WP/10/149

IMF Working Paper

Vietnam: Bayesian Estimation of Output Gap

Wojciech S. Maliszewski

INTERNATIONAL MONETARY FUND

 WP/10/149

IMF Working Paper

APD

Vietnam: Bayesian Estimation of Output Gap

Prepared by Wojciech S. Maliszewski[1]

Authorized for distribution by Shogo Ishii

June 2010

Abstract

The paper constructs a new output gap measure for Vietnam by applying Bayesian methods to a two-equation AS-AD model, while treating the output gap as an unobservable series to be estimated together with other parameters. Model coefficients are easily interpretable, and the output gap series is consistent with a broader analysis of economic developments. Output gaps obtained from the HP detrending are subject to larger revisions than series obtained from a suitably adjusted model, and may be misleading compared to the model-based measure.

JEL Classification Numbers: E32 E31 C51

Keywords: Output Gap, Inflation, Unobservable Component Model, Bayesian Methods

Author's E-Mail Address: wmaliszewski@imf.org

[1] The author would like to thank Jorge Iván Canales-Kriljenko, Do Viet Hung, Nikolay Gueorguiev, Ben Hunt and Shogo Ishii for helpful comments. All remaining errors are mine.

Contents

I. INTRODUCTION

Estimating potential output and the output gap is notoriously difficult, but particularly so for transition economies undertaking large structural changes. The production function approach usually cannot be applied because of scarcity of data. Exploiting the empirical relationship between output and the unemployment rate (Okun's law) is difficult as the natural rate of unemployment is unobserved and varies over time. The Hodrick-Prescott (HP) filter lacks economic context, as it imposes a standard degree of smoothness on the estimated potential output series, while the potential output volatility may be much larger in transition countries. It also suffers from the well-known end-point bias.[2]

The paper addresses the above problems by relying on a model-based multivariate filter, using economic theory and previous studies to guide the estimation of parameters. The model is a version of a two-equation AD-AS system. The unobservable output gap is estimated as a function of the past output gap, the real interest rate and the real exchange rate. The second equation is a Phillips-curve-type relation, describing inflation as a function of the output gap, exchange rate depreciation, and exogenous supply-shock variables. The inflation equation is included because inflation is assumed to respond to fluctuations in output gap, providing additional information useable in the estimation of the latter.

The proposed method is applied to the estimation of output gap for Vietnam—a transition economy with data shortcomings discussed above: data required for the production function approach and unemployment series are not available on quarterly basis; the potential output may be less smooth than in developed economies due to large structural changes; and the National Accounts series on quarterly basis are short, aggravating the end-point bias.

Several researchers have used multivariate models to estimate output gaps. Benes and N'Diaye (2004) applied a similar model with calibrated parameters to construct output gap series for the Czech Republic. Kuttner (1994) estimated a simpler model relating the output gap to inflation through the Phillips curve using the classical (frequentist) methodology. The same model was replicated by Kichian (1999) for G7 countries, and popularized by Gerlach and Smets (1999). Apel and Jansson (1999a, 1999b) extended the model to include unemployment. The European Commission used it to estimate structural unemployment (Planas et al., 2003), and the OECD applied a closely related version for estimating the NAIRU (OECD, 2000).

In the case of Vietnam the available series are too short to produce meaningful estimates with classical estimation procedures, and the paper uses Bayesian estimation methods instead. Bayesian methods usefully combine information in the data with priors derived from previous studies and economic theory, producing better interpretable results. While technically more challenging than classical methods, estimation of even fairly complex Bayesian models is nowadays straightforward due to great strides in econometric theory and

---

[2] End-points of the series have an exaggerated impact on the trend.

increasing computing power. Applications of Bayesian methods to estimating output gap have been scarce, with a notable exception of Planas et al. (2008), who estimate a simpler model based on Kuttner (1994) for EU and US, and Benes et al. (2010).

The paper is organized as follows. Section II provides an overview of growth and inflation developments in Vietnam. Section III presents the model and the estimation methodology used in the paper. Section IV discusses results and compares to traditional measures of output gap. Details of the estimation methodology are discussed in the appendix.

II. Growth and inflation developments

Vietnam experienced a bout of hyperinflation in the second half of the 1980s and early 1990s, but a major stabilization effort brought inflation under control. The restrictive monetary and fiscal policy played a key role in bringing inflation down from the annual rate of above 300 percent in 1986-88 to below 20 percent in 1992 and close to 10 percent in 1995 (Camen, 2006). The stabilization led to a strong growth performance in the early 1990s.

Growth slowed and inflation remained subdued in the late 1990s and early 2000s. While the Asian crisis was the principal cause of the slowdown in the late 1990s, it was also partly due to the increasingly unsustainable composition of growth in the past, heavily dependent on capital-intensive investment, mainly by SOEs in uncompetitive sectors. The economy began to rebound in late 1999—largely due to a revival of domestic investment—but it was growing at a slower rate than in the early 1990s. Vietnam experienced two years of a mild deflation in 2000-01 owing to excess capacity and depressed commodity prices, and both the headline and the core inflation rates remained low in 2002-03.

Real GDP picked up and inflation rose sharply between 2004 and 2007. The strong growth was fuelled by buoyant consumption and export growth, notwithstanding a number of supply shocks (the avian flu, a drought, and rising international prices of inputs). Inflation was rising sharply on the back of the sustained strength of international commodity prices and the growing excess demand.

Growth declined to 6¼ percent in 2008, the slowest pace since 1999. The slowdown was driven by subdued activity in the construction and services, following a steep downturn in the property market. Although inflation increased to a 17 year high in mid-2008, it moderated near the end of the year, due to the weakening domestic demand but also lower food and energy prices. Core inflation followed a similar pattern, but the decline was more gradual.

III. Model and Estimation Procedure

A. Model specification

The econometric model consists of behavioral equations describing the evolution of the output gap and inflation, and equations governing the dynamics of potential output. The behavioral equations are similar to those frequently used in small-scale models for policy analysis (see Berg et al. 2006a and Berg et al 2006b for a stylized model). The discussion above suggests that, while demand conditions contributed to the subdued inflation in the first half of 2000s and to the persistently high inflation later, supply shocks were also a major contribution to inflation dynamics. Moreover, the relatively recent experience of hyperinflation might have increased inflation persistence as often documented in the literature (e.g. Edwards and Lefort, 1988). The specification of the model and priors proposed for the coefficients aim to address these features of the inflation dynamics.

Output Gap Equation

The output gap is measured as $ygap_t = 100\left(\log(Y_t) - \log(Y_t^*)\right)$, where Y is the level of real GDP and Y* is an estimate of potential GDP. Its evolution is described by:

$$ygap_t = \beta_{lag} ygap_{t-1} - \beta_{RRgap}(RR_{t-1} - RR_{t-1}^*) + \beta_{zgap}(z_{t-1} - z_{t-1}^*) + \beta_{Wygap} ygap_t^W + u_t^{ygap} \qquad (1)$$

where RR is the real interest rate, z is (100×) log of real effective exchange rate, and the '*' denotes equilibrium values of these variables.[3],[4] $ygap_t^W$ denotes the HP-filter measure of output gap in trading partner countries, and u_t^{ygap} is normally and independently distributed random disturbance with zero mean and variance $\sigma^2_{u^{ygap}}$. This specification resembles micro-founded output gap equations, although it does not include a future output gap.

