Measuring Economic Slack in Asia and the Pacific

James Morley*
University of New South Wales

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Abstract

The presence of "economic slack" directly implies that an economy can grow quickly without any necessary offsetting slow growth or retrenchment in the future. Based on this link between economic slack and future economic growth, I argue for a forecast-based estimate of the output gap as a measure of economic slack. This approach has the advantage of being robust to different assumptions about the underlying structure of the economy and allows for empirical analysis of a Phillips Curve relationship between the output gap and inflation. I apply this approach to investigate economic slack and the Phillips Curve for selected economies in Asia and the Pacific, taking into account structural breaks in long-run growth and uncertainty about the appropriate forecasting model.

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1. Introduction

Orphanides (2002) argues that high inflation in the 1970s was due to mismeasurement of economic slack, not a failure of monetary policy to follow "best practices". He uses data available at the time to show that US monetary policy responses to inflation and economic slack were systematic, forward-looking, and much the same as they have been in later decades when inflation has been low and stable. What we now think of as the policy mistakes of the 1970s were only revealed with the hindsight of data revisions, especially in terms of measures of economic slack.

A worrisome implication of Orphanides's (2002) argument is that modern "best practices" for monetary policy provide no assurance that the mistakes of the 1970s will not be repeated, at least as long as measures of economic slack are subject to considerable uncertainty. Unfortunately, even ignoring the real-time data issues that are the focus of Orphanides (2002), but beyond the scope of this paper, accurate measurement economic slack remains a significant challenge for a variety of reasons.

First and foremost, there is no consensus about the policy-relevant measure of economic slack. Even settling on the output gap (i.e., the difference between actual and potential real GDP for an economy), there remains a question of how to define "potential". Based on the idea that economic slack implies a possibility for an economy to grow quickly without any necessary offsetting slow growth or retrenchment in the future, I argue for a forecast-based estimate of the output gap as the appropriate measure of economic slack. Specifically, if the optimal forecast of output growth is above/below average, then output is estimated to be below/above potential. This approach implicitly defines "potential" as the stochastic trend of output and has its origins in the influential study by Beveridge and Nelson (1981, BN hereafter), with this particular interpretation of the BN decomposition discussed in Morley (2011).

Second, given a forecast-based approach to estimating the output gap, there remains a question of how to construct the optimal forecast of output growth. BN consider low-order ARMA models, which suggest small output gaps, often with counterintuitive sign (e.g., the estimated gap is often positive during recessions). Motivated by the forecasting literature and recent studies on estimating the output gap by Garratt, Mitchell, and Vahey (2011) and Morley and Piger (2012), I consider model-averaged forecasts instead of relying on one particular time series model or class of models. Importantly, I follow Morley and Piger (2012) by including nonlinear time series models in the model set. Notably, this approach does not necessarily result in output gap estimates of counterintuitive sign as long as the model-averaged forecasts imply negative serial correlation in economic growth at longer horizons.

Third, a forecast-based output gap may not correspond to the theory-based measure implied by a structural model of the economy—e.g., the difference from a flexible-price equilibrium in a New Keynesian DSGE model. However, Kiley (2013) argues that a forecast-based trend may be a more appropriate target for policy than the flexible-price equilibrium in a medium-scale New Keynesian DSGE model. His argument hinges in part on some particular features of the model that he considers, including the existence of financial frictions. But his main point is that the flexible-price equilibrium converges to the stochastic trend of output, so a forecast-based output gap provides useful information about current and future theory-based gaps. Given lags in the implementation and transmission of monetary policy, information about future theory-based gaps is highly relevant for current policy decisions. Meanwhile, as noted by Kiley (2013) and many others, DSGE models imply reduced-form VAR, VECM, or VARMA models. Thus, forecast-based output gap estimates provide robust measures of economic slack across a wide range of different economic assumptions used to identify a structural model, at least as long as the reduced-form model or models used to calculate the optimal forecast capture the dynamics in the data (this point relates back to Sims, 1980).

Fourth, a key question in measuring slack is whether to impose a specific relationship between slack and inflation in estimation (for example, Kuttner, 1994, imposes a linear relationship, while King and Morley, 2007, test for a relationship). Related, there is a question of whether measurement should be based on multivariate information (for arguments in favour, see Evans and Reichlin, 1994, and Basistha and Startz, 2008). It might seem that the obvious answer to both questions is "yes". But if the deeper goal in measuring slack is to test hypotheses about its relationship with inflation or with other macroeconomic variables, it can be problematic to "assume the answer" by imposing a lot of structure on the multivariate relationships in the first place. As an example, consider Stock and Watson (2009). Their analysis suggests that inflation is difficult to forecast using standard measures of economic slack, except when the estimated output gap (or unemployment gap) is large in magnitude. This directly suggests possible mismeasurement and/or a nonlinear Phillips Curve relationship (see Dupasquier and Ricketts, 1998, and Meier, 2010). Thus, I consider univariate models of real GDP to estimate output gaps and then test their relationship with inflation and across economies.

With this background in mind, I investigate economic slack and the Phillips Curve for selected economies in Asia and the Pacific using model-averaged forecast-based estimates of the output gap. To address various data issues for these economies, my analysis takes into account structural breaks in long-run growth and allows the incorporation of prior beliefs in estimation of model parameters.

I find that different forecasting models produce very different estimates of the output gap for all of the economies. In most cases, the model-averaged output gaps are highly asymmetric and closely related to the narrower measures of slack given by the unemployment rate and capacity utilization, similar to what Morley and Piger (2012) found for the US data. Consistent with the notion of an output gap as a measure slack, the model-averaged output gaps have strong negative forecasting relationships with future output growth. The results for a Phillips Curve relationship with inflation are more mixed. But there is an apparent convex relationship in a number of cases, clearly providing a strong caution against imposing a linear relationship when estimating output gaps. Finally, I find notable links between the model-averaged output gaps across many economies in Asia and the Pacific based on pairwise Granger Causality tests.

The rest of this paper is organized as follows. Section 2 discusses the data, including the possible presence of structural breaks in long-run output growth for each economy. Section 3 motivates the model-averaging approach by demonstrating the sensitivity of the results to the time series model under consideration. Section 4 presents details of the methods employed in the empirical analysis. Section 5 reports the results for the benchmark US case and for a selection of economies in Asia and the Pacific. Section 6 concludes. Technical details are relegated to an appendix.

2. Data

I consider macroeconomic data for the United States (US) and 12 economies in Asia and the Pacific: Australia (AU), New Zealand (NZ), Japan (JP), Hong Kong (HK), Korea (KR), Singapore (SG), China (CN), India (IN), Indonesia (ID), Malaysia (MY), Philippines (PH), and Thailand (TH). Data series for real GDP, the price level, the unemployment rate, and capacity utilization were sourced by the BIS from IMF IFS, CEIC, Datastream, and the relevant national data sources.

For quarterly real GDP, I use the available seasonally-adjusted series for the United States, Australia, New Zealand, Japan, Korea, Singapore, and Thailand. In the cases of Hong Kong, China, India, Indonesia, Malaysia, and the Philippines, I apply X12 procedures to the non-seasonally-adjusted series, as these were available for the longest possible sample periods. I then construct quarterly growth rates by taking first differences of 100 times the natural logs of the seasonally-adjusted levels. The available sample periods for quarterly growth rates of real GDP are listed in Table 1.

For the price level, I use the core PCE deflator for the United States, core CPI for Japan and Indonesia, and headline CPI for the remaining economies. These choices were determined by a general preference for core measures, but only when they were available for a relatively long sample period in comparison to real GDP. I calculate inflation as the year-on-year percentage change in the price level and then construct 4-quarter-ahead changes in inflation. The relevant sample periods based on common availability of both real GDP and price level data are listed in Table 3.

Unemployment rate data were available for all economies except India and Indonesia, with relevant sample periods based on common availability with real GDP listed in Table 4. Capacity utilization was available for all economies except Hong Kong, Singapore, China, and India, with relevant sample periods based on common availability with real GDP listed in Table 5.

In addition to sample periods for real GDP growth data, Table 1 reports estimated structural break dates for long-run growth rates. Perron and Wada (2009) argue that it is crucial to account for a structural break in the long-run growth rate of US real GDP when measuring economic slack for the US economy. They impose a break date of 1973Q1 based on the notion of a productivity growth slowdown at that time.

However, applying Bai and Perron's (1998, 2003) sequential testing procedure for structural breaks in the mean growth rate of US real GDP does not detect a break in the early 1970s.[1] Instead, I find the estimated break date is 2002Q2. This break is significant at the 1% level and corresponds to a reduction in the mean growth rate. I discuss the consequences of imposing this break date when measuring economic slack for the US economy below.

For the other economies, there is mixed evidence of structural breaks in real GDP growth rates. Considering significance at least at a 10% level, I find no breaks for Australia, New Zealand, Singapore, China, and Thailand, one break for Hong Kong, Korea, India, Malaysia, and the Philippines, and two breaks for Japan and Indonesia. The estimated break dates and the corresponding sequence of mean growth regimes are reported in Table 1.[2] To account for structural breaks in subsequent analysis, the output growth series are adjusted based on the estimated mean growth rate in each regime until there is no remaining evidence for additional breaks.[3]

3. Motivation

To motivate the model-averaging approach to measuring economic slack presented in the next section, I begin by considering forecast-based estimates of the output gap based on two models: an AR(1) model and Harvey and Jaeger's (1993) unobserved components (UC) model that corresponds to the HP filter with a smoothing parameter of 1,600 (denoted UC-HP hereafter). The AR(1) model is estimated for quarterly real GDP growth and the output gap is estimated using the BN decomposition for an AR(1) model (see Morley, 2002, for details of this calculation). The UC-HP model is

[1] Following much of the applied literature, I consider trimming of 15% of the sample from its end points and between breaks for admissible break dates.

[2] The regression model for testing structural breaks includes only a constant. The evidence for structural breaks is generally weaker when allowing for serial correlation. However, I find that it is more problematic to underestimate than to overestimate the number of structural breaks when estimating forecast-based output gaps. Specifically, forecast-based output gaps can display permanent movements that proxy for large structural breaks in growth rates when these are not directly accounted for in the data, while allowing for extraneous structural breaks tends to have little impact on forecast-based output gaps.

