this issue further, we conducted a Monte Carlo study (with 5000 draws using the parameter estimates from the model for Hong Kong to generate the data) and found that in more than 99% of the draws an Augmented Dickey Fuller test falsely rejected the unit root hypothesis at the 5% level despite the fact that it was true by construction.

[9] King and Rebelo (1993) show that the HP filter is optimal under three conditions. First, the output gap is white noise. Needless to say, this assumption squares badly with the standard notion of the output gap as evolving

of potential output that are identical with those arising from the UC model (disregarding sampling uncertainty). However, if the restrictions are rejected, the more flexible UC model will generate better estimates of the gap.

To estimate the UC model we write it in state-space form.[10] To do so, let X_t denote the vector of unobserved state variables that we seek to estimate,

$$X_t^{\mathrm{T}} = \begin{bmatrix} y_t^{\mathrm{p}} & z_t & z_{t-1} & \mu_t \end{bmatrix}, \tag{5}$$

where X_t^{T} denotes the transpose of X_t. Next define the vector A as

$$A = \begin{bmatrix} 1 & 1 & 0 & 0 \end{bmatrix}. \tag{6}$$

We can then write

$$y_t = AX_t. \tag{7}$$

Equation (7) states that the observed level of real GDP is a linear combination of the unobserved level of potential output and the output gap. To proceed, we need to specify the law of motion of X_t. Since higher-order AR and ARMA models can be written in AR(1) form (with the state vector suitably redefined), we assume, without loss of generality, that

$$X_t = BX_{t-1} + \varepsilon_t, \tag{8}$$

where the transition matrix, which governs the evolution over time of the state variables in the X_t vector, is given by

$$B = \begin{bmatrix} 1 & 0 & 0 & 1 \\ 0 & \phi_1 & \phi_2 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}. \tag{9}$$

The vector of disturbances can then be written as $\varepsilon_t^{\mathrm{T}} = [\,\varepsilon_t^y \quad \varepsilon_t^z \quad 0 \quad \varepsilon_t^\mu\,]$. We assume that the covariance matrix of the disturbances Ω is diagonal. This assumption implies that shocks to the output gap are unrelated to the innovations in the growth rate of potential.[11]

To estimate the model, which is given by the *observation* equation (7) and the *transition* equation (8), we form the likelihood function:

$$\log L = -\frac{N}{2}\log(2\pi) - \frac{1}{2}\sum_{1}^{N}\log|F_t| - \frac{1}{2}\sum_{1}^{N} v_t^{\mathrm{T}} F_t^{-1} v_t, \tag{10}$$

where N, v_t, and F_t denote the sample size, the prediction errors and the mean square matrix of the prediction error, respectively. Estimates of the model can then be obtained

gradually over time. Second, the only innovations to potential output are shocks to the rate of drift. Third, the value of the "smoothing parameter" used in performing the HP filtering is equal to the ratio of the variance of the shocks to the output gap and the variance of the shocks to the drift of potential.

[10] For a discussion of state-space models and the Kalman filter, see Harvey (1989) or Hamilton (1994).

[11] One can think of situations in which large output gaps have a persistent impact on the long-run growth of the economy, for instance by influencing investment and the level of the capital stock. However, there appears to be no firm reason for believing that movements in the output gap have a first-order effect on the growth rate of potential and we therefore maintain the assumption that Ω is diagonal.

by numerically maximising the likelihood function, using the Kalman filter. Since the logarithm of real economic activity is non-stationary, in estimating the model we follow the suggestions of Harvey (1989) and assume that the prior X_0 is a random variable and has a diffuse distribution, that is, we let the covariance matrix be given by κI with $\kappa \to \infty$. This is tantamount to assuming that nothing is known about the initial state.

3. Empirical results

Next we turn to the empirical work. As a preliminary, panels a and b in Fig. 1 contain plots of the logarithm of seasonally adjusted quarterly real GDP, which we use to measure y_t, for Hong Kong (1973:1–2001:1), Indonesia (1980:1–2001:1), Japan (1973:1–2001:1), Korea (1973:1–2001:1), Malaysia (1975:1–2001:1), the Philippines (1981:1–2001:2), Singapore (1975:1–2001:1), and Taiwan (1973:1–2001:1).[12] For comparison purposes, we have normalised the data to equal 100 in 1990:1.

The plots show that the growth rate of the Asian economies has been declining somewhat over time. In particular, it appears that the average growth rate was lower in the 1990s than earlier. This suggests, as argued earlier, that it is appropriate to treat the

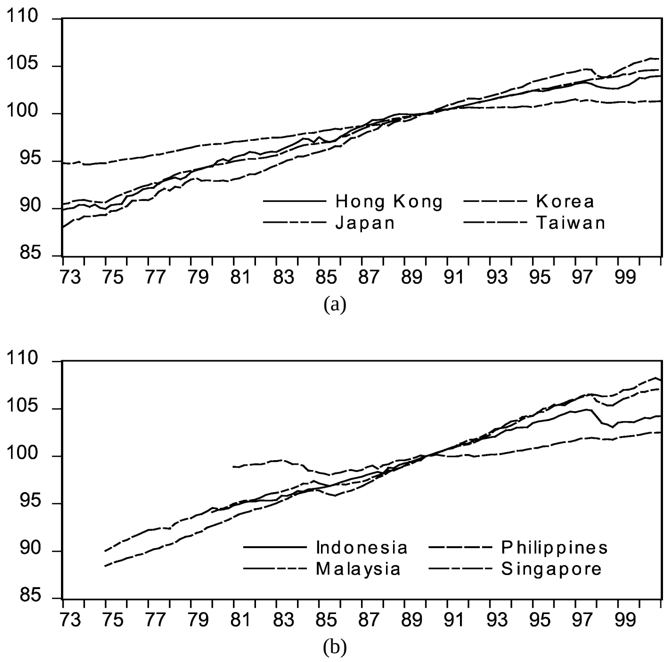


Fig. 1. Real GDR. (a) East Asian economies. (b) Southeast Asian economies.