Phillips Curve

The model is specified in terms of the core inflation $\pi_{c,t}$ (excluding raw food and energy components) to minimize the effect of supply shocks:

$$\begin{aligned} \pi_{c,t} &= \alpha_{\pi lag} \pi 4_{c,t-1} + \alpha_{ygap} ygap_{t-1} \\ &\quad + \alpha_z (z_t - z_{t-1}) + \alpha_{ecm} (\pi 4_{t-1} - \pi 4_{c,t-1}) + \alpha_f \pi_{rpfood,t} + u_t^{\pi c} \end{aligned} \qquad (2)$$

Inflation is measured as the annualized quarterly change, in percent, and so $\pi_{c,t} = 400[\log(cpi_{c,t}) - \log(cpi_{c,t-1})]$. It depends on past four-quarter inflation $\pi 4_{c,t-1} = 100[\log(cpi_{c,t-1}) - \log(cpi_{c,t-5})]$, lagged output gap, changes in the real exchange rate, and the difference between past headline and core inflations $\pi 4_{t-1} - \pi 4_{c,t-1}$. In addition, the

---

[3] The real interest rate is calculated using the core CPI to smooth out the effect of supply shocks.

[4] Equilibrium values are approximated by sample means. The sample mean may not reflect true equilibrium values of the variables, potentially biasing the results. A more elaborate version of the model could include separate equations governing the behavior of the equilibrium real exchange and interest rates, but correctly constructing such a system of equations is difficult both analytically (given uncertainty surrounding determinants of these variables) and econometrically (identification of potential output becomes more difficult). Simple alternatives to sample means, such as using time or HP trend to capture a potential Balassa-Samuelson effect in the real exchange rate, produced very similar results.

equation contains a relative change in the price of raw food $\pi_{rpfood,t}$ to capture contemporaneous effects of supply shocks on the core inflation. u_t^{π} is normally and independently distributed random disturbance with zero mean and variance $\sigma^2_{u^{\pi}}$. As above, this specification resembles micro-founded models, but does not include forward-looking components because data on inflation expectations in Vietnam are not available. The forward-looking element was initially proxied by inflation expectations of offshore financial institutions reported in Consensus Forecast. But reliable series from the survey could be constructed only for post-2001 period, and in any case the series closely tracks the lagged actual inflation. In the relatively unsophisticated economy of Vietnam, agents are likely to form expectations based on a limited information set, dominated by the past inflation. The full-sample Philips curve equation reported in this paper therefore uses the first lag of inflation as a proxy for expectations.

Potential output

The econometric model is completed by specifying the dynamics of potential output. It is assumed to follow a random walk process (in logs) with a time-varying slope μ_t :

$$\log(Y_t^*) = \log(Y_{t-1}^*) + \mu_{t-1} + u_t^{Y^*} \tag{3}$$

$$\mu_t = \mu_{t-1} + u_t^{\mu} \tag{4}$$

Where $u_t^{Y^*}$ and u_t^{μ} are normally and independently distributed random disturbances with zero means and variances $\sigma^2_{u^{Y^*}}$ and $\sigma^2_{u^{\mu}}$ respectively. This specification does not have a direct economic interpretation, but is sufficiently general to cover a broad range of potential stochastic processes for the potential output. In particular, the random walk process for the time-varying slope is general enough to approximate a wide range of transitional growth dynamics. The specification also encompasses the commonly used Hodrick-Prescott (HP) filter: it can be shown that the HP filter with a smoothing parameter of 1600 (typically used for quarterly data) is a special case of the above model, with $\sigma^2_{u^{Y^*}} = 0, \sigma^2_{u^{ygap}} = 1600\sigma^2_{u^{\mu}}, \beta_{\bullet} = 0$ and $\alpha_{ygap} = 0$.

B. Data

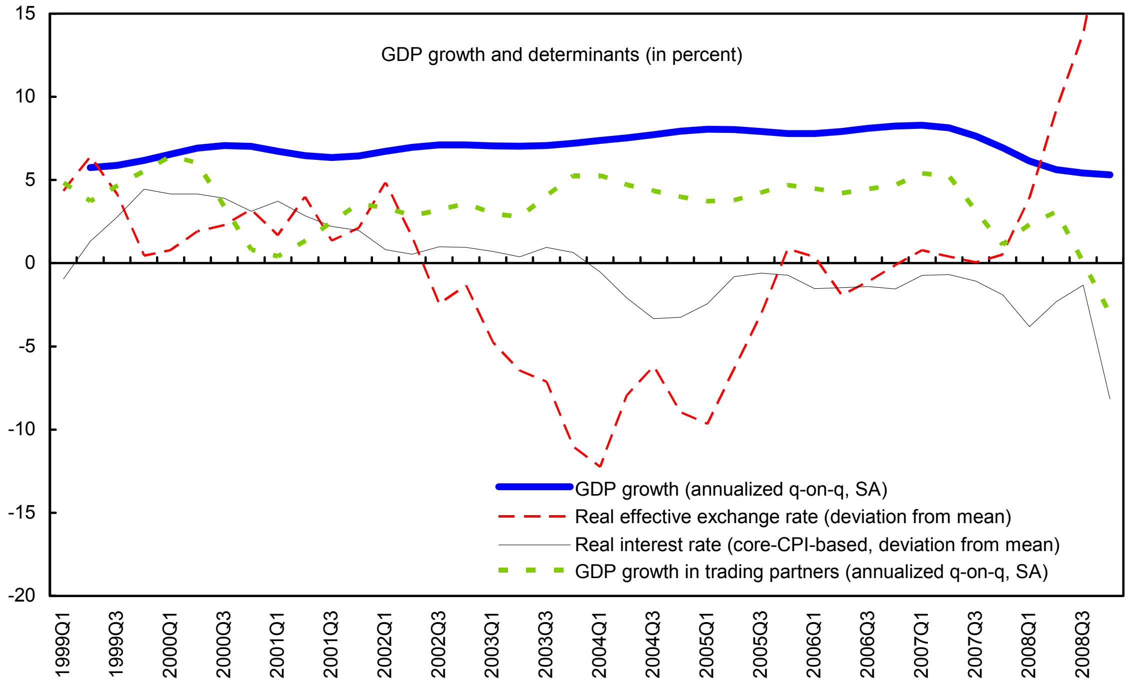
The model is estimated using quarterly data for 1999 Q2 to 2008 Q4, subject to standard adjustments. Time series are provided by the State Bank of Vietnam (commercial banks prime lending rate), General Statistical Office of Vietnam (GDP, CPI, core CPI excluding petroleum products and raw food prices, and raw food prices), and IMF WEO (real effective exchange rate and GDP in trading partner countries). The real interest rate is calculated using the core CPI to smooth out the effect of supply shocks. Equilibrium values for the real exchange rate interest rates are approximated by sample means. All series are seasonally adjusted using X12 procedure, except for the log of the GDP series, for which the seasonal pattern does not seem well captured by the X12 filter. The seasonal adjustment for this series is conducted through an auxiliary state-space model (details and comparisons with X12 results are reported in Appendix 1).