[3] This approach explains why there are two breaks within 15% of the sample of each other for Indonesia. The first break of 1996Q4 was found based on the original data and the second break of 1998Q4 was found based on the adjusted data based on the first break. These breaks correspond to the Asian financial crisis that hit Indonesia particularly hard and culminated in President Suharto's resignation in 1998. Failure to account for both breaks leads to estimates of the output gap with clear permanent movements corresponding to the crisis.

estimated for 100 times the natural logs of quarterly real GDP and the output gap is estimated using the Kalman filter. Although it is specified in terms of log levels, the UC-HP model provides an implicit forecast of output growth, with the Kalman filter calculating the long-horizon conditional forecast of output at each point of time.

Figure 1 plots the estimated output gaps based on the AR(1) and UC-HP models for US real GDP. As discussed in Morley and Piger (2012), these estimates are very different from each other, with the output gap based on the AR(1) model being of small amplitude and positive during NBER-dated recessions, while the output gap based on the UC-HP being of much larger amplitude and negative during NBER-dated recessions. It is worth noting that, for these two models at least, output gap estimates are virtually identical whether or not the structural break in 2002Q2 is taken into account.

It might seem obvious from visual inspection that the UC-HP output gap is preferable, especially given its more intuitive relationship with recessions. But, alas, there is an inconvenient reality that the AR(1) model fits the data much better than the UC-HP model by any standard metric used for model comparison, including AIC and SIC, a result that was highlighted in Morley and Piger (2012).[4]

Furthermore, as pointed out by Nelson (2008), the notion of an output gap as a measure economic slack directly implies that it should have a negative forecasting relationship with future output growth. Specifically, when the economy is above trend and the output gap is positive, future growth should be below average as the economy returns to trend and vice versa. Motivated by the analysis in Nelson (2008), I calculate the correlation between a given estimate of the output gap and the subsequent 4-quarter output growth.[5] Table 2 reports these correlations and, consistent with the

[4] I follow the approach in Morley and Piger (2012) to ensure the adjusted sample periods are equivalent for all models under consideration. For the linear and nonlinear AR models discussed below, this involves backcasting sufficient observations based on the long-run growth rate to condition on in estimation. For the UC models discussed below, it involves placing a diffuse prior on the initial level of the stochastic trend and evaluating the likelihood for the same observations as for the models of growth rates. See Morley and Piger (2012) for details.

[5] Nelson (2008) considers regressions that capture the correlation between a given estimate of the output gap and 1-quarter-ahead US output growth. My results for the US data are qualitatively similar to his even though I consider 4-quarter-ahead output growth, which arguably provides a better sense of forecasting ability at a policy-relevant horizon. Also, Nelson (2008) conducts a pseudo out-of-sample forecasting analysis by estimating models and output gaps using data only up to when the forecast is made (it is a pseudo out-of-sample forecast because the data are revised, although Orphanides and van

findings in Nelson (2008), the correlation for the US output gap based on the AR(1) model is negative, while the correlation for the UC-HP model is positive. This result directly suggests that the output gap based on the AR(1) model provides a more accurate measure of economic slack than the UC-HP model, even if its relationship with recessions is counterintuitive.

Figure 2 plots the estimated output gaps based on the AR(1) and UC-HP models for real GDP data from various economies in Asia and the Pacific. The figure makes it clear that the very different implications of the two models for the output gap are not just a quirk of the US data. As in Figure 1, the output gap based on the AR(1) model is always smaller in amplitude than the output gap based on the UC-HP model and often of the opposite sign. The correlation results for these other economies in Table 1 are a bit more mixed, but the correlation is still negative for 9 out of 12 economies for the AR(1) model output gap, while it is negative for only 5 out of 12 economies for the UC-HP model output gap. Finally, any formal model comparison, including based on AIC or SIC, strongly favours the AR(1) model in every case.

More favourable to the UC-HP model is the forecasting relationship between the competing model-based output gaps and future inflation. Table 3 reports correlations between output gap estimates and subsequent 4-quarter changes in inflation. Consistent with most conceptions of the Phillips curve, the correlation is always positive for the UC-HP model output gap. By contrast, it is negative for 9 out of 13 economies, including the United States, when considering the AR(1) model output gap.

Taken together, the results in Tables 2 and 3 suggest that neither forecast-based estimate of the output gap provides a particularly accurate measure of economic slack. Put another way, there is considerable uncertainty about the appropriate time series model for real GDP when trying to measure economic slack. The AR(1) model fits the data better and its corresponding output gap generally provides a better forecast of

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Norden, 2002, find that using revised or real-time data matters much less than incorporating future data in estimation of the output gap at any point in time). However, even though I use the whole sample to estimate models, I am implicitly using data only up to when the forecast is made to estimate output gaps. This is straightforward for the Harvey and Jaeger (1993) UC-HP model which directly allows for filtered inferences instead of the traditional HP filter, which is a two-sided filter, explaining why Nelson (2008) considers the out-of-sample forecasting analysis when evaluating the forecasting properties the output gap based on the traditional HP filter.

future real GDP growth. But the UC-HP model output gap is more consistent with widely-held beliefs about the relationship between economic slack and recessions, as well as generally providing a better forecast of future changes in inflation.

These results motivate two key aspects of the methods outlined in the next section. First, drawing from an insight going back at least to Bates and Granger (1969) that combined forecasts can outperform even the best individual forecast, I follow Morley and Piger (2012) and construct a model-averaged estimate of the output gap, averaging over a range of linear and nonlinear forecasting models. Second, the disconnect between certain aspects of an estimated gap (e.g., the sign of the AR(1) model output gap during recessions) and widely-held beliefs suggests the potential usefulness of incorporating informative priors in estimation when these beliefs are held for valid reasons. Thus, I take a Bayesian approach to estimation that allows me to incorporate prior beliefs without strictly imposing such beliefs in case they are strongly at odds with the data.

To be more concrete about this latter issue, an obvious example of a widely-held belief in this context is the idea that trends are smooth. Indeed, the UC-HP model imposes this as a dogmatic prior, while the estimated output gaps for AR(1) model suggest otherwise. In principle, then, one could incorporate the idea of smooth trends into an informative (but not dogmatic) prior, as in Harvey, Trimbur, and van Dijk (2007). Specifically, one could estimate the signal-to-noise ratio for the UC-HP model instead of imposing it, but consider an informative prior on this parameter that suggests the trend is relatively smooth. Likewise, one could consider an informative prior on the autoregressive coefficient in the AR(1) model that implies negative serial correlation in output growth.

Despite giving the example of a smoothness prior on the trend, I should emphasize that, in practice, I do not actually impose such a prior in my analysis. As will be seen below, imposing such a prior is not necessary to estimate output gaps that are negative in recessions. Meanwhile, the prior is strongly at odds with the data. Nelson and Plosser (1982) noted this within the context of the signal-to-noise ratio for the traditional HP filter. Perron and Wada (2009) have recently suggested that a smooth trend for US real GDP can be reconciled with parameter estimates as long as the time series model used to estimate the output gap allows for a structural break in long-run growth corresponding to the productivity growth slowdown in 1973. However, Morley and Piger (2012) and Morley, Panovska, and Sinclair (2013) find strong evidence for a relatively volatile stochastic trend in US real GDP even when allowing for the productivity growth slowdown.

4. Methods

As mentioned above, my analysis closely follows the approach to estimating a model-averaged output gap (MAOG) developed in Morley and Piger (2012) for US real GDP. However, I consider a few modifications that make the approach more easily applicable to data from other economies. I outline the approach, including the modifications, in this section. The full details of the approach are in the original study and are also set out in the appendix.

Morley and Piger (2012) consider only univariate models of real GDP. However, this includes the AR(1) and UC-HP models discussed in the previous section. Therefore, as is evident from Figures 1 and 2, the univariate models capture a range of possibilities about the nature of the output gap. Also, as mentioned in the introduction, univariate analysis allows us to test multivariate relationships rather than assume the answer *a priori*. The benefits of this approach for the relationship with inflation in particular will become evident when the results are presented below.

All of the models allow for a stochastic trend in real GDP, which is motivated by standard unit root and stationarity tests, even when allowing for structural breaks in long-run growth. This is important because many off-the-shelf methods such as linear detrending, traditional HP filtering, and Bandpass filtering produce spurious cycles when applied to time series with stochastic trends (see Nelson and Kang, 1981, Cogley and Nason, 1995, and Murray, 2003). By contrast, as long as the models under consideration avoid overfitting the data, the forecast-based approach will not produce spurious cycles.

Following Morley and Piger (2012), I consider linear AR(p) models of orders $p = 1$, 2, 4, 8, and 12 with Gaussian errors or Student t errors, the linear UC-HP model due to Harvey and Jaeger (1993), the linear UC0 and UCUR models with AR(2) cycles from Morley, Nelson, and Zivot (2003), the nonlinear bounceback (BB) models from Kim, Morley, and Piger (2005) with BBU, BBV, and BBD specifications and AR(0) or AR(2) dynamics, the nonlinear UC0-FP model with an AR(2) cycle from Kim and Nelson (1999), and the nonlinear UCUR-FP model with an AR(2) cycle from Sinclair (2009).[6] Again, see the appendix and the original studies for more details of these models.

The first major modification from Morley and Piger (2012), mentioned above, is that models are estimated using Bayesian methods instead of maximum likelihood estimation (MLE). This allows incorporation of informative priors in the estimation. Most priors are not particularly strong, with estimates based on the posterior mode virtually identical to MLE for many of the models.[7] However, for economies with relatively short samples for real GDP or other quirks in the data such as large outliers, there is some tendency for MLE of the UC models and the nonlinear models to overfit the data. By incorporating more informative priors about the persistence of the autoregressive dynamics or the persistence of Markov-switching regimes based on US estimates from Morley and Piger (2012), I am able to avoid problems associated with short samples and outliers, while obviating the need to undertake a long, protracted search for the best model specifications for each economy.[8] The full details of the priors are presented in the appendix.

The second major modification from Morley and Piger (2012) is that I consider equal-weights on the models when constructing MAOGs rather than weights based on Bayesian model averaging (BMA). Although a number of models receive nontrivial weight based on the SIC approximation of BMA when considering the US data in Morley and Piger (2012), this is not always the case for other economies. For example, a simple AR(0) model would receive all weight for Australian real GDP

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[6] As a minor modification to Morley and Piger (2012), I drop the linear AR(0) models and nonlinear Markov-switching model from Hamilton (1989) with AR(0) and AR(2) dynamics. In the former case, the output gap is always zero by construction, so its inclusion merely serves to shrink the model-averaged output gaps towards zero. In the latter case, the output gap is linear by construction, so its inclusion as a nonlinear model puts additional prior weight on a linear output gap. As demonstrated below, dropping these models has very little practical impact on the model-averaged estimate of the output gap for US real GDP.