[12] The data stem from the database of CEIC Data Ltd., except for Indonesia and Malaysia, for which the data were generously provided by the central banks in question.

Table 1
Maximum likelihood estimates

	Hong Kong 1973:1–2001:1	Indonesia 1980:1–2001:1	Japan 1973:1–2001:1	Korea 1973:1–2001:1	Malaysia 1975:1–2001:1	Philippines 1981:1–2001:2	Singapore 1975:1–2001:1	Taiwan 1973:1–2001:1
	1.401	1.576	1.870	1.801	1.618	1.589	1.701	1.664
ϕ_1	(0.206)	(0.013)	(0.133)	(0.158)	(0.082)	(0.091)	(0.150)	(0.152)
	[6.813]	[117.50]	[14.038]	[11.370]	[19.582]	[17.397]	[11.350]	[10.969]
	−0.531	−0.642	−0.933	−0.979	−0.709	−0.631	−0.790	−0.701
ϕ_2	(0.108)	(0.012)	(0.078)	(0.020)	(0.050)	(0.090)	(0.132)	(0.142)
	[−4.911]	[−53.454]	[−11.940]	[−49.198]	[−14.101]	[−7.024]	[−6.001]	[−4.927]
σ_y^2	0.607	0.730	0.5052	0.416	0.366	0.463	0.309	0.191
$\sigma_\mu^2 \times 100$	0.091	1.575	0.0875	0.145	1.10	0.357	0.749	0.387
σ_z^2	0.301	0.3311	0.0344	0.095	0.304	0.121	0.042	0.071
Log-likelihood	407.76	305.61	520.67	418.88	399.36	315.86	418.57	479.39

Note. Standard errors in parentheses and t-statistics in brackets.

Table 2
Time series models used in BN filters

	Hong Kong 1973:1–2001:1	Indonesia 1980:1–2001:1	Japan 1973:1–2001:1	Korea 1973:1–2001:1	Malaysia 1975:1–2001:1	Philippines 1981:1–2001:2	Singapore 1975:1–2001:1	Taiwan 1973:1–2001:1
AR lags	3,7	8	2	2,7	1,2	4,8	3	1,2,14
MA lags	8	1,2	3,4	8	4,6,8	3	1,4,10	4,10
R^2	0.1710	0.1559	0.1917	0.0651	0.1834	0.1813	0.2714	0.4064
	0.1260	0.0951	0.1917	0.0214	0.1007	0.1094	0.1596	0.1147
Log likelihood	262.82	191.95	382.44	269.31	276.99	200.34	300.96	330.68
	260.04	189.31	382.44	266.92	272.17	197.26	293.83	311.10
AIC	−4.9299	−4.9460	−7.0081	−5.0536	−5.4199	−5.3791	−5.9192	−6.6262
	−4.8580	−4.8502	−6.9896	−4.9890	−5.3434	−5.2675	−5.7765	−6.2468
LM test	0.54	0.37	0.47	0.66	0.77	0.45	0.78	0.75

Note. LM test denotes the p-value for a test of fourth-order serial correlation of the residuals. The first number of each cell stems from estimates of ARMA models of the form indicated, the second number stems from estimates of an AR(4) model.

growth rate of potential as time varying. Moreover, real economic activity fell during the Asian crisis, and, in some cases, in 1985–1986. Thus, there is clear evidence of cyclical fluctuations of the type the UC model is designed to extract from the data.

As a preliminary step to analysis below we need to estimate the UC model and the time series models underlying the BN filter. Table 1 contains the parameter estimates of the UC model for the eight economies. One interesting finding is that $\phi_1 > 1$ and $\phi_2 < 0$ in all cases. This implies that ε_t^z shocks will lead to "humped-shaped" responses of z_t. Thus, the output gap grows for several quarters after a positive disturbance and oscillates as it returns to the steady-state level of zero. Note also that since $\phi_1 + \phi_2$ is less than, but close to, unity, the output gap will display prolonged swings in response to disturbances.

Next we proceed by estimating the ARMA models for the quarterly growth rate of real GDP that underlie the BN filter. We also estimate AR(4) models and choose between models using the Akaike Information Criterion (AIC). Table 2 provides some summary statistics of the fit for the ARMA models we used to construct the BN-filtered estimates of the gap and for AR(4) models. These indicate that the ARMA models generally fit somewhat better, although the differences are generally minor.[13]

3.1. *Two-sided estimates of output gaps*

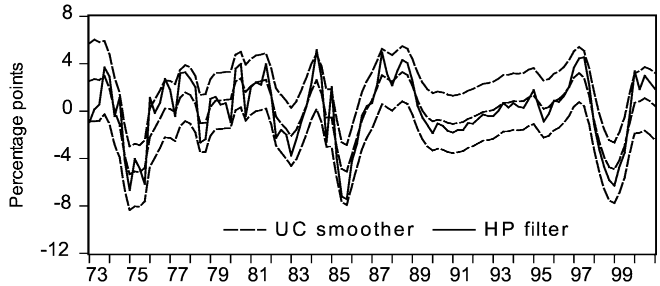
In this section we turn to a discussion of the output gaps resulting from the different methods. As noted in the introduction, it is useful to distinguish between these on the basis of the information used in constructing them. One possibility is to estimate the output gap at time t using all the data available to the analyst (that is, $z_{t|T}$ where $0 \leqslant t \leqslant T$). Following Stock and Watson (1991), these assessments may be thought of as *two-sided* or *retrospective estimates* of the gap in that they use future information to compute the current gap. An alternative strategy is to estimate the output gap at time t using only data up until time t (that is, $z_{t|t}$). The resulting assessments can be thought of as *one-sided* or *contemporaneous estimates* since they make use of current information.[14] Below we first present two-sided estimates of the output gap constructed using the UC model, the HP and BP filters.[15]