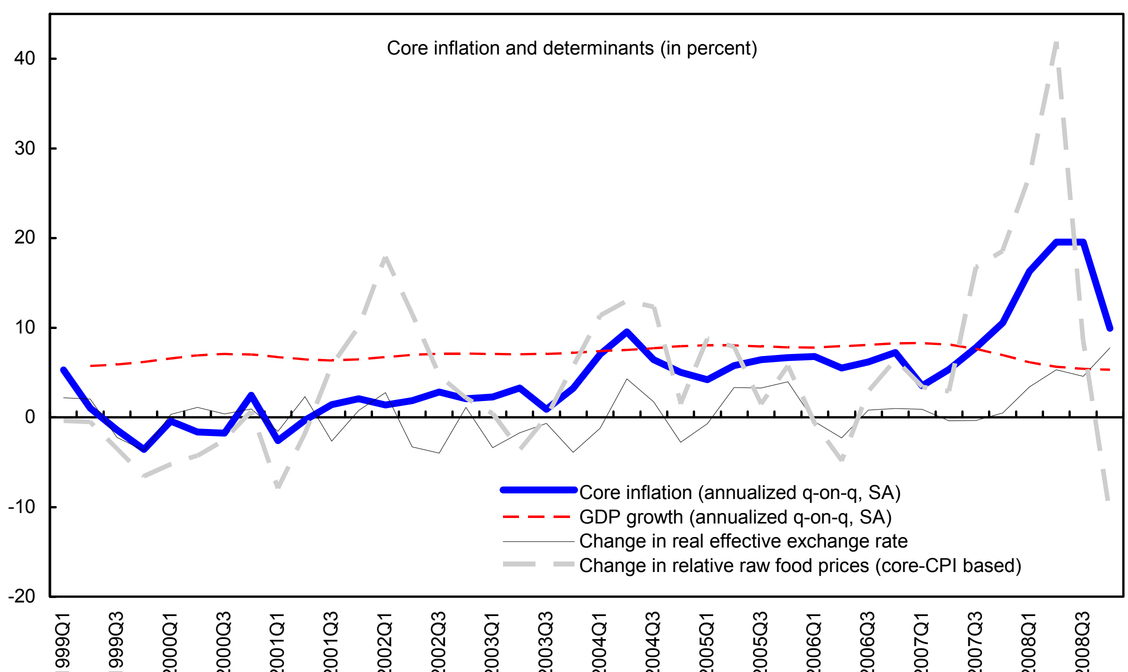
Figure 1 presents a graphical analysis of all series used in the model, with an annualized quarterly GDP growth series replacing output gaps:

- Vietnam GDP growth seems correlated with the foreign output growth and the real interest rate, as stipulated in equation (2) (Figure 1, upper panel). The relationship between the output growth and the real effective exchange rate is less pronounced, although a slower growth at the beginning and at the end of the sample coincides with a real appreciation.

- The lower panel shows the core inflation against theoretical determinants included in equation (1). Output growth seems to lead the core inflation series, but supply shocks (proxied by relative changes in food prices) also appear to have a strong effect on changes in core prices. The effect of the exchange rate is again less visible, except at the end of the sample.

Figure 1. Vietnam: Model variables





Source: State Bank of Vietnam; General Statistics Office of Vietnam; and staff calculations.

C. Estimation method

The Bayesian estimation procedure applied in this study combines researcher's priors with information contained in the data. A prior density $g(\Gamma)$ for all parameters of the model Γ is combined with data y to produce a posterior density $f(\Gamma|y)$:

$$f(\Gamma|y) = g(\Gamma)\frac{f(y|\Gamma)}{f(y)}, \tag{5}$$

where $f(y|\Gamma)$ and $f(y)$ are conditional and marginal densities of y.

The present model treats parameters of equations (2) and (1), parameters (variances of errors) of equations (3) and (4), and unobservable potential output and output gap series as unknown quantities to be estimated (elements of Γ). Given the complexity of the model, the posterior density $f(\Gamma|y)$ needs to be computed numerically. A common method in the Bayesian analysis is to compute these moments by applying Markov Chain Monte Carlo (MCMC) methods. The application of the MCMC method is described in the Appendix.

Prior Parameters

Priors for coefficients in the output gap and inflation equations reported in Tables 1 and 2 are broadly based on values reported in the literature (see Berg et al. 2006a, 2006b), with some modifications to reflect specific features on the Vietnamese economy. For instance, the lagged inflation coefficient in the Phillips curve is higher, because past inflation replaces both the backward and the forward-looking part of inflation expectations, and because the relatively recent experience of hyperinflation might have increased inflation persistence. All priors for coefficients in the output gap and inflation equations are distributed according to normal distributions conditional on other parameters of the model, and subject to restrictions $0 < \beta_{lag} < 1$, $\beta_{RRgap} < 0$, $\beta_{zgap} > 0$, $0 < \alpha_{\pi lag} < 1$, $\alpha_{ygap} < 0$, $\alpha_z < 0$. Priors are relatively imprecise, in order to allow information in the data have a meaningful influence on posteriors.

Priors for variances of shocks are also relatively non-informative and proportional to modeled time series. For $\sigma^2_{u^{ygap}}$ and $\sigma^2_{u^{Y^*}}$, prior means are equal to the variance of the HP measure of output gap, while the ratio $\sigma^2_{u^{ygap}} / \sigma^2_{u^{\mu}}$ is set to 1600, in line with the HP restriction. For $\sigma^2_{u^{\pi}}$, the prior mean is equal to the variance of core inflation. All prior variances are distributed according to inverse gamma distributions. Appendix 2 provides further details.

Initial values for unobservable components

Initial values for unobservable components of output are drawn from diffuse distributions for non-stationary components ($\log(Y_0^*)$ and μ_0) and an unconditional distribution for the stationary component ($ygap_0$).

IV. RESULTS

Posterior coefficients

Posterior coefficients of the model are in line with economic theory (Table 1). The effect of interest rate movements on output gap is small, but in line with the priors, while the effect of changes in the real exchange rate seems weaker:

- The interest rate coefficient is on the low side of the range reported in other studies, suggesting that the interest channel estimated in the model is weak in the short term (one-quarter). A degree of caution is needed when interpreting the results given that the real interest rate measure used in the model (deviations of the ex-post real interest rate from the mean), but results are robust to using alternative equilibrium real interest measures, such as deviations from HP or linear trends.[5] The low interest rate coefficient point to a still underdeveloped monetary transmission mechanism, and may also reflect the tendency of the authorities to rely on direct monetary policy instruments.

- The exchange rate coefficient is much lower than the literature-based prior—suggesting a weaker impact of deviations of the real exchange rate from equilibrium on output. As above, the results are robust to using alternative real exchange rate measures—deviations from HP and linear trends—which are potentially important to capture the Balassa–Samuelson effect from fast increases in productivity. The weak impact of the exchange rate on output gap is likely the effect of the large share of primary commodities in the Vietnam export basket, which are not sensitive to exchange rate changes.

- The coefficient of output gap in trading partner countries is close to the prior and estimated relatively precisely, which is consistent with the high openness of the Vietnamese economy.

- The lagged output gap coefficient is slightly lower than the prior, but in the range reported in the literature.[6]

---

[5] A more elaborate version of the model could include separate equations governing the behavior of the equilibrium real exchange and interest rates, but correctly constructing such a system of equations is difficult both analytically (given uncertainty surrounding determinants of these variables) and econometrically (identification of potential output becomes more difficult).

[6] Aiyar and Tchakarov (2008) reports a much lower value of the coefficient for Thailand.

The coefficients of the Phillips curve equation suggest a relatively high degree of inflation inertia, a substantial short-term impact of the output gap on inflation, and a dominant effect of supply shocks:

- The lagged inflation coefficient is high, although lower than the prior.