[7] The AR(1) and UC-HP models discussed in previous section were estimated using the posterior mode. But the estimated output gaps for these models are indistinguishable from those based on MLE. For example, for the US data, the correlation between the Bayesian and MLE output gaps is >0.999999 in both cases.

[8] In principle, this setup would also make it possible to apply the approach outlined in this paper even given severe data limitations (e.g., very small samples) or a desire to impose tighter priors based on strongly held beliefs.

based on SIC if it were included in the model set. But such a model implies the output gap is always zero by construction (not just zero on average), which clearly runs contrary to widely and strongly held beliefs and, as will be seen below, would produce inferior forecasts of future output growth and changes in inflation in comparison to the Australian MAOG.

The problem of BMA putting too much weight (from a forecasting perspective) on one model has been highlighted recently by Geweke and Amisano (2011). They find that linear pooling of models produces better density forecasts than BMA and discuss the calculation of optimal weights for linear pooling of models. However, as long as the model set is relatively diverse, applying equal weights to models works almost as well as optimal weights and is much easier to implement. Thus, I take this simple approach of using equal weights.[9] Again, see the appendix for more details of the model averaging.

5. Results

Before proceeding to the results for the Asian and Pacific economies, I first consider results the United States as a benchmark case in order to provide perspective on the impact of the modifications to Morley and Piger (2012) described in the previous section, as well as providing context for the other results.

To begin, I compare the updated MAOG based on the US real GDP data described in Section 2, equal weights, and Bayesian estimation to the original MAOG reported in Morley and Piger (2012) based on a shorter sample period, a different vintage of data, BMA weights, and MLE. For completeness, I also consider the updated MAOG based on the Morley and Piger (2012) vintage of data, equal weights, and Bayesian estimation. Figure 3 plots these three MOAGs together. The most noticeable thing is their similarity, with the major finding in Morley and Piger (2012) of a highly asymmetric shape holding for the updated MAOGs. The correlation between the updated MAOGs and the original MAOG is about 0.94. The most notable difference is in terms of the behaviour of the output gap around the 2001 recession. However, as

[9] In practice, I place equal weights on linear and nonlinear classes of models and divide those equal weights up evenly amongst the models within the classes. Because the nonlinear models include linear dynamics in their parameter space, there is still more prior weight on linear than nonlinear dynamics, although this is addressed somewhat by the somewhat informative priors for parameters in the nonlinear models.

the updated MAOG based on the vintage sample reveals, this difference is largely due to data revisions, not to modifications in the approach.

The impact of incorporating prior information about parameters may be obscured in Figure 3 given that the priors were calibrated based on the estimates for US data in Morley and Piger (2012). However, it is important to emphasize that the asymmetric shape of the output gap is in no way driven by the priors on the nonlinear models. The priors favour Markov-switching in the mean growth rate corresponding to business cycle phases along the lines of Hamilton (1989). But there is no strong prior that shocks have more temporary effects in recessions than in expansions. Figure 4 makes this clear by applying the modified approach to data simulated from a simple random walk with drift.[10] For this data, the true output gap is always zero. The estimated MAOG is not always zero, but it is small in magnitude relative to the US MAOG and, importantly, fluctuates symmetrically around zero. Thus, any finding of asymmetry for the MAOGs reflects the data, not the incorporation of prior information in estimating model parameters.

One possibly surprising result for the updated US MAOG displayed in Figures 3 and 4 is that it implies little remaining economic slack for the US economy at the end of the sample in 2012Q3. This result turns out to be sensitive to allowing for a structural break in long-run growth in 2002Q2. Figure 5 plots the updated US MAOG against a version under the assumption of no structural break. Assuming no change in the long-run growth, the US economy appears to still be below trend at the end of the sample. Given uncertainty about the structural break, it might make sense to average across these two scenarios, which would still imply the economy remains below trend at the end of the sample, although not by as much as in the no break case.

But is it completely outlandish to infer that the US economy is close to trend by the end of the sample? This would clearly imply that recessions can permanently shift the trend path of output downwards, which is the implication of many forecasting models for US real GDP, including low-order AR(p) models, Hamilton's (1989) Markov-switching model, and, to some extent, the bounceback models of Kim, Morley, and Piger (2005). Figure 6 plots the estimated trend in US real GDP based on the model-

[10] The drift and standard deviation of shocks are both set to 1, which is a surprisingly reasonable calibration for 100 times the natural logs of quarterly US real GDP.

averaged output gap. A permanent negative effect of the Great Recession of the trend path is quite evident for this estimate of trend and is much larger than for previous recessions.

One way to judge the plausibility of the US economy being at trend at the end of the sample is to compare the US MAOG to other narrower measures of slack. Figure 7 plots the US MAOG against the US unemployment rate and US capacity utilization. Similar to the findings in Morley and Piger (2012), there is a clear relationship between the MAOG and these variables. Meanwhile, in terms of the question of whether there remains a lot of slack in the US economy at the end of the sample, though, the unemployment rate provides a different answer than capacity utilization. The unemployment rate has not returned to its pre-recession levels, consistent with the MAOG in the no break case, while capacity utilization has essentially returned to its pre-recession level, consistent with the MAOG allowing for a structural break. The historical persistence of the unemployment rate suggests that it can often remain elevated long after the MAOG has returned to zero, while the relationship with capacity utilization is a bit tighter in terms of timing (although correlations with the MAOG are similar in magnitude for the two series, with a correlation of -0.52 for the unemployment rate and 0.59 for capacity utilization). Thus, these results are mildly supportive of the MAOG allowing for a structural break.

More supportive of relatively little remaining slack at the end of the sample is the simple fact that the MAOG in the no break case would imply relatively fast growth and downward pressure on inflation in the period immediately after the Great Recession. In particular, returning to Tables 2 and 3, the US MAOG has a reasonably strong negative correlation of -0.31 with future output growth and positive correlation of 0.51 with future changes in inflation. These results are much stronger than those for the output gaps based on the AR(1) and UC-HP models and support the MAOG as a highly relevant measure of economic slack. But, given lacklustre growth and stable inflation after the Great Recession, these also support the MAOG allowing for a structural break and the idea that the economy is close to trend at the end of the sample, noting that the trend path is lower than before the recession, as suggested in Figure 6.

Having demonstrated how the modified approach works in the benchmark US case, I now apply the approach to real GDP data for 12 economies in Asia and the Pacific.

Figure 8 plots MAOGs for the various economies. In most of the cases, the MAOGs are highly asymmetric, similar to the US results. Specifically, the output gaps for Australia, Japan, Hong Kong, Korea, Singapore, China, India, Malaysia, and Thailand have much larger negative fluctuations than positive ones. The exceptions are New Zealand, Indonesia, and the Philippines, all of which have more symmetric fluctuations of relatively small amplitude. The implication for these economies is that more of the fluctuations in real GDP are permanent, including during recessions.

How plausible are the MAOGs as measures of economic slack? As with the US benchmark, I compare the MAOGs to other narrower measures of slack when available for a given economy. Table 4 reports the correlation of each MAOG with the corresponding unemployment rate for all but India and Indonesia. For comparison, I also report correlations for output gaps based on AR(1) and UC-HP models. Corresponding to an Okun's Law relationship, the MAOG has the most negative correlation with the unemployment rate in 8 out of 11 cases (including the US benchmark), with many of the correlations being quite large in magnitude. In the remaining cases, the correlations are small for all estimates of the output gap.

Table 5 reports the corresponding correlations with capacity utilization for all but Hong Kong, Singapore, China, and India. The MAOG has the most positive correlation with capacity utilization in 6 out of 9 cases (including the US benchmark) and has very high correlations in two of the other cases. Surprisingly, the correlation is negative for the Philippines. But this is true for all three estimates of the output gap, perhaps raising doubts about capacity utilization as a measure of slack in this case, especially given that the UC-HP output gap and the MAOG have the expected negative correlations with the unemployment rate.

Overall, the strong coherence with other measures of slack lends credence to the MAOGs. The result is particularly notable given that the MAOGs are estimated using only univariate models of real GDP.

Revisiting Table 2, the MAOGs provide a stronger signal about future economic growth than the two other output gap estimates in 11 out of 13 cases (including the

US benchmark), with reasonably large negative correlations in all but one case. Beyond supporting the MAOGs as measures of economic slack, this result also provides direct support for idea that output growth is somewhat predictable even when standard model comparison metrics would select a random walk model, as the SIC would in the case of Australia.

Looking back at Table 3, the results for the MAOGs in terms of correlation with future changes in inflation are more mixed. The MAOGs provide a stronger signal than the UC-HP model output gap in only 6 of the 13 cases (including the US benchmark). However, a correlation coefficient may be too simplistic as a measure of the relationship between the output gap and inflation. Figure 9 displays a scatterplot of the US MAOG (x-axis) against the subsequent 4-quarter change in US inflation (y-axis) and there is a clear nonlinear, convex Phillips Curve relationship between the output gap and future changes in inflation that would only be partially captured by a correlation coefficient.

Figure 10 displays the corresponding scatterplots for the 12 economies in Asia and the Pacific. The same convex relationship as for the US data is evident for Australia, Japan, Korea, and, to a lesser extent, India. These are all cases where the correlation in Table 3 was largest for the MAOG and for which there were relatively long samples for the inflation data. For some of the other cases, such as New Zealand, Malaysia, and Thailand, the Phillips Curve relationships look more linear. Meanwhile, the results for Singapore, China, and Indonesia are more puzzling, although this could be due to a number of factors including the measure of inflation, sample period, or the behaviour of the MAOG in these cases.

But a clear implication of Figures 9 and 10 is that it is important not to impose a specification for the Phillips Curve relationship *a priori*, as is done in some approaches to estimating output gaps (e.g., Kuttner, 1994). If the imposed relationship is incorrectly specified, then the resulting output gap estimate will be distorted and cannot be used to determine a better specification of a Phillips Curve relationship. The convexity of the Phillips Curve in some cases argues against a linear specification. Also, there is some evidence that the relationship between the output gap and inflation has changed over time, with many of the observations of stable inflation following large negative output gaps corresponding to the recent Global

Financial Crisis. This change in the relationship could be due to an anchoring of inflation expectations (see IMF, 2013) and argues strongly against imposing a fixed Phillips Curve relationship when estimating the output gap.