Figures 2–9 contain the extracted value of z_t for the eight economies. In panel a of each figure we present the UC estimates of the gap, together with a ± 2 standard deviations broad confidence band. We also include output gaps constructed using the HP filter. The smoothing parameter, λ, was set equal to 1600. In panel b of the figures we replace the HP-filtered output gap with that constructed using the BP filter. The BP filter is set to extract information from the frequency band corresponding to a periodicity of between 6 and 32 quarters. As suggested by Baxter and King (1999), we drop the first and last twelve observations of the sample.

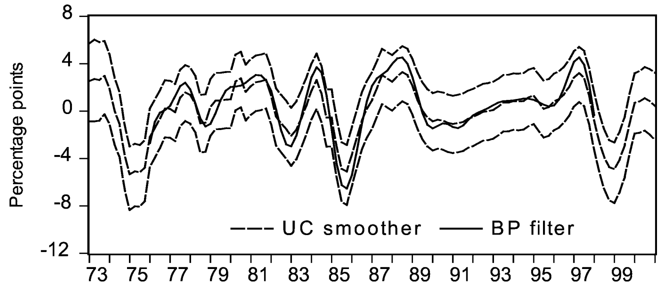
[13] Informal comparisons of the output gaps that are generated by the different models also indicate that they are not particularly sensitive to the exact choice of time series model. More information on the estimated ARMA models is available on request.

[14] Note that for the last observation in the sample, the two methods give identical results.

[15] As pointed out by a referee, the one-sided estimates correspond to Kalman filtering while the two-sided estimates correspond to Kalman *smoothing*. See Harvey (1989) or Hamilton (1994).

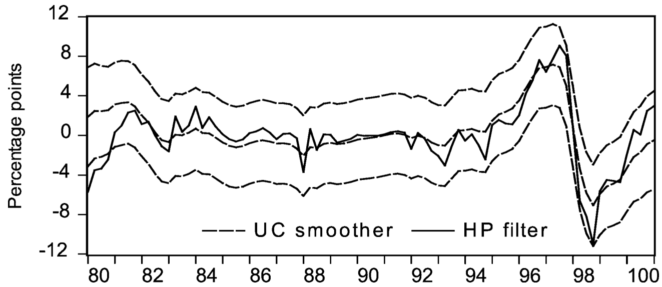


(a)

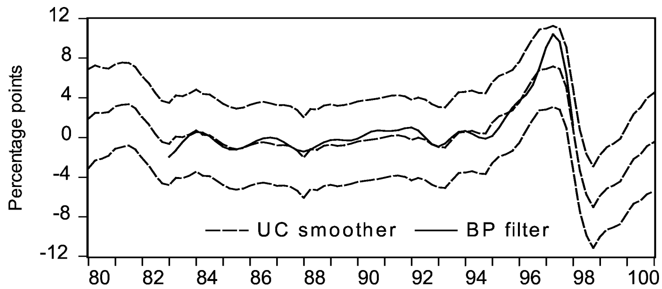


(b)

Fig. 2. Hong Kong: two-sided estimates of the output gap (with 95% confidence band).



(a)



(b)

Fig. 3. Indonesia: two-sided estimates of the output gap (with 95% confidence band).

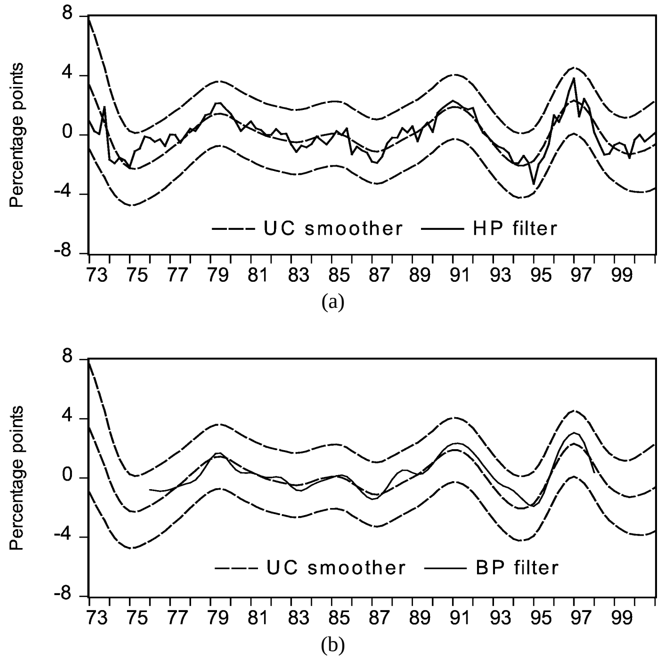


Fig. 4. Japan: two-sided estimates of the output gap (with 95% confidence band).