- The coefficient of the output gap is higher than the literature-consistent prior. This result is key to the estimation of the output gap series, as it indicates that there is a significant amount of information about output gap dynamics to be extracted from the behavior of inflation.

- The coefficient of the real exchange rate is close to the prior.

- The coefficient of relative changes in food prices is high and precisely estimated, suggesting that the immediate impact of a supply shock on our measure of core inflation is strong. The estimated short-term influence of second round effects (the one-quarter lagged difference between the headline and core inflation rates) is relatively weak.

The posterior distributions for variances of shocks are far from the prior distributions:

- The posterior mean of the variance of output gap shocks $\sigma^2_{u^{ygap}}$ is smaller, while the posterior mean of the variance of potential output *slope* shocks $\sigma^2_{u^{\mu}}$ is close to the prior. As a result, the ratio $\sigma^2_{u^{ygap}} / \sigma^2_{u^{\mu}}$ is lower than the restriction imposed by the HP filter (Figure 2).

- The posterior mean of the variance of potential output shocks $\sigma^2_{u^{Y^*}}$ is also lower than the prior. The inverse of the signal-to-noise ratio—a ratio of shocks to the permanent and temporary components of output defined as $\sigma^2_{u^{ygap}} / \sigma^2_{u^{Y^*}}$—is close to the prior.

Figure 2. Vietnam: Variance ratios

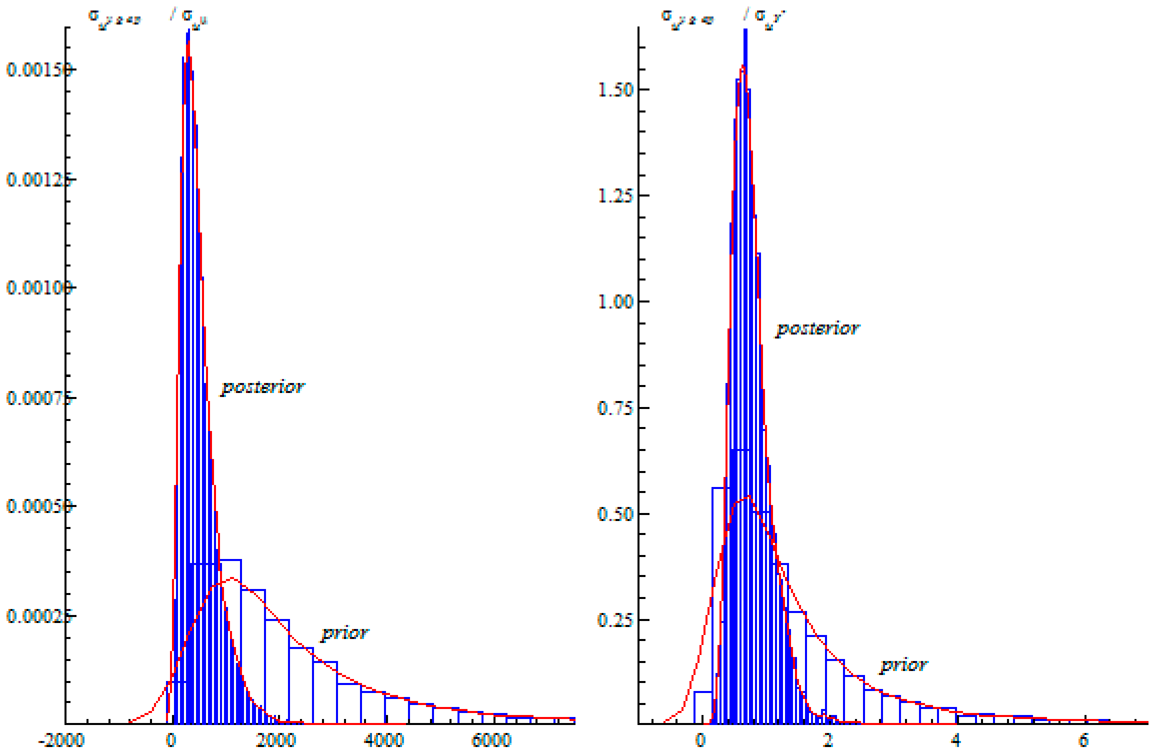


Table 1. Vietnam: Prior and Posterior Model Parameters

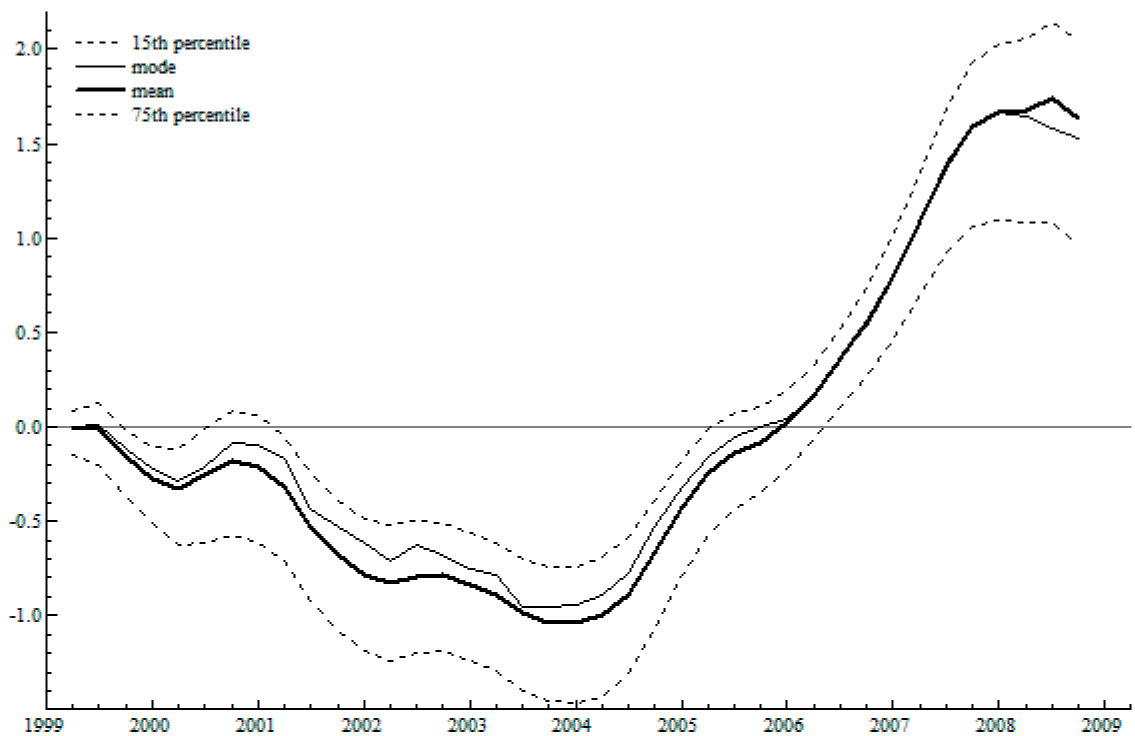
	Prior		Posterior			
	Mean	Std. Dev.	5th percentile	Mean	95th percentile	Std. Dev.
Variances on innovations						
$\sigma^2_{u^{ygap}}$	0.166	0.166	0.0224	0.0364	0.0563	0.0107
$\sigma^2_{u^{Y^*}}$	0.166	0.166	0.0306	0.0561	0.0790	0.0153
$\sigma^2_{u^{\mu}}$	0.0001	0.0001	0.0000	0.0001	0.0003	0.0001
$\sigma^2_{u^{\pi}}$	28.179	28.179	5.9458	8.5793	12.1437	1.9348
Output gap equation						
β_{lag}	0.700	0.700	0.3543	0.6562	0.8646	0.1568
β_{RRgap}	-0.100	0.100	-0.1285	-0.0730	-0.0224	0.0320
β_{zgap}	0.050	0.050	0.0007	0.0104	0.0264	0.0083
β_{Wygap}	0.250	0.250	0.0849	0.2211	0.3635	0.0848
Phillips curve equation						
α_{ygap}	0.300	0.300	0.0605	0.4041	0.08189	0.2325
$\alpha_{\pi lag}$	0.900	0.900	0.5263	0.7375	0.9324	0.1225
α_{z}	0.200	0.200	0.0311	0.2059	0.4162	0.1181
α_{f}	0.200	0.200	0.1459	0.2172	0.2884	0.0432
α_{ecm}	0.100	0.100	-0.0767	0.0754	0.2280	0.0925