Given general support for the MAOGs as measures of economic slack, especially in the sense of forecasting future economic growth, the last question considered in this paper is whether the MAOGs are related across economies. To answer this question, I conduct pairwise Granger Causality tests. Table 6 reports the results for these tests. At the 10% level, the output gaps appear to be related across many of the economies, with 46 rejections of no Granger Causality. The patterns are generally sensible, although the 10% may include some rejections of the null merely due to random sampling given that a total of 156 tests were conducted. However, the fact that the number of rejections holds up at 31 for the tests at the 5% level and 19 for tests at the 1% level suggests that many of rejections are simply because the null hypothesis is false.

Notably, the Granger Causality tests using MAOGs provide more support for cross-economy spillovers than when using output gap estimates for the AR(1) and UC-HP models or the underlying real GDP growth rate data.[11] In terms of general patterns and focusing on the results at the 5% level, the output gaps for Singapore and Hong Kong appear to influence the largest number of other economies, while the output gaps for Hong Kong and Malaysia are influenced by the largest number of other economies.

6. Conclusions

There is more uncertainty about the degree of economic slack than is commonly acknowledged in academic and policy discussions, which often treat the output gap as if is directly observed. Canova (1998) argues that this uncertainty has huge implications in terms of "stylized facts" about the business cycle used to motivate theoretical analysis. Also, according to Orphanides (2002), this uncertainty is responsible for huge policy mistakes in the past, especially in terms of the high inflation in the 1970s.

[11] The respective number of rejections at the 10%, 5%, and 1% levels is 33, 21, and 11 for the AR(1) model output gap, 43, 30, and 14 for the UC-HP model output gap, and 39, 23, and 13 for the underlying real GDP growth rate data.

In light of this uncertainty about the degree of economic slack prevailing in an economy at any given point of time and its importance for policy, I argue for a model-averaged forecasting-based estimate of the output gap. For most economies, the model-averaged estimate is closely related to the narrower measures of slack given by the unemployment rate and capacity utilization and, consistent with the notion of an output gap as a measure economic slack, has a strong negative forecasting relationship with future output growth. The model-averaged output gaps are also generally highly asymmetric, as was found for US real GDP in Morley and Piger (2012).

Evidence for a Phillips Curve relationship between the model-averaged output gap and inflation is more mixed. But the results provide a strong caution against imposing a linear relationship in estimating output gaps. Meanwhile, there are notable linkages between the model-averaged output gaps across many economies in Asia and the Pacific based on pairwise Granger Causality tests.

The estimates of output gaps in this paper were deliberately based on univariate models. But it would be interesting to see the influence of multivariate information on the estimated output gap. Also, further analysis of the Phillips Curve relationship in each economy, allowing different specifications and taking other shocks into account, would be helpful to better understand what drives inflation in each case. Finally, it is likely that the correlations between output gaps across economies have changed over time, which could be considered with a factor model with time-varying loadings (e.g., Del Negro and Otrok, 2008). But these extensions are left for future research.

Appendix

Following Morley and Piger (2012), I define the output gap, c_t, as the deviation of log real GDP, y_t, from its stochastic trend, τ_t, as implied by the following trend/cycle process:

$$y_t = \tau_t + c_t, \tag{1}$$

$$\tau_t = \tau_{t-1} + \eta_t^*, \tag{2}$$

$$c_t = \sum_{j=0}^{\infty} \psi_j \omega_{t-j}^*, \tag{3}$$

where $\psi_0 = 1$, $\eta_t^* = \mu + \eta_t$, and $\omega_t^* = \varpi + \omega_t$, with η_t and ω_t following martingale difference sequences. The trend, τ_t, is the permanent component of y_t in the sense that the effects of the realized trend innovations, η_t^*, on the level of the time series are not expected to be reversed. By contrast, the cycle, c_t, which captures the output gap, is the transitory component of y_t in the sense that the Wold coefficients, ψ_j, are assumed to be absolutely summable such that the realized cycle innovations, ω_t^*, have finite memory. The parameter μ allows for non-zero drift in the trend, while the parameter ϖ allows for a non-zero mean in the cycle, although the mean of the cycle is not identified from the behaviour of the time series alone, as different values for ϖ all imply the same reduced-form dynamics for Δy_t, with the standard identification assumption being that $\varpi = 0$.

The optimal estimate of trend for a range of trend/cycle processes as in (1)-(3), including those with regime-switching parameters, can be calculated using the regime-dependent steady-state (RDSS) approach developed in Morley and Piger (2008). The RDSS approach involves constructing long-horizon forecasts using a given time series model to capture the dynamics of the process. Importantly, the long-horizon forecasts are conditional on sequences of regimes and then marginalized over the distribution of the unknown regimes. Specifically, the RDSS measure of trend is

$$\hat{\tau}_t^{RDSS} \equiv \sum_{\tilde{S}_t} \left\{ \hat{\tau}_t^{RDSS}\left(\tilde{S}_t\right) \cdot p^M\left(\tilde{S}_t \middle| \Omega_t\right) \right\}, \tag{4}$$

$$\hat{\tau}_t^{RDSS}\left(\tilde{S}_t\right) \equiv \lim_{j \to \infty} \left\{ E^M\left[y_{t+j} \middle| \left\{ S_{t+k} = i^* \right\}_{k=1}^{j}, \tilde{S}_t, \Omega_t \right] - j \cdot E^M\left[\Delta y_t \middle| \left\{ S_t = i^* \right\}_{-\infty}^{\infty} \right] \right\}, \tag{5}$$

where $\tilde{S}_t = \{S_t, \ldots, S_{t-m}\}'$ is a vector of relevant current and past regimes for forecasting a time series, $p^M(\cdot)$ is the probability distribution with respect to the forecasting model, S_t is an unobserved state variable that takes on *N* discrete values according to a fixed transition matrix, and i^* is the "normal" regime in which the mean of the transitory component is assumed to be zero. The choice of "normal" regime i^* is necessary for identification. Meanwhile, for a given forecasting model with Markov-switching parameters, the probability weights in (4), $p^M\left(\tilde{S}_t \middle| \Omega_t\right)$, can be obtained from the filter given in Hamilton (1989). Note that the RDSS trend simplifies to the Beveridge and Nelson (1981) trend in the absence of regime switching.

In practice, the correct model for the dynamics of the time series process is unknown. Thus, following Morley and Piger (2012), I consider a range of models, as listed in the main text. The linear and nonlinear AR(p) models are specified as follows:

$$\phi(L)\left(\Delta y_t - \mu_t\right) = e_t \tag{6}$$

$$\mu_t = \mu(S_t, \ldots, S_{t-m}), \tag{7}$$

where $\phi(L)$ is p^{th} order. I consider versions of the AR(p) models with Gaussian errors (i.e., $e_t \sim N(0, \sigma_e^2)$) or Student *t* errors (i.e., $e_t \sim t(\nu, 0, \sigma_e^2)$). $S_t = \{0,1\}$ is a Markov state variable with fixed continuation probabilities $\Pr[S_t = 0 \mid S_{t-1} = 0] = p_{00}$ and $\Pr[S_t = 1 \mid S_{t-1} = 1] = p_{11}$. In the linear case, $\mu_t = \mu$, while there are three different specifications of μ_t in the nonlinear case that correspond to the BB models developed by Kim, Morley, and Piger (2005):

1. "U"-Shaped Recessions (BBU)

$$\mu_t = \gamma_0 + \gamma_1 S_t + \lambda \sum_{j=1}^{m} \gamma_1 S_{t-j}, \tag{8}$$

2. "V"-Shaped Recessions (BBV)

$$\mu_t = \gamma_0 + \gamma_1 S_t + (1 - S_t)\lambda \sum_{j=1}^{m} \gamma_1 S_{t-j}, \tag{9}$$

3. Recovery based on "Depth" (BBD)

$$\mu_t = \gamma_0 + \gamma_1 S_t + \lambda \sum_{j=1}^{m} (\gamma_1 + \Delta y_{t-j}) S_{t-j}, \tag{10}$$

where the state $S_t = 1$ is labeled as the low-growth regime by assuming $\gamma_1 < 0$. Following Kim, Morley, and Piger (2005), I assume $m = 6$. See the original study for a full motivation of these specifications.

The linear and nonlinear UC models are based on (1)-(3), with the following parametric specification of the transitory component in (3):

$$\phi(L) c_t = \omega^*_{t-j}, \tag{11}$$

where $\varpi = 0$ for the linear UC0 and UCUR models and $\varpi = \tau S_t$ for the nonlinear UC0-FP and UCUR-FP models, with the state $S_t = 1$ labeled by assuming $\tau < 0$. The shocks to the trend and cycle are Gaussian (i.e., $\eta_t \sim N(0, \sigma^2_\eta)$, $\omega_t \sim N(0, \sigma^2_\omega)$ for the UC0 and UC0-FP models and $(\eta_t, \omega_t)' \sim N(0, \Sigma_{\eta\omega})$ for the UCUR and UCUR-FP models). Given an AR(2) cycle, the covariance for the UCUR and UCUR-FP models is identified (see Morley, Nelson, and Zivot, 2003).

As mentioned in the main text, Bayesian estimates for these models are based on the posterior mode. The priors for the various model parameters are set out in Table A.1. Note that the prior for bounceback coefficient has zero mean, implying a prior mean of zero for the output gap. The prior for the mean of the transitory shock for the UC-FP models has a negative mean, but this has very little impact on the prior mean of the model-averaged output gap given the small weights on any given model. The prior on the AR coefficients clearly places them in the stationary region. Finally, the prior for the continuation probabilities is centered at 0.95 for the expansion regime and 0.75 for the other regime. This is calibrated based on the results for US data in Morley and Piger (2012).

In practice, given parameter estimates, I use the BN decomposition or, in the case of the UC models, the Kalman filter to estimate the output gap for the linear models. Note that the filtered inferences from the Kalman filter are equivalent to the BN decomposition using the corresponding reduced-form of the UC model, while the BN decomposition is equivalent to the RDSS approach in (4)-(5) in the absence of regime-switching parameters. To estimate the output gap for the nonlinear forecasting models, I use the RDSS approach or, in the case of the nonlinear UC models, the Kim (1994) filter, which combines the Kalman filter with Hamilton's (1989) filter for Markov-switching models. For the nonlinear models, I follow Kim and Nelson (1999) and Sinclair (2010) by assuming the "normal" regime $i^* = 0$, which corresponds to an assumption that the cycle is mean zero in expansions.