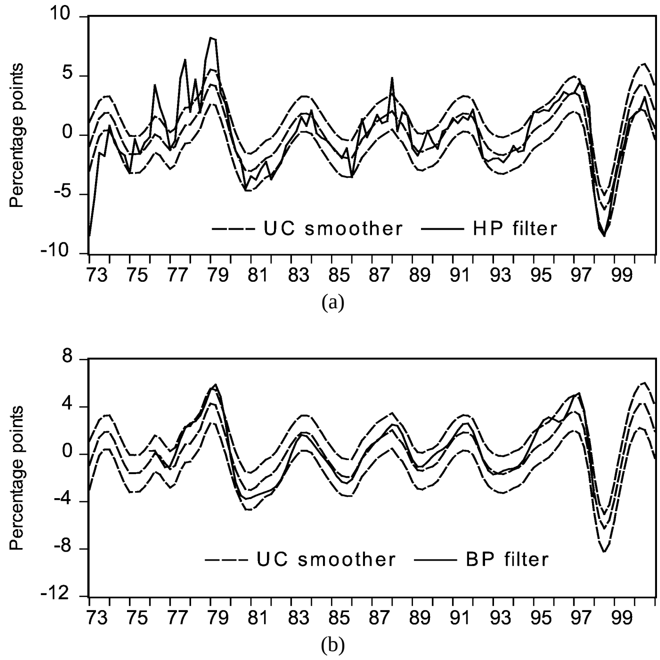


Fig. 5. Korea: two-sided estimates of the output gap (with 95% confidence band).

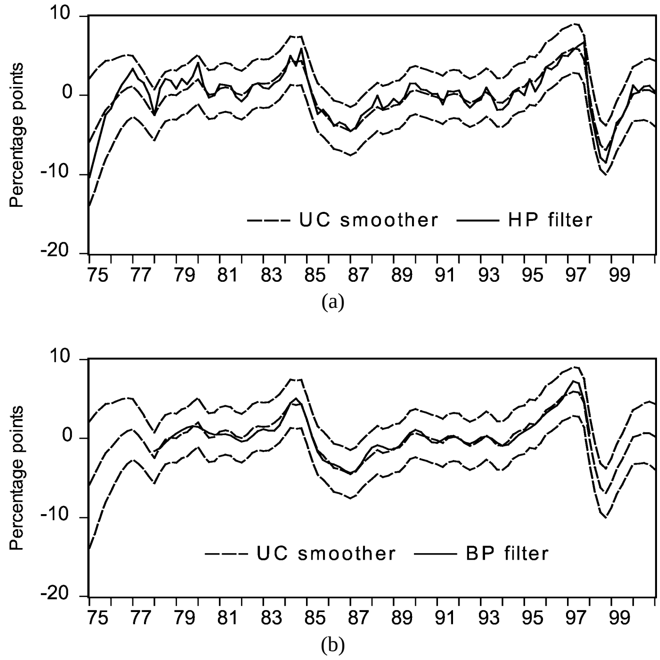


Fig. 6. Malaysia: two-sided estimates of the output gap (with 95% confidence band).

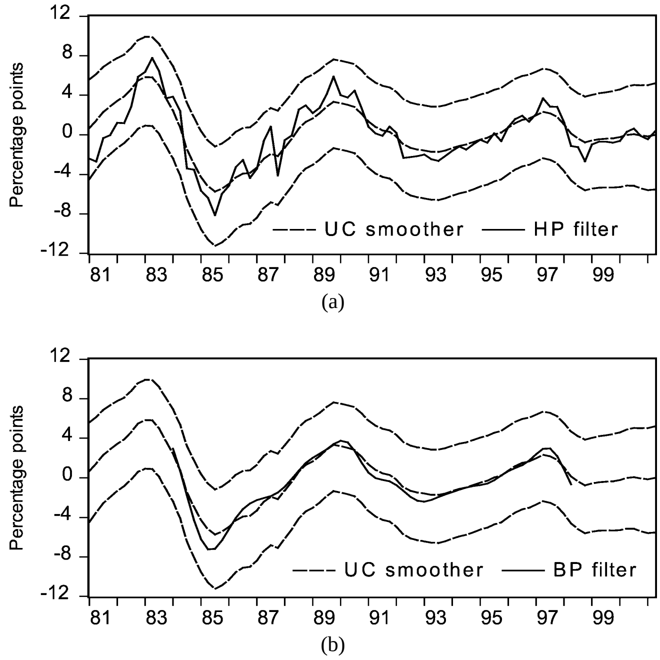


Fig. 7. Philippines: two-sided estimates of the output gap (with 95% confidence band).

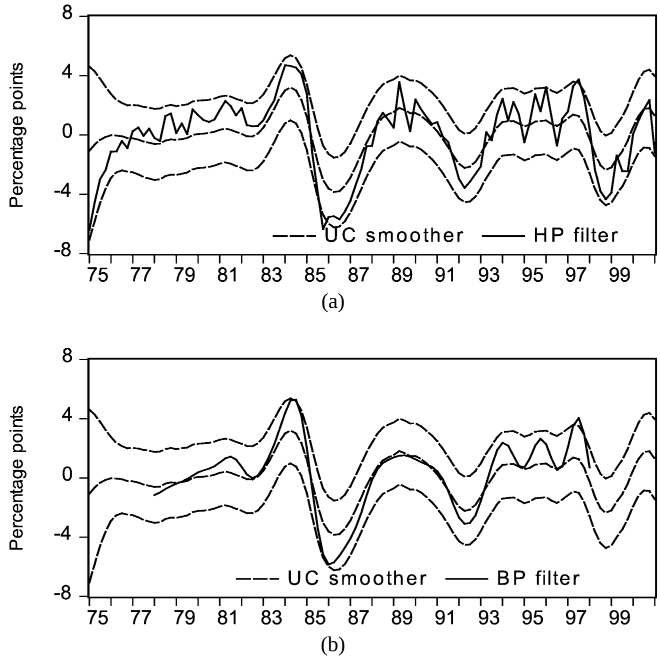


Fig. 8. Singapore: two-sided estimates of the output gap (with 95% confidence band).