Output gap series

The estimated output gap indicates below-potential economic activity between late-1999 to 2005, overheating in 2006-08, and a turnaround in the cyclical position in late 2008 (Figure 3). The results are easily interpretable. The initial negative output gap reflects the effect of monetary tightening at the end of 1999 and the global slowdown starting in 2001, There is also anecdotal evidence of the presence of overheating in 2006-08—such as skilled labor shortages.

The model-based output gap is subject to considerable uncertainty near the end of the sample, but it is significantly different from zero during the 2006-08 overheating. The wide confidence intervals are mainly the result of somewhat imprecise estimates of model coefficients reported in Table 1. It is also worth noting that the distribution is slightly skewed, with its mode closer to zero than the mean, particularly in the middle of the sample.

Figure 3. Vietnam: Model-based estimates of output gap

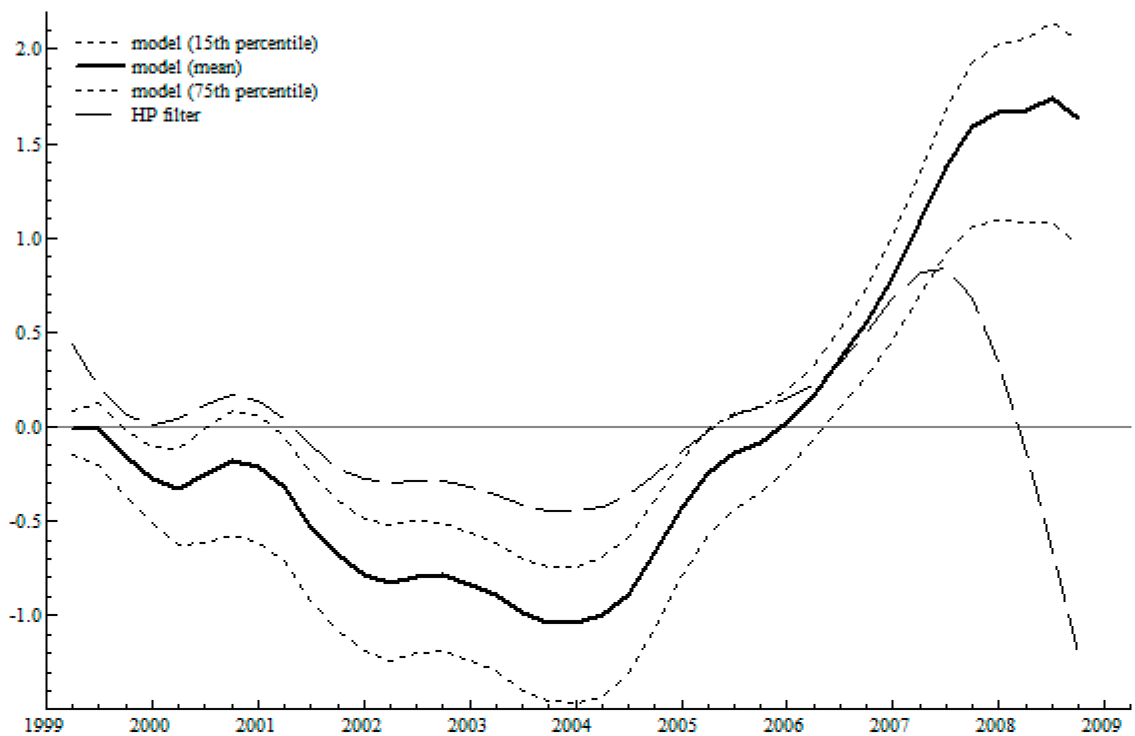


Source: Staff estimates.

Comparison with the HP filter

The output gap series constructed from the model is significantly different from the HP estimate (Figure 4). In particular, the model-based series shows a significantly wider output gap in 2001-04. It moves in line with the HP-measure between 2002 and 2006, but the HP-based measure then peaks in mid-2007 and drops to a negative territory at the end of the sample, while the model-based series reaches the maximum in the first quarter of 2008 and remains positive till the end of 2008. The model-based measure seems easier to interpret throughout the period as discussed above. In particular, the earlier and sharper drop in the HP-measure is difficult to interpret given that the signs of economic overheating were present until the second quarter of 2008.

Figure 4. Vietnam: Model-based output gap vs. HP estimates



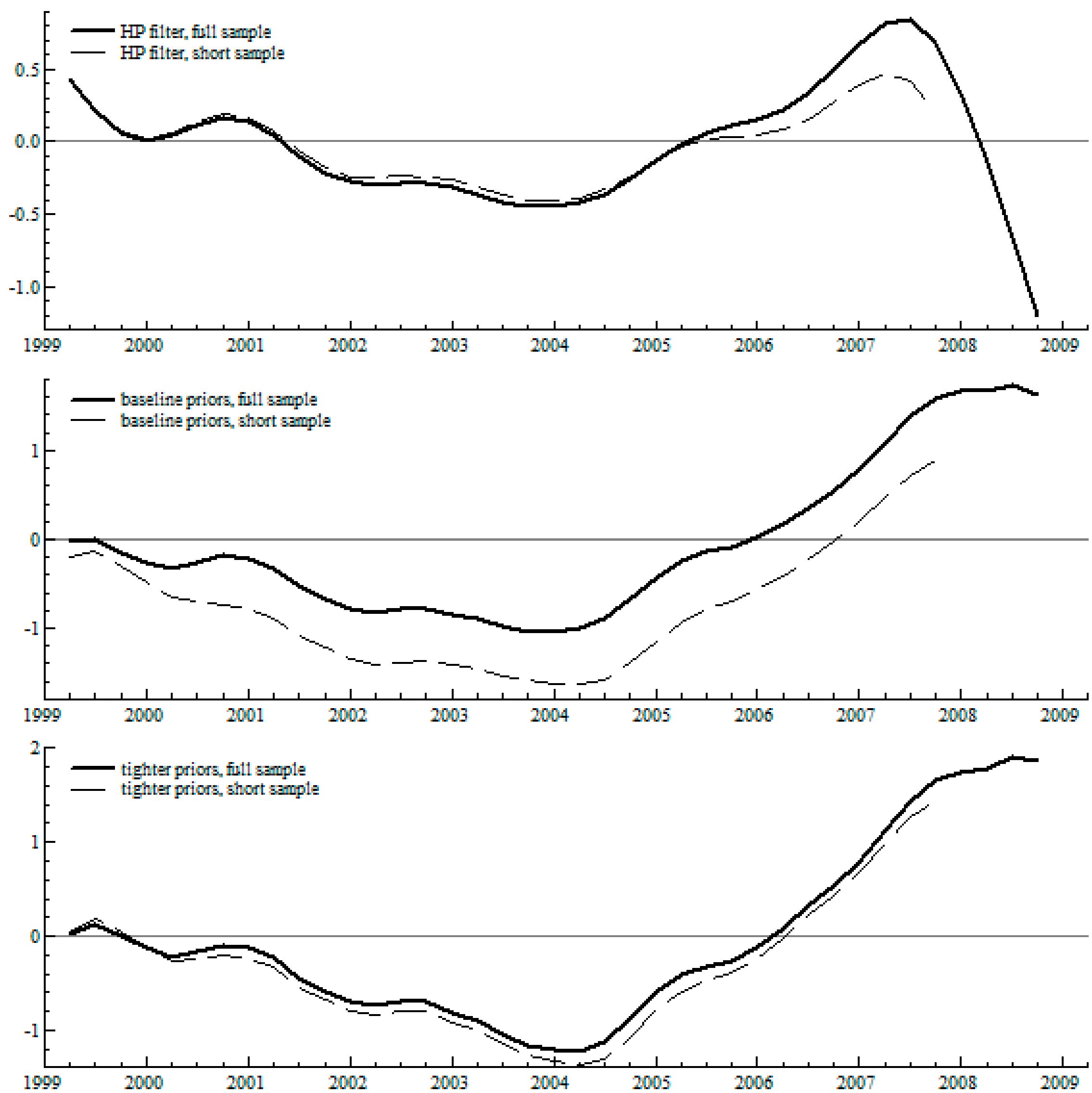
Source: Staff estimates.