Finally, the MAOG is calculated as follows:

$$\tilde{c}_t = \sum_{i=1}^{N} c_{i,t} \Pr\left(M_i\right), \tag{12}$$

where i indexes the N models under consideration, $c_{i,t}$ is the estimated output gap for model i, M_i is an indicator for model i, and $\Pr\left(M_i\right)$ denotes the weight placed on model i. As discussed in footnote 9, I place equal weights on linear and nonlinear classes of models and divide those equal weights up evenly amongst the models within the classes. Given 13 linear models (five linear AR models with two types of errors and three linear UC models) and 14 nonlinear models (two nonlinear AR models with three BB specifications and two types of errors and two nonlinear UC models), the weight on each linear model is 3.9% and the weight on each nonlinear model is 3.6%.

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Table 1
Structural Breaks in Long-Run Growth Rates of Real GDP

	Sample Period	Break Dates	Sequence of Growth Regimes
United States	1947Q2-2012Q3	2002Q2	H, L
Australia	1959Q4-2012Q3		
New Zealand	1977Q3-2012Q3		
Japan	1955Q3-2012Q3	1973Q1, 1991Q2	H, M, L
Hong Kong	1973Q2-2012Q3	1988Q3	H, L
Korea	1970Q2-2012Q3	1997Q2	H, L
Singapore	1975Q2-2012Q3		
China	1992Q2-2012Q3		
India	1960Q2-2012Q1	1979Q4	L, H
Indonesia	1980Q2-2012Q3	1996Q4, 1998Q4	H, L, M
Malaysia	1991Q2-2012Q2	1997Q3	H, L
Philippines	1981Q2-2012Q2	1985Q3	L, H
Thailand	1993Q2-2012Q3		

Notes: Estimated break dates are based on Bai and Perron's (1998, 2003) sequential procedure. Breaks are significant at least at 10% level. "H", "M", "L" denote high, medium, and low mean growth regimes, respectively.

Table 2
Correlation with Subsequent 4-Quarter Output Growth

	Sample Period	AR(1) Model Output Gap	UC-HP Model Output Gap	Model-Avg. Output Gap
United States	1947Q2-2011Q3	-0.15	0.07	**-0.35**
Australia	1959Q4-2011Q3	-0.05	0.01	**-0.22**
New Zealand	1977Q3-2011Q3	0.03	0.04	**-0.17**
Japan	1955Q3-2011Q3	0.00	0.08	**-0.19**
Hong Kong	1973Q2-2011Q3	-0.05	0.05	**-0.38**
Korea	1970Q2-2011Q3	-0.03	-0.04	**-0.17**
Singapore	1975Q2-2011Q3	**-0.11**	-0.03	-0.03
China	1992Q2-2011Q3	-0.28	0.45	**-0.51**
India	1960Q2-2011Q1	-0.07	-0.15	**-0.27**
Indonesia	1980Q2-2011Q3	-0.25	**-0.44**	-0.41
Malaysia	1991Q2-2011Q2	-0.04	-0.14	**-0.29**
Philippines	1981Q2-2011Q2	-0.10	0.35	**-0.55**
Thailand	1993Q2-2011Q3	0.17	0.17	**-0.17**

Note: Bold denotes the most negative correlation for each economy.

Table 3
Correlation with Subsequent 4-Quarter Change in Inflation

	Sample Period	AR(1) Model Output Gap	UC-HP Model Output Gap	Model-Avg. Output Gap
United States	1960Q1-2011Q3	-0.13	0.33	**0.51**
Australia	1959Q4-2011Q3	0.20	0.34	**0.42**
New Zealand	1977Q3-2012Q3	-0.30	**0.25**	0.09
Japan	1971Q1-2011Q3	0.21	0.17	**0.28**
Hong Kong	1973Q2-2011Q4	-0.34	**0.31**	0.09
Korea	1970Q2-2011Q4	-0.12	0.33	**0.43**
Singapore	1975Q2-2011Q4	-0.27	**0.17**	-0.07
China	1992Q2-2011Q4	-0.23	**0.19**	-0.41
India	1989Q4-2011Q3	-0.01	0.07	**0.14**
Indonesia	2000Q3-2011Q4	0.14	0.11	**0.19**
Malaysia	1991Q2-2011Q4	-0.27	**0.30**	0.25
Philippines	1981Q2-2012Q2	-0.18	**0.43**	0.22
Thailand	1993Q2-2012Q4	0.27	**0.32**	0.23

Note: Bold denotes the most positive correlation for each economy.

Table 4
Correlation with the Unemployment Rate

	Sample Period	AR(1) Model Output Gap	UC-HP Model Output Gap	Model-Avg. Output Gap
United States	1947Q2-2012Q3	0.06	-0.16	**-0.58**
Australia	1978Q1-2012Q2	0.05	0.00	**-0.42**
New Zealand	1977Q3-2012Q3	0.05	0.13	**-0.72**
Japan	1955Q3-2012Q3	0.02	**-0.05**	-0.03
Hong Kong	1981Q4-2012Q3	-0.01	-0.07	**-0.33**
Korea	1993Q1-2012Q3	-0.11	-0.07	**-0.76**
Singapore	1987Q2-2012Q3	-0.16	0.17	**-0.48**
China	1999Q4-2012Q3	-0.26	0.25	**-0.27**
Malaysia	1997Q1-2012Q2	-0.14	-0.03	**-0.21**
Philippines	1985Q1-2012Q2	0.10	**-0.19**	-0.14
Thailand	2001Q1-2012Q3	**0.01**	0.38	0.13

Note: Bold denotes the most negative correlation for each economy.

Table 5
Correlation with Capacity Utilization

	Sample Period	AR(1) Model Output Gap	UC-HP Model Output Gap	Model-Avg. Output Gap
United States	1967Q1-2012Q3	-0.08	0.31	**0.59**
Australia	1989Q3-2012Q2	0.17	0.42	**0.65**
New Zealand	1977Q3-2012Q3	-0.33	**0.50**	0.47
Japan	1978Q1-2012Q3	0.27	0.46	**0.52**
Korea	1980Q1-2012Q3	-0.32	0.43	**0.76**
Indonesia	2003Q1-2012Q3	0.18	0.25	**0.53**
Malaysia	1999Q1-2012Q2	-0.30	**0.76**	0.64
Philippines	2001Q1-2012Q2	**-0.09**	-0.22	-0.10
Thailand	1995Q1-2012Q3	0.19	0.14	**0.52**

Note: Bold denotes the most positive correlation for each economy.

Table 6
Granger Causality Tests for Model-Averaged Output Gaps

	US	AU	NZ	JP	HK	KR	SG	CN	IN	ID	MY	PH	TH
10% Level													
US	•	✓			✓							✓	
AU		•	✓					✓	✓			✓	
NZ			•				✓	✓					✓
JP	✓			•	✓		✓					✓	
HK	✓			✓	•		✓			✓	✓		✓
KR			✓		✓	•			✓	✓	✓		✓
SG	✓		✓	✓	✓	✓	•			✓	✓	✓	✓
CN							✓	•					
IN						✓			•				
ID						✓				•	✓		
MY											•	✓	✓
PH									✓	✓		•	✓
TH					✓						✓		•
5% Level	US	AU	NZ	JP	HK	KR	SG	CN	IN	ID	MY	PH	TH
US	•	✓			✓								
AU		•	✓						✓			✓	
NZ			•				✓	✓					
JP				•	✓							✓	
HK	✓			✓	•					✓	✓		✓
KR					✓	•			✓		✓		✓
SG			✓	✓	✓	✓	•				✓		✓
CN								•					
IN						✓			•				
ID						✓				•	✓		
MY											•		✓
PH									✓			•	
TH					✓						✓		•
1% Level	US	AU	NZ	JP	HK	KR	SG	CN	IN	ID	MY	PH	TH
US	•	✓			✓								
AU		•	✓										
NZ			•										
JP				•	✓								
HK				✓	•						✓		✓
KR						•			✓		✓		✓
SG					✓		•				✓		✓
CN								•					
IN						✓			•				
ID						✓				•	✓		
MY											•		✓
PH									✓			•	
TH											✓		•

Notes: Results are based on pairwise Granger Causality tests with 2 lags of quarterly data. A checkmark denotes that the output gap in the row economy “causes” the output gap in the column economy. See the data description in the text for details on economy abbreviations. The pairwise regressions in each case are based on the shorter available sample period in Table 1.

Table A.1
Prior Distributions for Model Parameters

	Parameter Description	Model(s)	Prior
μ	Unconditional mean growth	All except UC-HP and BB	$N(1,3^2)$
γ_0	Growth in expansion regime	BB	$N(2.5,3^2)$
$-\gamma_1$	Impact of other regime	BB	$Gamma(\frac{15}{2},\frac{5}{2})$
λ	Bounceback coefficient	BB	$N(0,0.25^2)$
$-\tau$	Mean of transitory shocks in other regime	UC-FP	$Gamma(\frac{15}{2},\frac{5}{2})$
ϕ_j	AR parameter at lag j	All except UC-HP	$TN(0,(0.25/j)^2)_{[\lvert z\rvert>1,\phi(z)=0]}$
p_{00}	Expansion regime continuation probability	BB, UC-FP	$Beta(1,20)$
p_{11}	Other regime continuation probability	BB, UC-FP	$Beta(5,15)$
ν	Degree of freedom for Student t errors	All except UC	$Gamma(\frac{1}{2},\frac{0.1}{2})$
$\frac{1}{\sigma_e},\frac{1}{\sigma_\eta},\frac{1}{\sigma_\omega}$	Precision for independent shocks	All except UCUR and UCUR-FP	$Gamma(\frac{5}{2},\frac{2}{2})$
$\Sigma_{\eta\omega}^{-1}$	Precision for correlated shocks	UCUR and UCUR-FP	$Wishart(5,2\times I_2)$