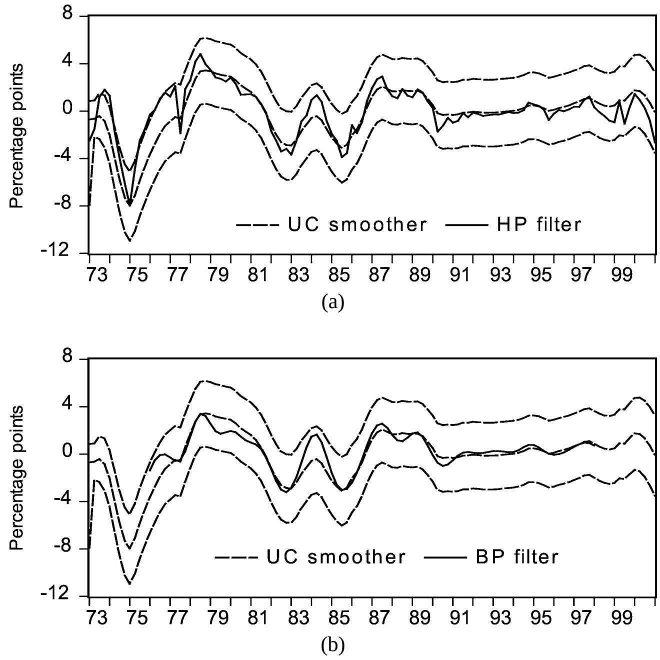


Fig. 9. Taiwan: two-sided estimates of the output gap (with 95% confidence band).

Rather than focusing on the precise movements of the output gaps over time, we consider some of the general features of the results. First, note that the output gaps stemming from the HP and BP filters are typically within the confidence bands arising from the UC model. In this sense, the three methods give rise to similar assessments of the output gap. Second, while the HP-filtered gaps are quite irregular, those based on the BP filter and the UC model are smooth. While smoothness may be an attractive feature, it should be noted that theory does not in fact offer any strong prior as to the behaviour of the output gap over time. Thus, there is no formal reason why this criterion should be used to choose between alternative estimates of the gap. Third, the confidence bands, which can only be computed for the UC model, tend to be quite "broad" in the sense that they rarely suggest that the gap is significantly different from zero. One possible reaction to this is to argue that the estimates of the state-space model are too imprecise to be useful. However, the large confidence bands are better interpreted as indicating the inherent difficulty of estimating the output gap. It should be emphasised that estimates from other methods, such as the HP or BP filters or regressions of the log of real GDP on a polynomial in time, are sensitive to the exact ways in which they are arrived at and thus vary between methods.[16] Since they are presented without confidence bands, in interpreting them one tends to forget that the methods do not provide exact indications of the size of the gap at any point in time. By contrast, the state-space methodology renders this uncertainty explicit. Thus, the broad confidence bands should not be taken as evidence that the UC method is inferior to alternative modelling approaches.

Turning briefly to the estimates for the individual economies, consider first the results for Hong Kong. Figure 2 indicates that the gap has turned sharply negative on three occasions: around 1975–1976, around 1985–1986 and 1998–2000. The results also suggest that in the autumn of 1998, before the Asian crisis reached Hong Kong, the economy was experiencing a cyclical boom with actual output exceeding potential by as much as 4%. The results more generally indicate that several of the economies studied experienced a cyclical boom before the Asian crisis started in the summer of 1997. The estimates suggest that in Indonesia, actual output was approximately 8% above potential, while in Malaysia and Korea the output gaps were in the order of 4−6%.

The results for Japan in Fig. 4 also warrant commentary. While growth has been poor since the bursting of the asset price bubble in the early 1990s, the estimates do not suggest that a large output gap developed. This suggests that most of the slowdown reflects a reduced growth rate of potential output, with the output gap playing a limited role. Since a Phillips-curve analysis implies that a substantial negative output gap would lead to considerable deflation, the fact that prices in Japan were broadly stable towards the end of the estimation period supports the finding that the slowdown is largely due to a reduction of the growth rate of potential. However, the time-series methods we use may not work well if the output gap is subject to large and protracted swings, which they instead will attribute to movements in potential output. For this reason, it would be desirable to compare the

[16] Thus, output gaps resulting from the HP filter are sensitive to the choice of the smoothing parameter, and those from the BP are sensitive to the choice of frequency band.

time-series estimates for Japan with estimates from structural models. However, such an exercise is beyond the scope of this study.

The results for Philippines, Singapore, and Taiwan are provided in Figs. 7–9; in the interest of brevity we do not comment on them.