Robustness to revisions over time

Substantial revisions over time—which are related to the end-point bias—are a significant drawback of the HP filter, but model-based estimates score no better in this area. The first panel of Figure 5 illustrates the problem in the case of Vietnam, where short-sample HP-based estimates of output gap (dashed line—estimated on the sample finishing in Q4 2007) would underestimate excess demand at the end of 2007 compared to the full sample estimate (solid line—sample ending in Q4 2008). Model-based estimates (Figure 5, second panel) suffer from an even worse problem, as output gap is underestimated on the basis of partial data throughout the sample.

However, the revisions in the model-based method mainly reflect changes in the estimates of model parameters, and these changes are likely to be smaller in larger samples or with tighter priors. Indeed, imposing tighter priors for parameters in both equations of the model (with mean-to-standard-deviation ratios for all parameters set to 5, compared to 1 in the baseline priors) generates a full-sample output gap estimate similar to the model with more diffuse priors, but subject to substantially less revisions over time (Figure 5, last panel). While there is a considerable degree of subjective judgment in choosing the specification of the model and priors, the model—even with strong priors—is still better rooted in economic theory then the atheoretical HP filter.

Figure 5. Vietnam: Model-based output gap vs. HP estimates



Source: Staff estimates.

V. Conclusions

The paper has refined a methodology for estimating the output gap to provide a more meaningful measure of excess demand for policy analysis. It is done by applying Bayesian methods to a standard two-equation model of output and inflation, while treating the output gap series as an unobservable series to be estimated together with other parameters. The priors imposed in the Bayesian estimation allow for a meaningful estimation of the model even for countries with relatively weak data or short data series.

The methodology is applied to estimate the output gap series for Vietnam. The Bayesian econometric procedure is successful in producing easily interpretable results despite various data problems. The coefficient of the estimated equations are in line with economic theory, and the output gap series is consistent with a broader analysis of economic developments and more anecdotal evidence of excess demand. Compared to the new model-based measure, the traditional output gap measure obtained from the HP de-trending appears harder to interpret.

With appropriate priors, the newly developed measure is subject to less revision over time than output gap estimates derived from the HP filter. There is an obvious tradeoff between improving the robustness to revisions, and ability to extract information from the data. While stronger priors make the procedure more robust, they also dampen information contained in the data. But this feature may be desirable in cases where data are short or of a poor quality, and a researcher has some prior knowledge about the structure of the economy based on theory and country-specific circumstances. The model—even with strong priors—is still better rooted in economic theory then the HP filter.

APPENDIX[7]

A. Economic model in the state-space form

The output gap and potential output are not observable, but the system of equations (2) to (4) can be cast in a convenient state-space form, allowing for the estimation of these series together with other parameters of the model. In this framework, the lagged output gap $ygap_{t-1}$, potential output Y_t^* and the slope of the potential output trend μ_t are *state variables*, and their evolution is described by the *transition equation*. They are not observable, but their linear combinations—referred to as *signals*—can be observed, albeit possibly with random errors, through *measurement variables* in the *measurement equation*. The measurement variables in the model are the log of GDP (with the measurement equation defined as the sum of the log of potential output and the RHS of equation (1)), and inflation (with the measurement equation defined as in (2)).

The general state-space form can be written as (Koopman et al. 1998):

$$\alpha_{t+1} = d_t + T\alpha_t + H\varepsilon_t, \quad \alpha_1 \sim N(a,P), \quad t = 1,\ldots,n \tag{6}$$

$$\theta_t = c_t + Z\alpha_t \tag{7}$$

$$y_t = \theta_t + G\varepsilon_t, \quad \varepsilon_t \sim NID(0,I) \tag{8}$$

where $NID(\mu,\Psi)$ is an independent normal distribution with mean μ and variance matrix Ψ and similarly $N(\cdot,\cdot)$ is a normally distributed variable. The $m \times 1$ state vector α_t contains unobservable stochastic processes governed by equation (6). The initial state vector α_1 is random with mean *a* and variance matrix *P*. The signal θ_t is a function of the state vector α_t in equation (7). The signal is observable through the $N \times 1$ vector of variables y_t in the measurement equation (8) with random errors ε_t. Matrices d_t, *T*, *H*, c_t, *Z* and *G* contain parameters of the model—often called hyper-parameters to distinguish them from unobservable components in α_t, which are also treated as 'parameters' of the model.

The inclusion of time-varying matrices d_t and c_t facilitates putting the model described by equations (2) to (4) into the state-space form. For instance, combinations of variables $-\beta_{RRgap}(RR_{t-1} - RR_{t-1}^*) + \beta_{zgap}(z_{t-1} - z_{t-1}^*)$ and $\alpha_{\pi lag}\pi 4_{t-1} + \alpha_z(z_t - z_{t-1}) + \alpha_{ecm}(\pi 4_{t-1} - \pi 4_{c,t-1}) +$ $\alpha_f \pi_{rpfood,t}$ enter measurement equations as parameters in the matrix c_t.