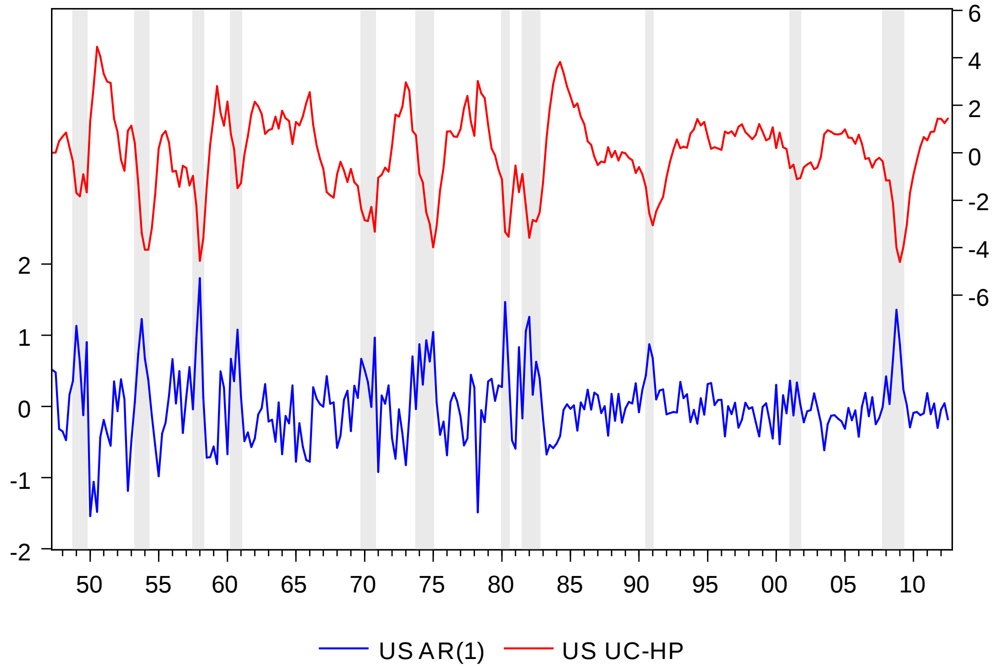


Fig. 1 – Output gaps based on competing models of US real GDP (NBER recessions shaded)

Note: The output gap for an AR(1) model for 1947Q2-2012Q3 is in blue and the output gap for a UC-HP model for the corresponding sample period is in red.

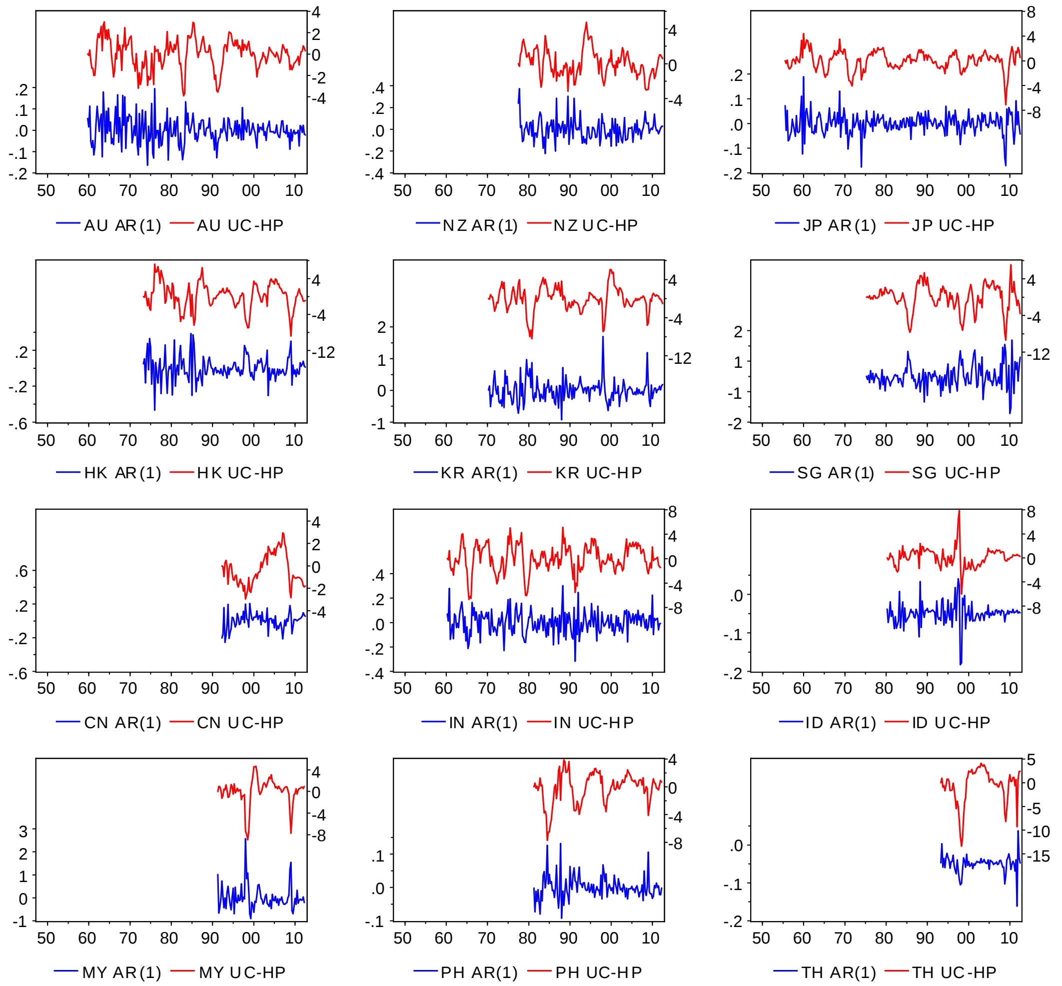


Fig. 2 – Output gaps based on competing models of real GDP for selected economies in Asia and the Pacific

Notes: From the top left and by row, the economies are Australia, New Zealand, Japan, Hong Kong, Korea, Singapore, China, India, Indonesia, Malaysia, Philippines, and Thailand. The output gap for an AR(1) model is in blue and the output gap for a UC-HP model is in red. The horizontal axis runs from 1947Q2-2012Q3. See Table 1 for details of the available sample period for each economy.

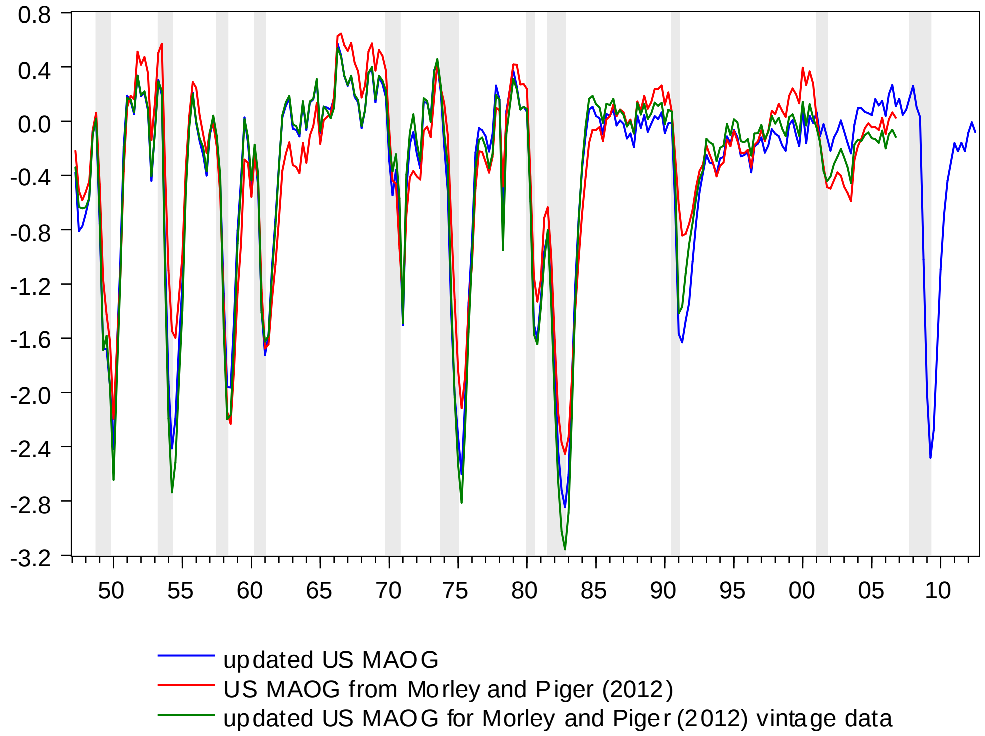


Fig. 3 – Model-averaged output gap for US real GDP for different weighting schemes, estimation methods, and sample periods (NBER recessions shaded)

Note: The model-averaged output gap for the 1947Q2-2012Q3 sample based on equal weights and Bayesian estimation is in blue, the model-averaged output gap for the vintage 1947Q2-2006Q4 sample from Morley and Piger (2012) based on BMA weights and MLE is in red, and the model-averaged output gap for the vintage 1947Q2-2006Q4 sample from Morley and Piger (2012) based on equal weights and Bayesian estimation is in green.

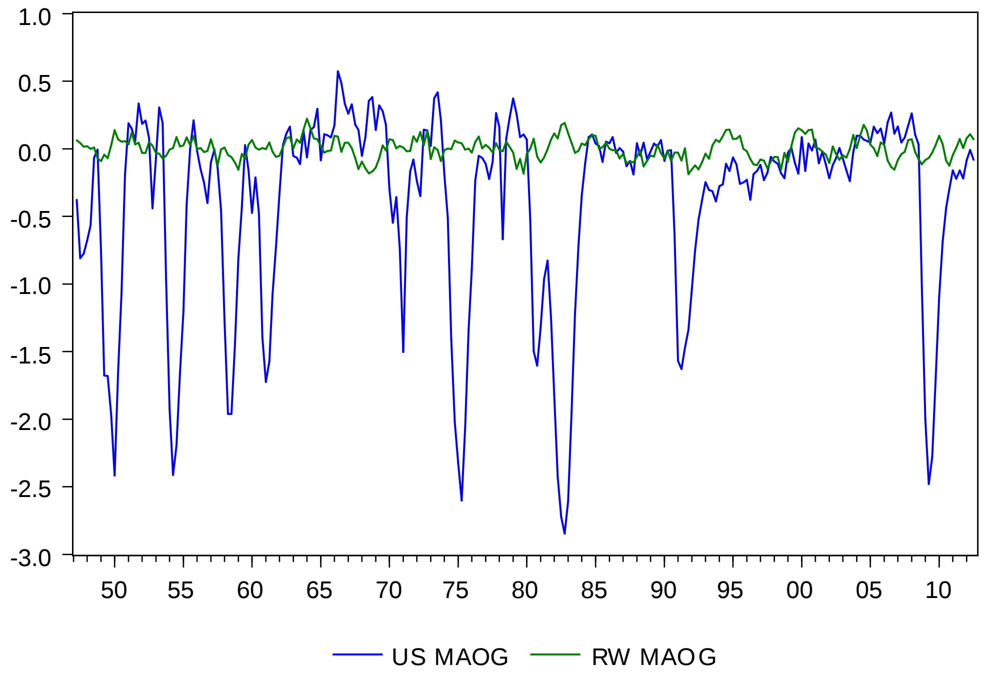


Fig. 4 – Model-averaged output gaps for US real GDP and a simulated random walk

Note: The model-averaged output gap for US real GDP for 1947Q2-2012Q3 is in blue and the model-averaged output gap for a simulated random walk of the corresponding sample length is in green.