3.2. One-sided estimates of output gaps

Next we turn to the one-sided estimates of the output gap. As discussed earlier, these are formed using only data up until time t so that the resulting estimate of the output gap can be written as $z_{t|t}$. We provide estimates for each economy by applying the BN filter and Kalman filter to the UC model estimated above.[17]

The results are available in Figs. 10–17. As before, in the interest of brevity we do not discuss them in any detail. Several comments are however warranted. First, the two methods give relatively similar results except for Japan. Second, the confidence bands stemming from the UC approach are much broader, particularly in the beginning of the sample, than those arising from the two-sided approach. Of course, this finding merely reflects the fact that one-sided estimates are based on less information than the two-sided estimates. Third, the one-sided results appear much worse than two-sided estimates in the sense that the gaps are rarely significantly different from zero. Thus, while it ex post may

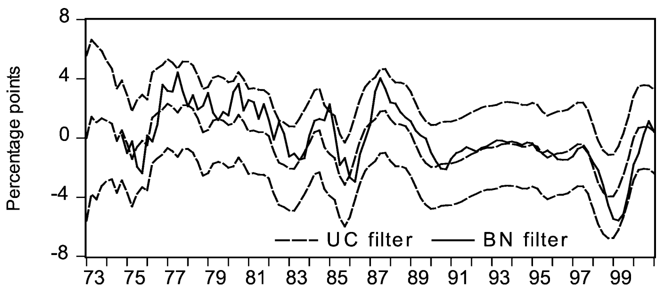


Fig. 10. Hong-Kong: one-sided estimates of the output gap (with 95% confidence band).

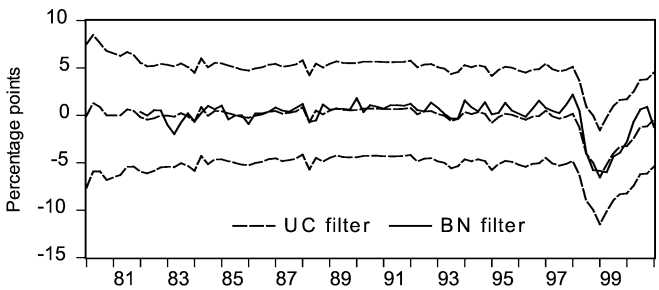


Fig. 11. Indonesia: one-sided estimates of the output gap (with 95% confidence band).

[17] In the case of the BN models the first few observations are needed to initialise the ARIMA models used in constructing the estimates of the permanent component.

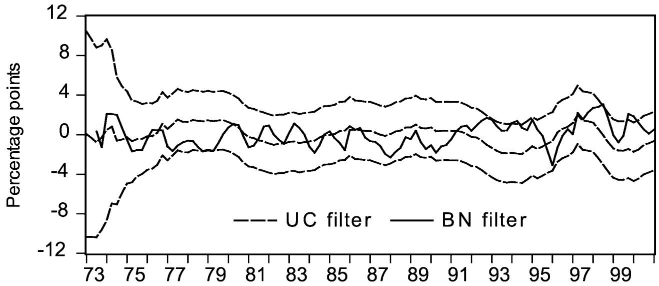


Fig. 12. Japan: one-sided estimates of the output gap (with 95% confidence band).

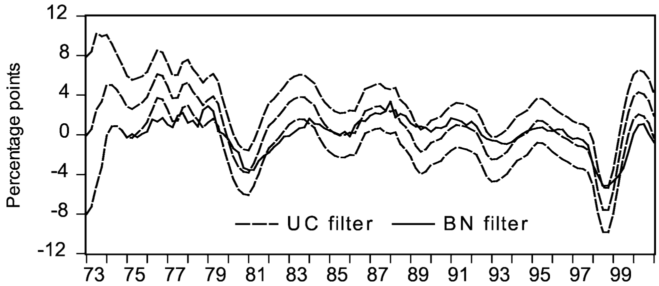


Fig. 13. Korea: one-sided estimates of the output gap (with 95% confidence band).

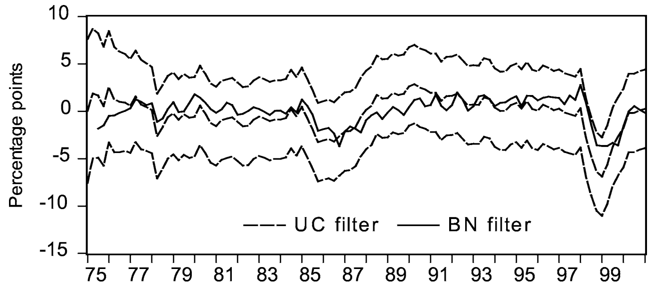


Fig. 14. Malaysia: one-sided estimates of the output gap (with 95% confidence band).

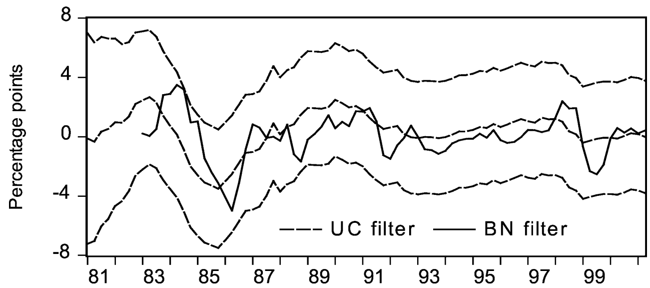


Fig. 15. Philippines: one-sided estimates of the output gap (with 95% confidence band).

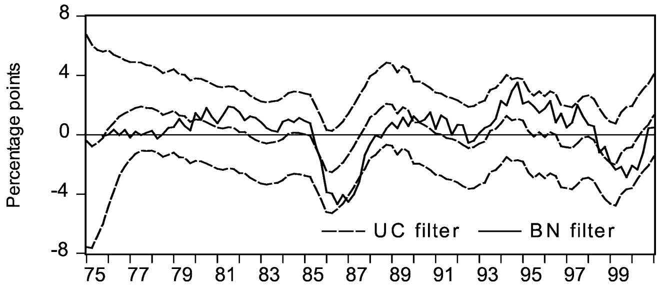


Fig. 16. Singapore: one-sided estimates of the output gap (with 95% confidence band).