A full translation of the model into the state-space form takes the following form:

[7] The code for the estimation of the model and the seasonal adjustment of GDP series—written in Ox (Doornik 2007) with the SSFPack package (Koopman et al. 1999)—is available on request from the author.

$$\alpha_t = \begin{pmatrix} Y_t^* \\ \mu_t \\ ygap_{t-1} \end{pmatrix} \tag{9}$$

$$y_t = \begin{pmatrix} Y_t \\ \pi_t \end{pmatrix} \tag{10}$$

$$T = \begin{pmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ -1 & 0 & 0 \end{pmatrix} \tag{11}$$

$$d_t = \begin{pmatrix} 0 \\ 0 \\ Y_t \end{pmatrix} \tag{12}$$

$$c_t = \begin{pmatrix} -\beta_{RRgap}(RR_{t-1} - RR_{t-1}^*) + \beta_{zgap}(z_{t-1} - z_{t-1}^*) + \beta_{Wygap} ygap_t^W \\ \alpha_{\pi lag}\pi 4_{t-1} + \alpha_z(z_t - z_{t-1}) + \alpha_{ecm}(\pi 4_{t-1} - \pi 4_{c,t-1}) + \alpha_f \pi_{rpfood,t} \end{pmatrix} \tag{13}$$

$$Z = \begin{pmatrix} 1 & 0 & \beta_{lag} \\ 0 & 0 & \alpha_{ygap} \end{pmatrix} \tag{14}$$

$$H = \begin{pmatrix} \sigma_{u^{Y^*}} & 0 & 0 & 0 \\ 0 & \sigma_{u^{\mu}} & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} \tag{15}$$

$$G = \begin{pmatrix} 0 & 0 & \sigma_{u^{ygap}} & 0 \\ 0 & 0 & 0 & \sigma_{u^{\pi}} \end{pmatrix} \tag{16}$$

B. Bayesian Estimation

The Bayesian estimation procedure combines the researcher's prior knowledge with information contained in the data. The prior density $g(\Gamma)$ for parameters Γ is combined with data y to produce the posterior density $f(\Gamma | y)$:

$$f(\Gamma|y) = g(\Gamma)\frac{f(y|\Gamma)}{f(y)}, \quad (17)$$

where $f(y|\Gamma)$ and $f(y)$ are conditional and marginal densities of y.

In the application to the state-space model, the posterior density needs to be computed numerically: it can be derived only up to proportionality and obtaining posterior moments is difficult, as it involves further integration. A common method in the Bayesian analysis is to compute these moments by applying Markov Chain Monte Carlo (MCMC) methods. The MCMC repeatedly draws from conditional densities of parameters, which form a Markov Chain whose invariant distribution is the density of interest $f(\Gamma|y)$. These conditional densities are typically easier to derive than the marginal density of the parameters. The iteration starts from drawing a parameter or a group of parameters from the distribution conditional on data and initial guesses of other parameters. The initial guesses are subsequently replaced by draws conditional on data and parameters from previous iterations. After disregarding initial draws from a 'burn-in' period, the remaining draws can be used to make inference about the posterior moments and marginal densities of the parameters.

Prior parameters

Priors for variances of shocks are relatively non-informative. The parameters $\sigma^2_{u^{ygap}}, \sigma^2_{u^{\pi}}, \sigma^2_{u^{Y^*}}, \sigma^2_{u^{\mu}}$ are distributed as inverse gamma $\sigma^2_{\bullet} \sim IG\left(\frac{c}{2}, \frac{S_\sigma}{2}\right)$ with:

$$E(\sigma^2_{\bullet}) = \frac{S_\sigma}{c-2}, \quad Var(\sigma^2_{\bullet}) = \frac{2}{(c-4)}E(\sigma^2_{\bullet})^2 \quad (18)$$

The priors set c to 4.01, and S_σ to $c-2$ times appropriate scale variables (the variance of the HP measure of output gap for $\sigma^2_{u^{ygap}}$ and $\sigma^2_{u^{Y^*}}$, 1/1600 of this variance for $\sigma^2_{u^{\mu}}$, and the variance of inflation for $\sigma^2_{u^{\pi}}$).

The baseline prior densities for parameters in the output gap and inflation equations (conditional on remaining parameters of the entire model) are normal, with mean values discussed in the main text and standard deviations equal to the means.

MCMC algorithm

Application of the MCMC in this paper uses numerical algorithms developed by Koopman et al. (1998), drawing on the idea of augmentation proposed by Fruhwirth-Schnatter (1994). The method simulates draws from the joint density $f(\Gamma|y) = f(\varphi, \alpha|y)$ of hyper-parameters φ and unobservable elements of the state-vector α. Marginal densities $f(\varphi|y)$ and $f(\alpha|y)$

are recovered by ignoring the simulated α and φ respectively. Since the main goal of the paper is to generate estimates of unobservable elements of the state vector, $f(\alpha|y)$ is the main density of interest. The following MCMC algorithm is applied to estimate hyper-parameters and the states:

1. Initialize φ.

2. Sample from the distribution of $u|y,\varphi$ (where $u_t = \left(u_t^y, u_t^\pi, u_t^{Y^*}, u_t^\mu\right)'$ for $t = 1,\ldots,n$) and from the distribution of states $\alpha|y,\varphi$ using the simulation smoother algorithm proposed by de Jong and Shephard (1995).

3. Draw from $\varphi|y,\alpha$. This step is implemented as follows:

   3.1. Given errors u (from step 2), calculate conditional posterior densities $\sigma^2_{u^{ygap}}, \sigma^2_{u^\pi}, \sigma^2_{u^{Y^*}}, \sigma^2_{u^\mu}$. Draw a new set of parameters from the conditional densities. Prior and conditional posterior densities are inverse gamma, and therefore numerical implementation of this step is straightforward.

   3.2. Given states α (from step 2) and the variance $\sigma^2_{u^{ygap}}$ (from step 3.1), calculate conditional posterior density for the coefficients in the output gap equation (1). Draw a new set of parameters. Prior and conditional posterior densities are normal, so again the numerical implementation is easy. If $0 < \beta_{lag} < 1, \beta_{RRgap} < 0, \beta_{zgap} > 0$, accept the draw. Reject the draw and go back to 2 otherwise.

   3.3. Given states α (from step 2) and the variance $\sigma^2_{u^\pi}$ (from step 3.1) calculate conditional posterior density for the parameters in the Phillips curve equation (2) and draw a new set of parameters (the posterior conditional density is again normal). Accept the draw if $0 < \alpha_{\pi lag} < 1, \alpha_{ygap} < 0, \alpha_z < 0$. Reject and go back to 2 otherwise.

4. Go to 2.

After the initial burn-in period of 10000 draws, the remaining 100000 draws from the parameters and states are used for the inference. The procedure is repeated with various starting points to establish that draws converge to the same target distribution.