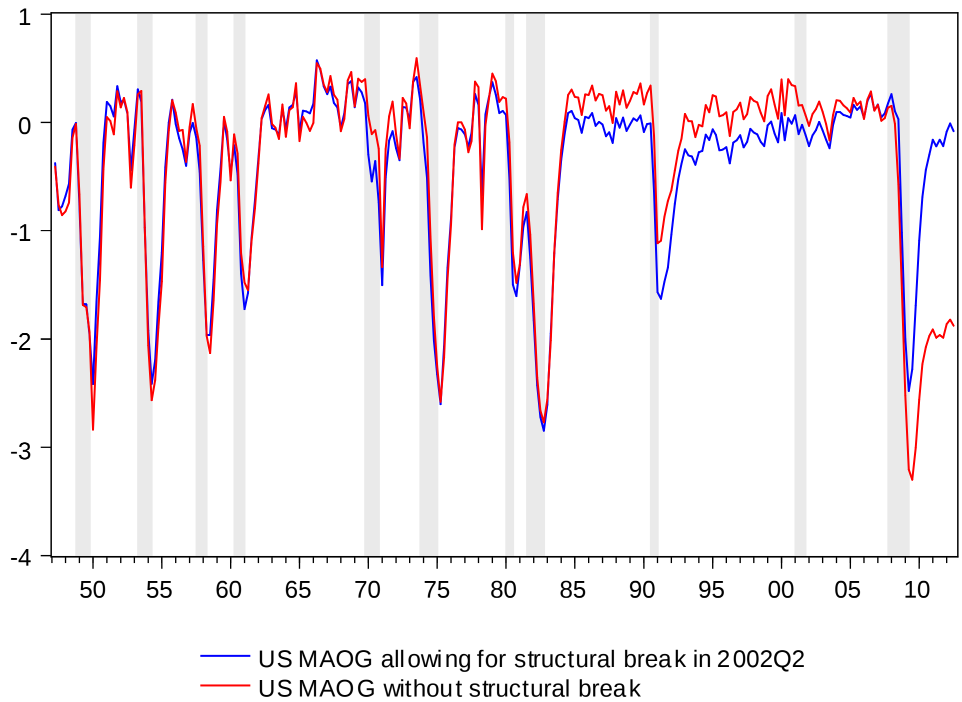


Fig. 5 – Model-averaged output gap for US real GDP with and without structural break in long-run growth (NBER recessions shaded)

Note: The model-averaged output gap for US real GDP for 1947Q2-2012Q3 allowing for a structural break in long-run growth in 2002Q2 is in blue and the model-averaged output gap for US real GDP for the corresponding sample period, but assuming no structural break is in red.

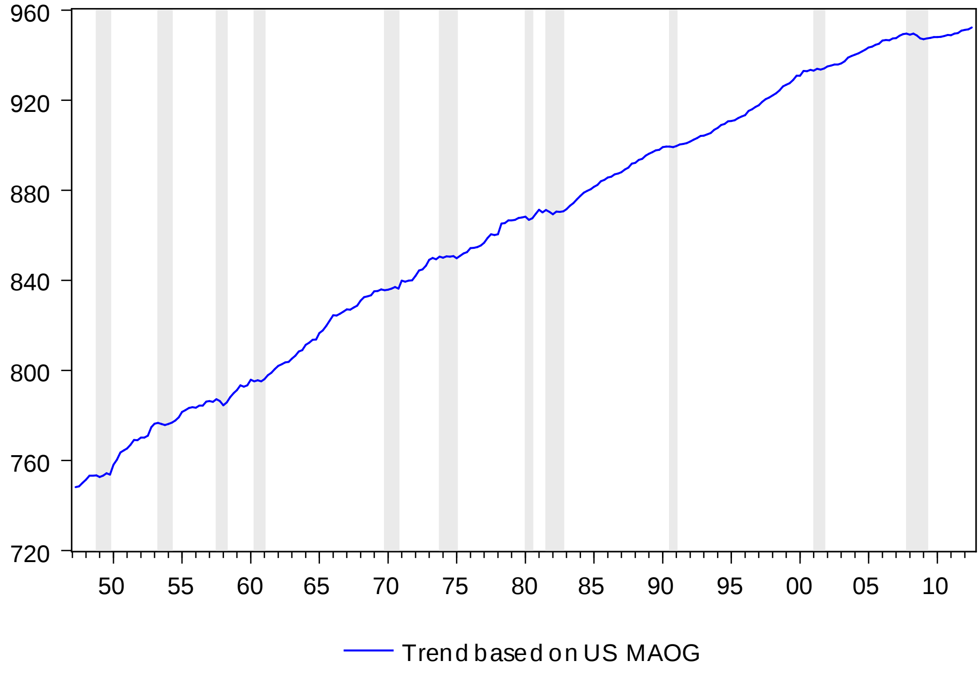
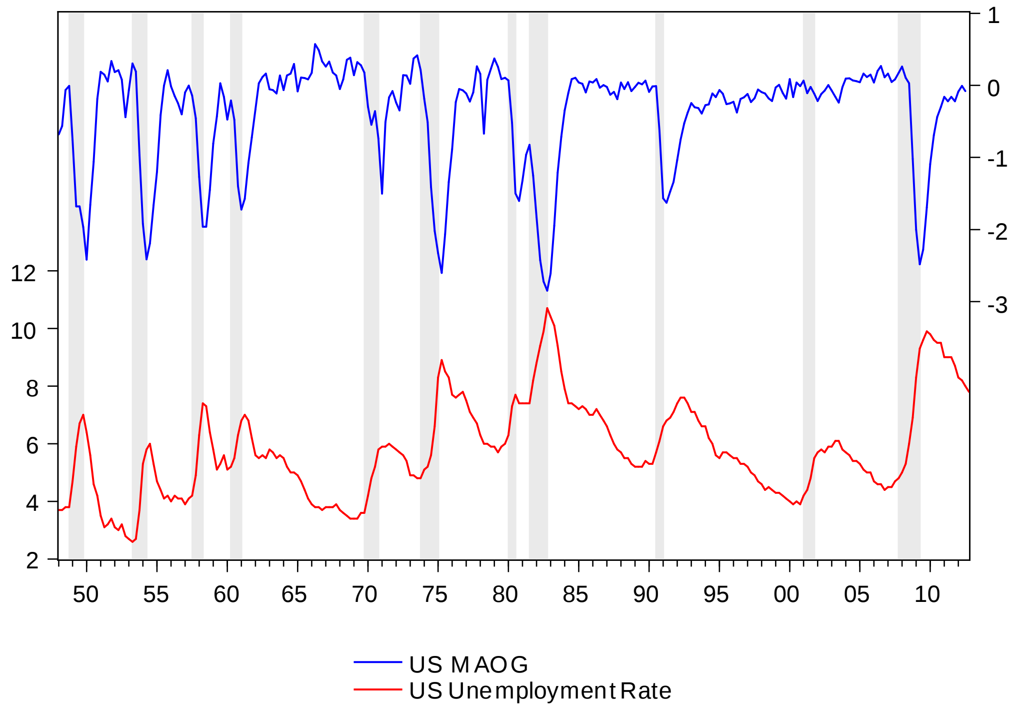


Fig. 6 – Estimated trend in US real GDP based on model-averaged output gap (NBER recessions shaded)

Note: The trend estimate is calculated as the difference between 100 times log US real GDP and the US model-averaged output gap for 1947Q2-2012Q3.



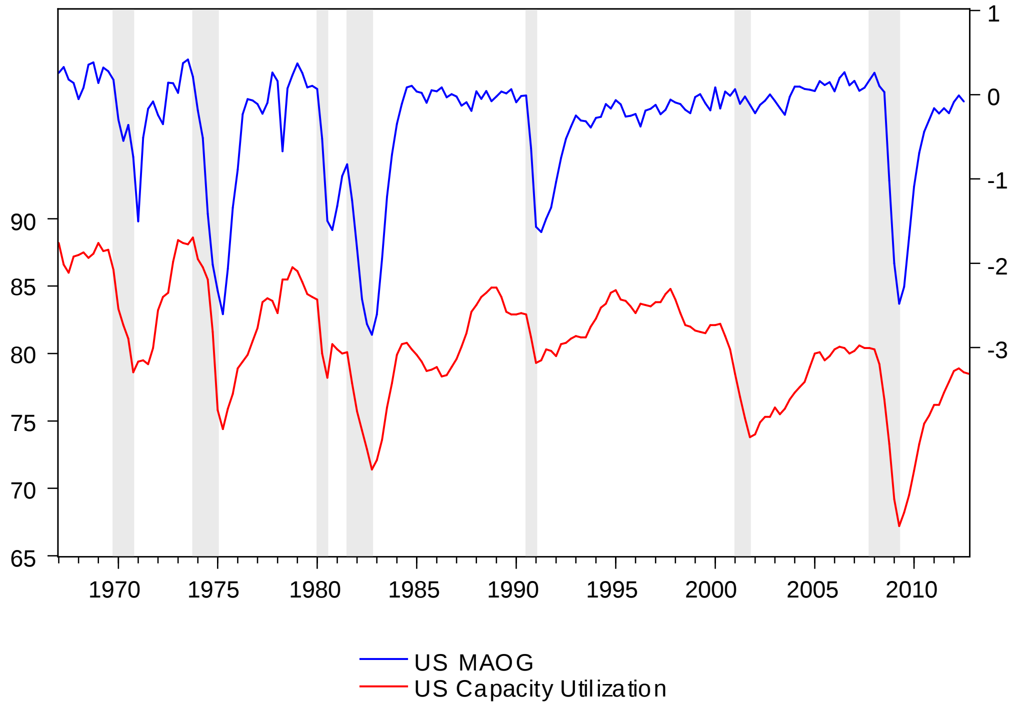


Fig. 7 – Model-averaged output gap for US real GDP and other measures of economic slack (NBER recessions shaded)

Notes: In the top panel, the model-averaged output gap for US real GDP for 1948Q1-2012Q3 is in blue and the unemployment rate for the corresponding sample period is in red. In the bottom panel, the model-averaged output gap for US real GDP for 1967Q1-2012Q3 is in blue and capacity utilization for the corresponding sample period is in red.