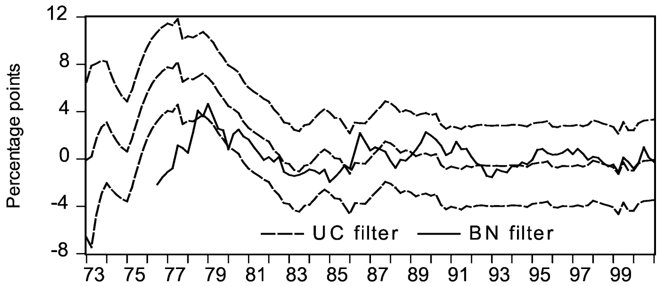


Fig. 17. Taiwan: one-sided estimates of the output gap (with 95% confidence band).

appear clear that the economy is undergoing well-defined cyclical fluctuations, real-time estimates of the output gap will generally be much less informative.

3.3. *Estimating the growth rate of potential output*

The emphasis in this paper has been on disentangling the level of output into potential output and the output gap because of the importance of the latter component for monetary policy purposes. However, estimates of potential output, in particular its growth rate, are also of relevance for policy makers. It is therefore of interest to explore how the different methods can be used for this purpose. Given space constraints, in doing so we focus on the two-sided methods.

It is useful to note that Eq. (1) implies that $\Delta y_t^{\mathrm{p}} \equiv \Delta y_t - \Delta z_t$, so that estimates of the growth rate of potential can be formed by subtracting the change in the output gap from the change in output. To proceed, note that the BP filter implicitly views output as consisting of *three* components (capturing the low, business cycle and high frequency parts of the spectrum) and eliminates *both* the low and high parts. While the estimate of Δz_t is smooth, the implied measure of Δy_t^{p} is given by the change in the low and high frequency components. Since the latter is erratic, its first difference is even more so, implying that the estimate of Δy_t^{p} will be implausibly volatile.[18] We therefore do not analyse it further below.

[18] We are grateful to an anonymous referee for drawing this to our attention.

By contrast, the HP filter yields a smooth estimate of Δy_t^{p} at the cost of a relatively volatile output gap. We therefore use the first difference of the HP filtered real GDP as a measure of the growth rate of potential below. We also use the UC model to estimate the growth rate of potential. Recall from Eq. (5) that the state vector is $X_t^{\mathrm{T}} = [\, y_t^{\mathrm{p}} \quad z_t \quad z_{t-1} \quad \mu_t \,]$. Kalman smoothing can thus be applied to obtain a direct estimate of μ_t. While Δy_t is quite erratic, the estimates of (as opposed to the unobserved realisations of) the output gap, $z_{t|t}$, and the growth rate of potential, $\mu_{t|t}$, are both smooth.

The growth rates of potential output for the eight economies we study are presented in Figs. 18–25. Note that in both the case of the HP filter and the UC model the growth rates are measured per quarter so that we need to multiply by four to obtain the corresponding annual rates. While the estimates of the different models are quite similar, it is notable that those stemming from the state-space model are much smoother. In fact, the estimates from the HP filter display considerable variation and are quite frequently outside the $\pm 2\sigma$ broad confidence bands arising from the state-space model. This finding suggests that the untested restrictions the HP filter imposes on the UC model are rejected by the data.[19]

While commenting in detail on the estimates for the different economies is beyond the scope of this paper, it is interesting to note that in most cases the growth rate of potential has been declining in the 1990s. Thus, the point estimates indicate that the quarterly growth

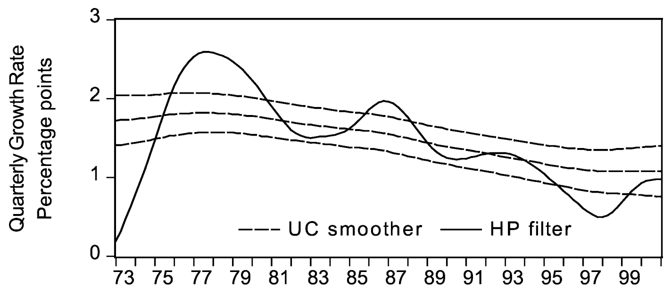


Fig. 18. Hong-Kong: growth of potential (with 95% confidence band).

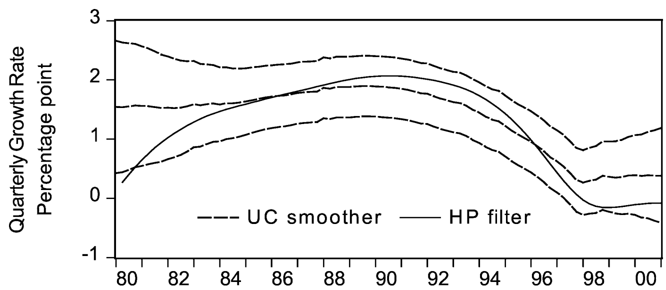


Fig. 19. Indonesia: growth of potential (with 95% confidence band).

[19] More formally, the estimates in Table 1 indicate that the restrictions under which the HP filter is equivalent to the UC model (in particular, that the variance of the shocks to Eq. (2) and that autoregressive parameters in Eq. (4) are all zero) are rejected by the data (see also footnote 9).