C. Seasonal adjustment of GDP series

Seasonal adjustment of the Vietnam GDP series poses a challenge due to a time-varying character of the seasonal pattern. The paper applies an auxiliary state-space model to seasonally adjust the series. State-space models allow for formulating and estimating parameters of a stochastic process governing seasonality. The estimation is tailored to a specific series and allows for time-variation in the seasonal component. The applied model decomposes the series into trend μ, seasonal γ and irregular component ξ:

$$y_t = \mu_t + \gamma_t + \xi_t, \quad \xi_t \sim NID(0, \sigma_\xi^2) \tag{19}$$

The trend is assumed to follow a random walk with stochastic slope:

$$\mu_{t+1} = \mu_t + \beta_t + \eta_t, \quad \eta_t \sim NID(0, \sigma_\eta^2) \tag{20}$$

$$\beta_{t+1} = \beta_t + \zeta_t, \quad \zeta_t \sim NID(0, \sigma_\zeta^2) \tag{21}$$

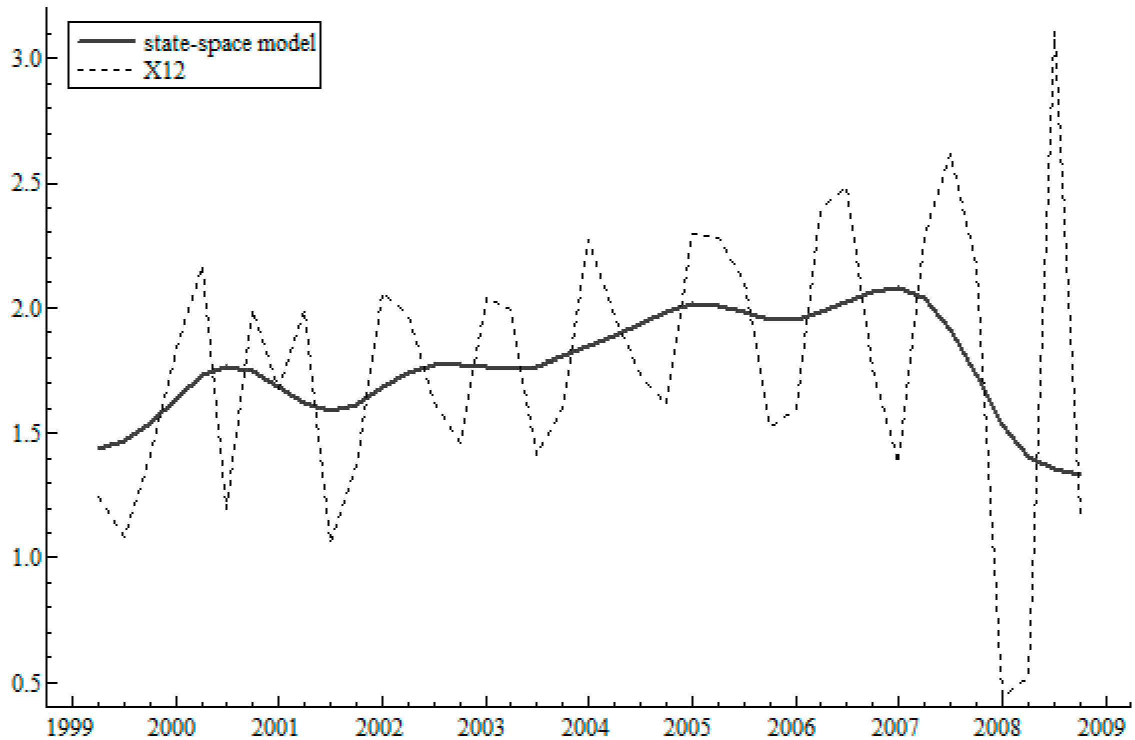
The evolution of the seasonal component is described by:

$$\begin{pmatrix} \gamma_t \\ \gamma_{t-1} \\ \gamma_{t-2} \end{pmatrix} = \begin{pmatrix} -1 & -1 & -1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} \gamma_{t-1} \\ \gamma_{t-2} \\ \gamma_{t-3} \end{pmatrix} + \begin{pmatrix} \omega_t \\ 0 \\ 0 \end{pmatrix}, \quad \begin{pmatrix} \gamma_1 \\ \gamma_0 \\ \gamma_{-1} \end{pmatrix} \sim N(0, \kappa I_3), \quad \omega_t \sim NID(0, \sigma_\omega^2) \tag{22}$$

Seasonal effects sum to zero over the previous year if $\sigma_\omega^2 = 0$. When $\sigma_\omega^2 > 0$, the sum of seasonal effects is a white noise, allowing seasonality to vary over time.

Figure below illustrates how the state-space seasonal adjustment helps alleviating problems with the X12 procedure. It plots first differences of (logs of) seasonally adjusted GDP series. The X12 procedure fails to fully remove the seasonal component. It initially over-adjusts for seasonality in the last quarter (which shows as positive spikes in the first quarter of first-differenced SA series) and then under-adjusts near the end of the sample (negative spikes in the first quarter). The state-space seasonal adjustment model is successful in identifying and removing the time-varying seasonal component.

Figure 6. Vietnam: First-differences of (logs of) GDP using alternative SA methods



Source: General Statistics Office of Vietnam and staff calculations.

REFERENCES

Aiyar, Shekhar & Ivan Tchakarov, 2008. "Much Ado About Nothing? Estimating the Impact of a U.S. Slowdown on Thai Growth," IMF Working Papers 08/140, International Monetary Fund.

Benes, Jaromir & Kevin Clinton & Roberto Garcia-Saltos & Marianne Johnson & Doug Laxton & Troy Matheson, 2010. "The Global Financial Crisis and Its Implications for Potential Output," IMF Working Papers (forthcoming), International Monetary Fund.

Benes, Jaromir & Papa M'B. P. N'Diaye, 2004. "A Multivariate Filter for Measuring Potential Output and the NAIRU: Application to the Czech Republic," IMF Working Papers 04/45, International Monetary Fund.

Camen, Ulrich, 2006. "Monetary policy in Vietnam: the case of a transition country," in: "Monetary policy in Asia: approaches and implementation", BIS Papers volume 31, pages 232-252, Bank for International Settlements.

de Jong, P. & N. Shephard, 1995. "The simulation smoother for time series models," Biometrika 82, 339-50.

Doornik, J.A. (2007), Object-Oriented Matrix Programming Using Ox, 3rd ed. London: Timberlake Consultants Press and Oxford: www.doornik.com

Edwards, Sebastian & Fernando Lefort, 1998. "Stabilization, Persistence, and Inflationary Convergence: A Comparative Analysis," Working Papers Central Bank of Chile 37, Central Bank of Chile.

Fruhwirth-Schnatter, S., 1994. "Data augmentation and dynamic linear models," J. Time Series Analysis 15, 183-202.

Kaiser, Regina and Agust´ın Maravall, 2001. Measuring Business Cycles in Economic Time Series, Lecture Notes in Statistics 154, New York: SpringerVerlag.

Karam, Philippe D & Douglas Laxton & Andrew Berg, 2006a. "Practical Model-Based Monetary Policy Analysis--A How-To Guide," IMF Working Papers 06/81, International Monetary Fund.

Karam, Philippe D & Douglas Laxton & Andrew Berg, 2006b. "A Practical Model-Based Approach to Monetary Policy Analysis--Overview," IMF Working Papers 06/80, International Monetary Fund.

Kichian, M., 1999. "Measuring potential output with a state-Space framework", Working Paper 99-9, Bank of Canada.

Koopman, Siem Jan & Neil Shephard & Jurgen A. Doornik, 1999. "Statistical algorithms for models in state space using SsfPack 2.2," Econometrics Journal, Royal Economic Society, vol. 2(1), pages 107-160.

Kuttner, Kenneth N, 1994. "Estimating Potential Output as a Latent Variable," Journal of Business & Economic Statistics, American Statistical Association, vol. 12(3), pages 361-68, July.

Ozbek, Levent & Umit Ozlale, 2005. “Employing the extended Kalman filter in measuring the output gap,” Journal of Economic Dynamics and Control, Volume 29, Issue 9, September 2005, Pages 1611-1622

Planas, Christophe & Rossi, Alessandro & Fiorentini, Gabriele, 2008. "Bayesian Analysis of the Output Gap," Journal of Business & Economic Statistics, American Statistical Association, vol. 26, pages 18-32, January.