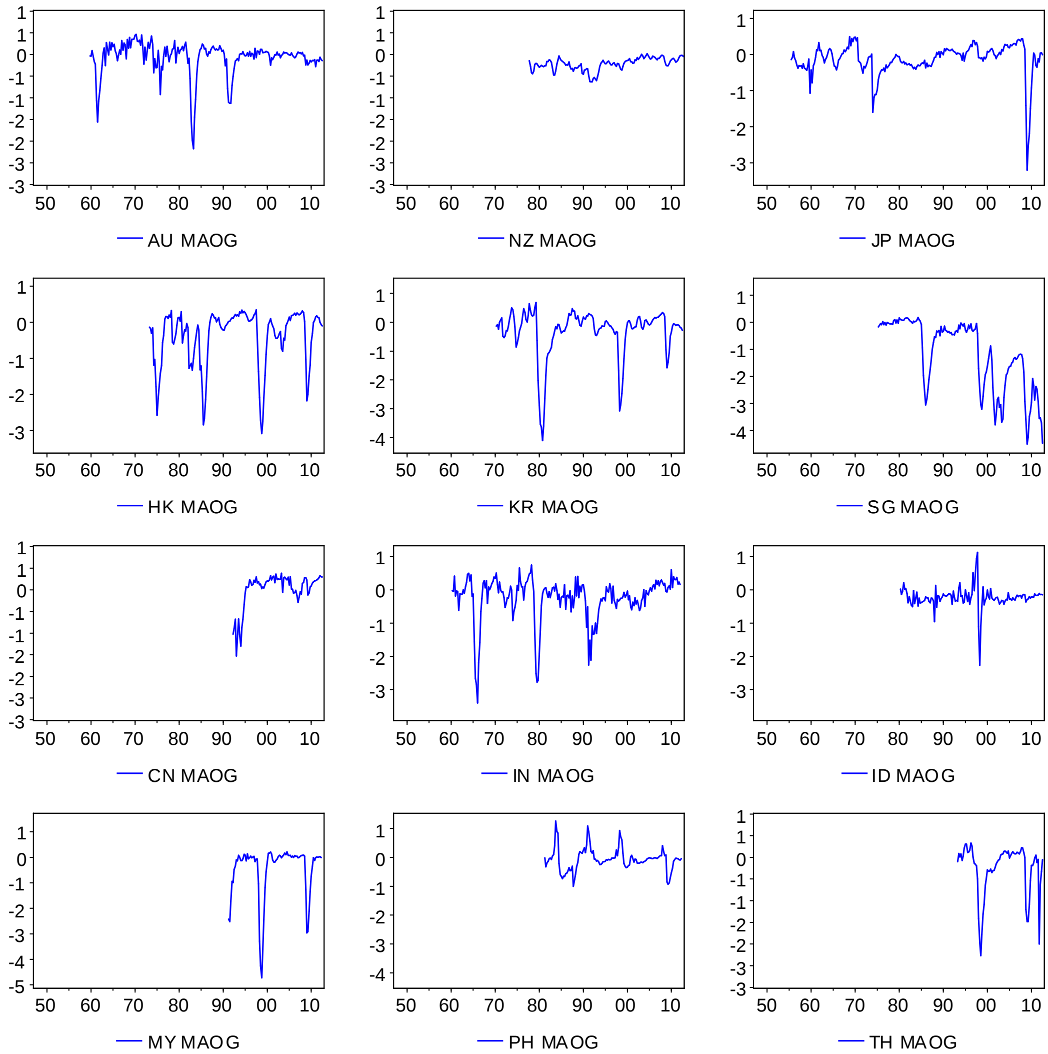


Fig. 8 – Model-averaged output gaps for real GDP from selected economies in Asia and the Pacific

Notes: From the top left and by row, the economies are Australia, New Zealand, Japan, Hong Kong, Korea, Singapore, China, India, Indonesia, Malaysia, Philippines, and Thailand. The horizontal axis runs from 1947Q2-2012Q3. See Table 1 for details of the available sample period for each economy.

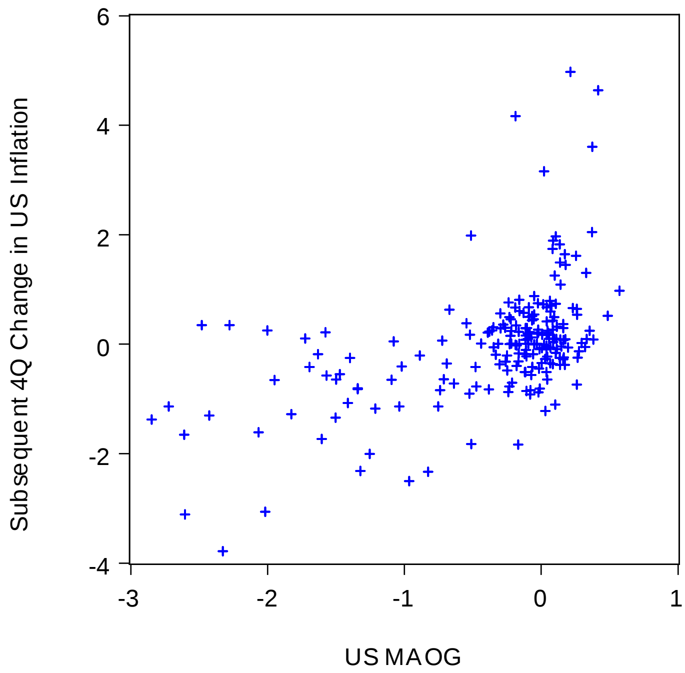


Fig. 9 – US Phillips Curve based on model-averaged output gap

Note: The scatterplot is for the sample period of 1960Q1-2011Q3 based on availability of the core PCE deflator measure of US inflation.

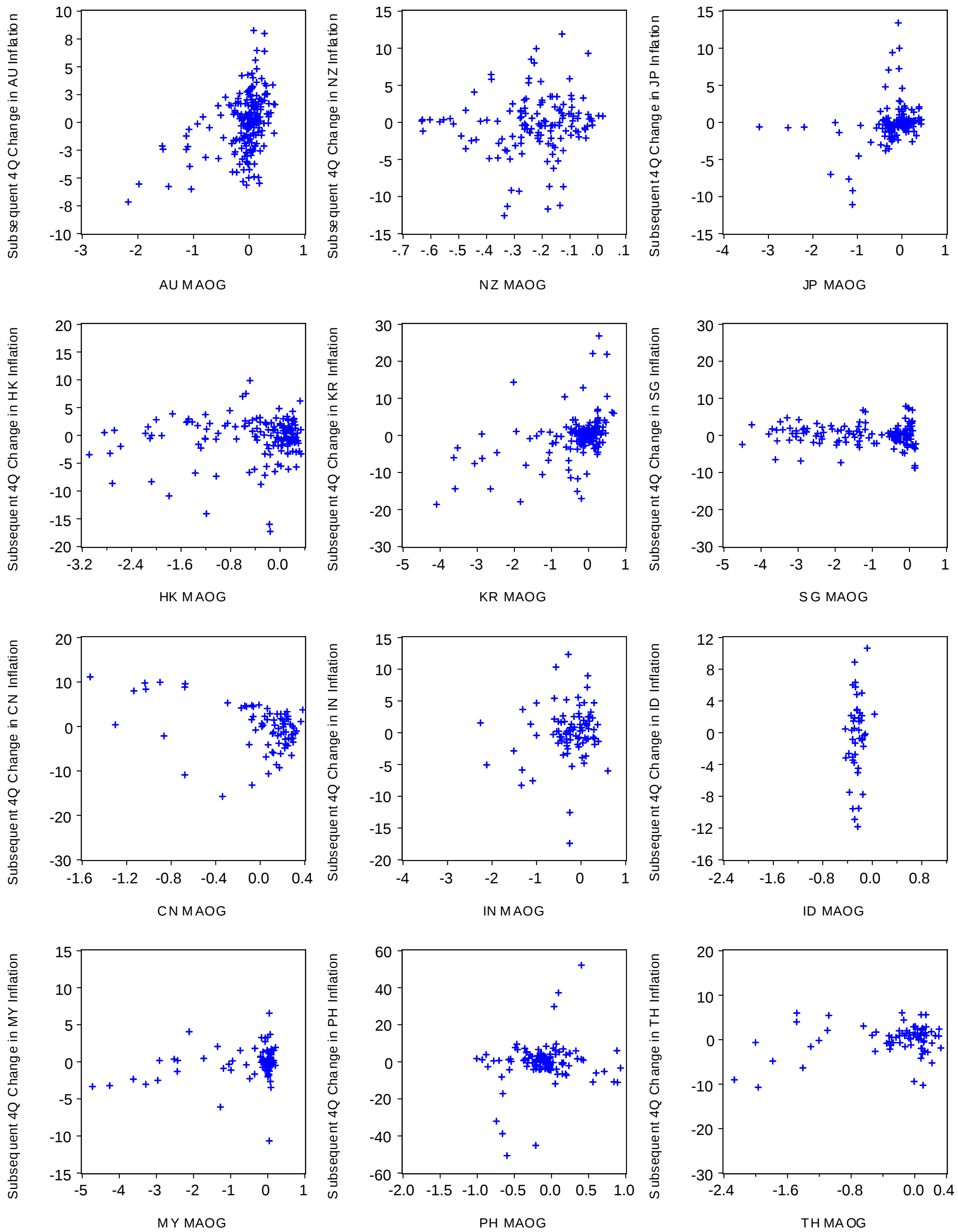


Fig. 10 –Phillips Curves based on model-averaged output gaps for selected economies in Asia and the Pacific

Notes: From the top left and by row, the economies are Australia, New Zealand, Japan, Hong Kong, Korea, Singapore, China, India, Indonesia, Malaysia, Philippines, and Thailand. See Table 3 for details of the sample period for each economy and the data description in the text for the corresponding inflation measure.