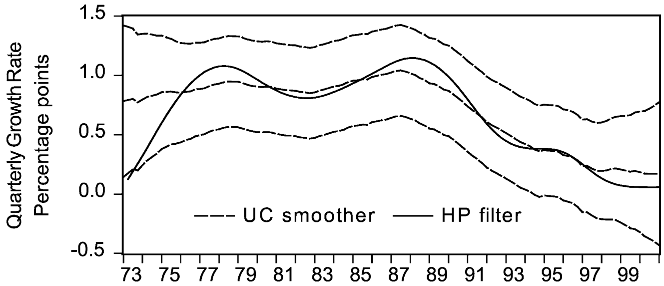


Fig. 20. Japan: growth of potential (with 95% confidence band).

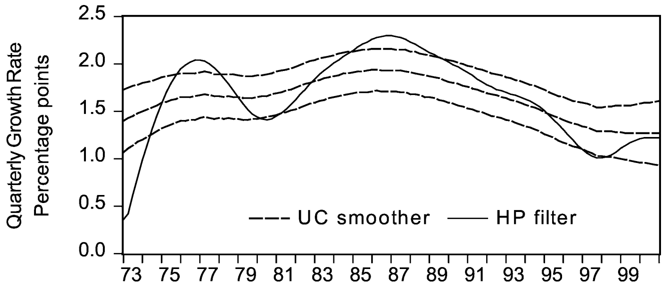


Fig. 21. Korea: growth of potential (with 95% confidence band).

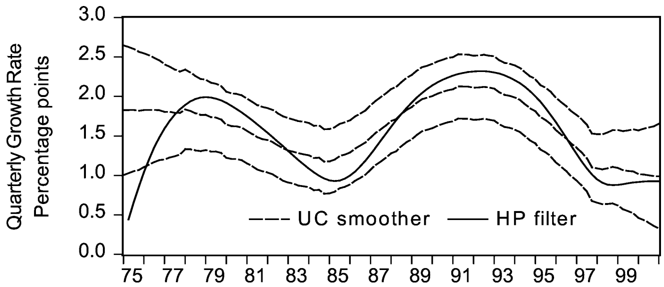


Fig. 22. Malaysia: growth of potential (with 95% confidence band).

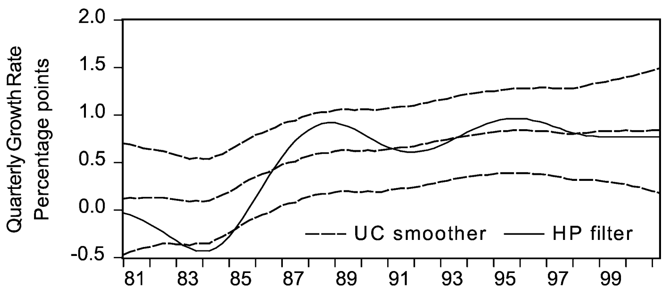


Fig. 23. Philippines: growth of potential (with 95% confidence band).

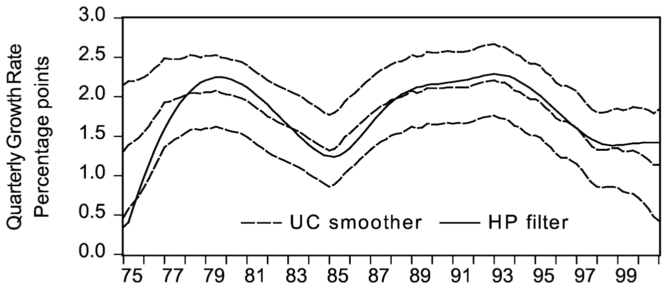


Fig. 24. Singapore: growth of potential (with 95% confidence band).

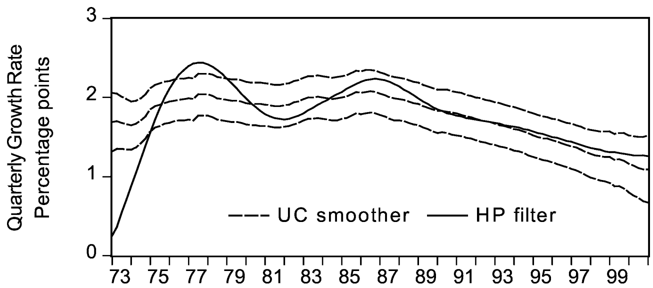


Fig. 25. Taiwan: growth of potential (with 95% confidence band).

rate of potential is typically 1–1.4% (around 0.8% in the Philippines) at the end of the sample period. However, the broad confidence bands suggest that these (and any other) estimates of μ_t should be taken with a grain of salt.

4. Conclusions

Several aspects of the results discussed in this paper are worth emphasising. First, the main lesson we draw is that it does not appear more difficult to estimate output gaps in Asian than in other advanced economies in the sense that the different methods generate broadly similar results that match well with common perceptions of business fluctuations in these economies. This is despite the fact that, as noted by Coe and McDermott (1997), the Asian region has experienced rapid growth and has been exposed to large disturbances, in particular to a sharp contraction in real economic activity following the onset of the Asian crisis in 1997.

Second, estimating the output gap or, equivalently, potential output using the UC approach appears to work well in practice. The main benefit of this modelling strategy is that it permits the construction of confidence bands around the estimated output gaps. This is desirable because they show how much (or how little) in fact is known about the precise size of the gap. It also yields plausible estimates of the growth rate of potential output. Such estimates may be of independent interest to policy makers.

Third, output gaps generated using the HP and BP filters and the UC approach appear quite similar, suggesting that they contain much the same information for inflation and other variables that policy makers are interested in. Since the HP filter is implemented in a number of software packages, it seems likely that it will remain the preferred method for constructing output gaps in applied econometric research.

Acknowledgments

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